Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions

Faber, R. M.; Jonkeren, O.; de Haas, M. C.; Molin, E. J.E.; Kroesen, M.

DOI
10.1016/j.tra.2022.06.003

Publication date
2022

Document Version
Final published version

Published in
Transportation Research Part A: Policy and Practice

Transportation Research Part A 162 (2022) 282–295

Contents lists available at ScienceDirect

Transportation Research Part A

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

Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions

R.M. Faber[a,b,*], O. Jonkeren[a], M.C. de Haas[a], E.J.E. Molin[b], M. Kroesen[b]

[a] KiM Netherlands Institute for Transport Policy Analysis, Bezuidenhoutseweg 20, The Hague, The Netherlands
[b] Delft University of Technology, Faculty of Technology, Policy, and Management, Jaffalaan 5, Delft, The Netherlands

A R T I C L E I N F O

Keywords:
Multimodality
Latent class choice model
Modality style
Weather

A B S T R A C T

To inform policies aimed at more sustainable travel behaviour, previous research has investigated the concept of multimodality. The notion underlying this line of research is that increasing the degree of multimodality will lead to less car dependence and therefore more sustainable travel behaviour. This paper investigates multimodality by inferring modality styles and revealing their response to exogenous variation in the form of the weather. The main idea of this paper is that travellers with a more multimodal modality style are more sensitive to exogenous variation, and that they are therefore more likely to resort to the use of the car when 'car-favouring' conditions present themselves. The results show that the effects of weather conditions on mode choices do indeed differ between three modality styles. The identified modality styles can be summarised as (1) bike + car; (2) car mostly and (3) multimodal. For the third class, which has the highest degree of multimodality, the use of the sustainable modes is more strongly affected by weather conditions when compared to the first, less multimodal, class. The least multimodal second class meanwhile is least affected by a change in weather conditions. More multimodal travellers thus seem to be more susceptible to exogenous variation, which might prevent the formation of sustainable travel habits or patterns. Based on these results, the claim that a higher degree of multimodality will lead to more sustainable behaviour and that policy makers should aim to realise a shift towards more multimodal modality styles needs to be nuanced. Policy makers should instead focus directly on increasing the attractiveness of sustainable travel modes, which will inadvertently lead to more multimodal modality styles.

1. Introduction

With climate change becoming an ever more pressing concern, policy makers are trying to find effective climate change mitigation and adaptation strategies. As part of these efforts, sustainability is becoming a key policy objective. Sustainable policies often seek to reduce greenhouse-gas emissions and/or decrease the dependency on non-renewable resources. Sustainability is also a key objective in the field of (personal) transportation, which has popularised policies aimed at increasing the use of non-motorised travel modes.

To inform policies that seek to increase the uptake of these sustainable travel modes, recent research has focused on the concept of multimodality, which is typically defined as the degree to which a person uses multiple distinct modes within a certain time period (Nobis, 2007). Based on the (implicit) notion that multimodal travellers are more sustainable than the (strict) car user, recent research

* Corresponding author.
E-mail address: roel.faber@minienw.nl (R.M. Faber).

https://doi.org/10.1016/j.tra.2022.06.003
Received 4 July 2020; Received in revised form 29 April 2022; Accepted 16 June 2022
Available online 29 June 2022

has focused on questions whether multimodal travellers emit less CO_2 (Heinen and Mattioli, 2019b; Keskisaari et al., 2017), use the car less (Heinen and Mattioli, 2019a), and are overall more sustainable (Nobis, 2007). In general, it is found that multimodal travel patterns are more sustainable than unimodal travel patterns.

Hence, there seems to be consensus in the literature that more multimodal travel patterns are more sustainable, and therefore increasing the number of multimodal travellers should be a policy objective. This paper argues that there is also a downside to the notion of multimodality. Assuming that multimodal travellers consider the use of various travel modes (at least more deliberately than habitual unimodal travellers), it can be hypothesized that these travellers will resort to the use of the car when "car-favouring" conditions present themselves. In short, the multimodal traveller runs a higher risk of falling back into an unsustainable car using pattern. Multimodal travellers for example might be more affected by seasonal effects, where sustainable travel behaviour is only realised in seasons with more pleasant weather conditions. On the other hand, unimodal *sustainable* travellers (e.g., those who exclusively use the bicycle or public transport) may be expected to keep travelling by their respective sustainable modes even in the face of such "car favouring" conditions.

In this paper, this notion is examined by determining how travellers with different modality styles react to variations in the weather. The weather is an exogenous factor that changes the utility of different travel modes on a daily and immediate basis. Travellers with different modality styles are thus subjected to similar exogenous variation, enabling valid comparisons of the effects of these shocks. The expectation is that unimodal travellers, i.e. those with a relative high baseline utility for a single mode, will be less affected by variations in the weather conditions (temperature, wind, etc.) than those with high baseline utility for multiple modes. The former group may be expected to keep travelling with their preferred mode (due to travel habits and/or structural constraints) while the latter group may be expected to deliberately take the weather into account in their decision to either travel by car in case of inclement weather or by bicycle or public transport in case of more favourable weather.

This research adds to the literature in two ways: first, by enriching our understanding of multimodality, more specifically modality styles, by showing how people within various modality styles react to the same exogenous variation. Second, by looking at the heterogeneity within the population with respect to the effect of weather on travel behaviour using revealed preference data. Both strands of the literature and these contributions are discussed in more depth in the next section of this paper.

To attain these objectives, a latent class discrete mode choice model is estimated using revealed preference data, in which alternative specific constants (ASC) of the considered modes and the parameters related to weather are freely estimated across the classes, while all other parameters (e.g., related to trip characteristics) are kept constant across the classes. Freely estimating the ASCs enables the effective capture of the existing multi- and unimodal preference profiles in the population. Freely estimating the weather parameters captures each latent group's sensitivity to the effects of the considered weather variables. To estimate the model, revealed preference data from the Netherlands Mobility Panel (MPN) are used. The MPN is a longitudinal panel dataset, where respondents participate across multiple years (Hoogendoorn-Lanser et al., 2015). The MPN consists of a three-day online travel diary and multiple questionnaires pertaining to, amongst other things, socio-demographic information and mode attitudes of the respondents. Both parts are combined for this research. This research uses the first five waves of data from the MPN, which are collected from 2013 through 2017.

The remainder of this paper is organised as follows. First, previous literature on multimodality, including modality styles, and the effect of weather on travel behaviour are described. This previous literature is used to establish a conceptual model. The research methods and data are described in the section thereafter, which is followed by the results section. Finally, the main conclusions, research contributions, and practical implications are discussed.

2. Previous studies and conceptual model

This research aims to synthesize two strands of the literature: one focusing on multimodality and modality styles and another on the influence of weather on travel behaviour. The information from both strands that is relevant for this research is summarized below, followed by a synthesis and the formulation of a conceptual model.

2.1. Multimodality and modality styles

Mode choice has long been one of the cornerstones of travel behaviour research as one of the four steps in the traditional four-step approach to transport modelling (McNally, 2000). A relatively recent research stream has focused on the intrapersonal variability of mode choices, also referred to as modal variability (Heinen and Chatterjee, 2015). This is defined as the number of different modes used during some observational period. The more distinct modes are used, the more multimodal a traveller is said to be (Nobis, 2007). Note that this definition does not refer to using multiple modes during a single journey, which is defined in this literature as intermodal behaviour (Crainic and Kim, 2007).

This intrapersonal modal variability can be analysed using segmentation techniques, where many different patterns are reduced to a smaller number of segments, clusters, or classes of individuals (Ton et al., 2019). These multimodal travel segments are also referred to as modality styles, under the assumption that the observed modal variability reflects behavioural predispositions to the use of travel modes (Vij et al., 2013). These behavioural predispositions are based on latent goals, where the use of a travel mode is a means to attaining these goals. Research into modality styles has been complemented by an analysis of the relation with socio-demographics (Nobis, 2007; Olafsson et al., 2016), mobility attributes (Vovsha et al., 2013) and mode attitudes (Diana and Mokhtarian, 2009; Molin et al., 2016; Ton et al., 2019).

With respect to socio-demographics often-reported findings are that younger, higher-educated, and more urban-oriented travellers are more likely to adopt a multimodal behavioural pattern (Nobis, 2007). Research into attitudes has found that most people's behaviour is congruent with their attitudes, which means that they travel more with a mode that they have positive attitudes towards and vice versa (Molin et al., 2016; Ton et al., 2019).

To further understand the modality styles, a modelling approach can be taken, which is able to provide information about the effect of trip circumstances or mode attributes on mode choice for each modality style. The first application of this modelling approach is described in research by Vij et al. (2013). Their approach enables the distinction between two multimodal modality styles, where one is time-sensitive whereas the other is not. Two more recent studies, Prato et al. (2017) and Keskisaari et al. (2017) use a similar approach to identify relations between modality styles and mode choice probabilities. Prato et al. (2017) focus on short distance trips, as substitutions between motorised and non-motorised modes are more likely to be made for these shorter distance trips. They show that there is indeed taste heterogeneity between the different modality styles, which leads them to recognise that travellers within more multimodal modality styles are more easily swayed to move towards the use of active modes by policies. Keskisaari et al. (2017) show that the effect of travel distances on choice probabilities is heterogeneous across the modality styles they identify and go on to show that the greenhouse-gas emissions caused by the travel of the different modality styles varies considerably, partly because of the aforementioned heterogeneity.

2.2. *Influence of weather on travel behaviour*

The effects of weather on travel behaviour are discussed in the recent reviews of this literature by Böcker et al. (2013a) and Liu et al. (2017) who show that weather (forecasts) systematically alter both travel demand and mode choices. This research area is growing rapidly, partly because of the increasing prominence of climate change prompting the question what the effects of climate change on our travel behaviour might be (see e.g. Böcker et al., 2013b; Markolf et al., 2018; Mathisen et al., 2015).

Use of the active modes is generally more sensitive to weather changes than use of motorised travel (Böcker et al., 2016; Sabir et al., 2010), with public transport falling somewhere in-between. Increasing levels of rain and wind especially have negative effects on the use of active modes (Gallop et al., 2018; Rérat, 2018; Zhao et al., 2018), with a smaller positive effect on the use of the private car (Hyland et al., 2018; Liu et al., 2015; van Stralen et al., 2015). Research suggests that there is an ideal temperature for active mode use (Khattak and De Palma, 1997; Miranda-Moreno and Nosal, 2011; Wadud, 2014), with both colder and hotter (Nkurunziza et al., 2012) temperatures leading to declined travel with active modes. The exact value of this ideal temperature could vary based on the local climate and the infrastructural and cultural adjustments that have been made to suit this climate. Importantly, evidence can thus be found that all modes are affected by weather circumstances although to varying degrees (Liu et al., 2017).

The circumstances of the trip are found to moderate the relationship of weather and travel behaviour. The effect of weather is stronger for leisure trips when compared to commute trips (Cools and Creemers, 2013; Helbich et al., 2014) and varies between inner-city and more peripheral regions (Helbich et al., 2014; Miao et al., 2019; Tao et al., 2018). One thus needs to control for trip circumstances when estimating the effect of the weather on the mode choice probabilities of the different modality styles.

Finally there has been limited research into inter-individual heterogeneity within the population with respect to the effect of weather on their travel behaviour. Heinen et al. (2011) and Motoaki and Daziano (2015) both use stated preference data to show that less experienced cyclists are affected by bad weather to a greater extent than more experienced cyclists, whilst Nordbakke and Olsen (2019) show that travel habits and environmental attitudes are strongly related to weather tolerance, which they have defined as using non-motorized transport modes despite poor weather conditions.

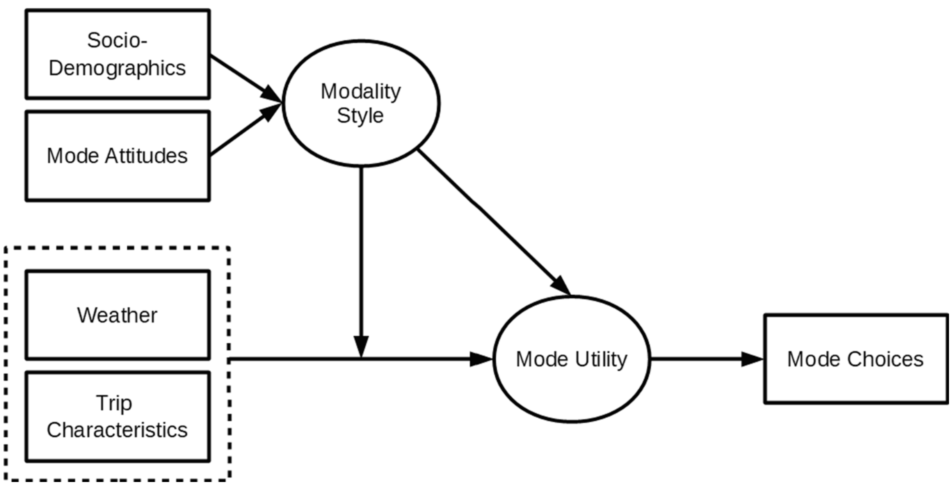

Fig. 1. Conceptual model.

2.3. Synthesis and conceptual model

The literature shows that most papers do find a sizeable effect of weather on travel behaviour. Inter-individual heterogeneity is hypothesized and investigated using stated preference (survey) data. The effect of the weather is incorporated into the conceptual model as an effect of weather variables on the utility of travel modes. To investigate the hypothesized heterogeneity this research estimates a latent class choice model. The latent classes within this model are assumed to be segments of the population with different behavioural predispositions towards travel modes. These segments can then be interpreted as modality styles (Vij et al., 2013). The modality styles then have a direct effect on a mode's utility, as a result from the behavioural predisposition towards travel modes. As a result, the latent classes both moderate the relationship between weather and utility (as hypothesized in the literature on weather and travel behaviour) and directly affect mode utility (as stated in the literature on multimodality and modality styles). Further information from the literature on multimodality and modality styles is used to identify the factors that influence the likelihood that one is a member of a certain latent class (i.e., the modality style). Both socio-demographics and mode attitudes are included as antecedents of the modality style, based on previous research findings in the literature on multimodality (amongst others Diana and Mokhtarian, 2009; Molin et al., 2016; Nobis, 2007).

The main hypothesis of this paper is that modality styles moderate the relation between weather and mode utilities, meaning that the mode choices of people with different modality styles will respond differently to the same change in weather circumstances. Heterogeneity with respect to the influence of weather on travel behaviour is then captured and explained as a result from different behavioural predispositions towards travel modes. Fig. 1 graphically presents the hypothesized relationships discussed above.

3. Research methods

In this chapter the data and methods used for this paper will be introduced and discussed. The travel data are described first, followed by a description of the weather data and the combination of both data sources. The research methods used to analyse the data are discussed afterwards.

3.1. Travel data

Travel behaviour data is obtained from the Netherlands Mobility Panel (MPN). The MPN is a longitudinal panel dataset, where respondents participate across multiple years (Hoogendoorn-Lanser et al., 2015). As the MPN is a household panel, each household member of 12 years and older is asked to participate. The first five waves of the MPN (2013–2017) are used for this analysis. Since attitudes were only recorded in waves 2 and 4 of the MPN, only people who participated in at least one of these waves are included in the analysis. In total, data from 6.715 unique respondents are used in these analyses. The MPN consists of both online questionnaires and a travel diary, where travel for three consecutive days is collected. The data for these diaries are collected yearly in the months of September through November. The trips recorded in the travel diaries are analysed using a latent class choice model. The modelling procedure is described in Section 3.3.

Table 1
Descriptive statistics for the socio-demographic variables.

Variable	Levels	Distribution (%)
Gender	Female	54
	Male	46
Employment Status	Employed	54
	Unemployed	46
Age (years)	12–39	47
	40–59	36
	60 +	17
Educational level	Low	32
	Med	37
	High	31
Urban density at residence (addresses/km^2)	<500	9
	500–1000	20
	1000–1500	22
	1500–2500	32
	>2500	17
Car owner	Yes	68
	No	32
Car driver's license holder	Yes	81
	No	19
Electric bicycle owner	Yes	12
	No	88

The observation period of the travel diaries is relevant when estimating modality styles. The shorter this period, the less likely it is that multimodal behaviour, defined as using multiple modes for travel, is observed. The five available waves are combined to get information on as many days as possible for each respondent, with a minimum of one wave equalling three days of observation and a maximum of five waves equalling 15 days spread evenly throughout the five years.

Socio-demographic variables from the questionnaire are included in the modelling as well. Gender, employment status, education, and the urban density at the residential location of the respondent are all included. Three variables relating to the availability of travel modes are included. The first two concern personal ownership of a travel mode, namely the car and the electric bicycle. Ownership of an electric bicycle is included under the assumption that use of this mode is less sensitive to weather changes due to the electric assistance meaning both wind and rain cause less discomfort. The last variable is the ownership of a driver's license. The driver's license and car ownership are included under the assumption that people who have easy access to a car are more likely to switch to this mode during inclement weather conditions. The sample distribution of these variables as recorded in the latest year of participation for each respondent is given in Table 1.

To aid in identifying and profiling the latent classes mode attitudes are included in the class membership function (see Fig. 1). These attitudes were collected as part of the questionnaire in both wave 2 and wave 4 of the MPN. For respondents who participated in both waves the attitudes from wave 4 were used. The attitudes towards travel modes are measured using six questions for each mode. Under the assumption that the response to these individual questions is caused by a latent attitude towards the travel mode in question, a factor analysis is used to determine the value of this underlying attitude for everyone. For each of the modes only one factor has an Eigenvalue larger than 1, resulting in the extraction of just this singular factor. The indicators and their factor loadings are given in Table 2.

Almost all factor loadings are higher than 0.7, whilst all loadings are higher than 0.5. The factor scores for all attitudes are thus calculated using these six items. To calculate the latent factor a weighted regression is used, and the resulting values are standardized, resulting in factor scores with a mean of 0 and a standard deviation of 1.

Travel purpose is operationalized using dummy-coding with three levels: trips made for work, trips made for one's education, and leisure trips. The last level is used as the reference in the dummy coding scheme. Of all trips, 72% are made for a leisure purpose, 22% are made for work, and 7% are made for educational purposes. Finally, alternative specific travel times for each trip are derived using the Google Maps directions API. The origin- and destination addresses of each trip, as well as the time of travel are used for input of the API, which generates alternative specific travel times. In doing so, it accounts for the public transport network and any expected congestion on the road. The API was called roughly a month after the data was collected using a date that corresponds to the day of the week on which the actual trip took place. The distribution of the alternative specific travel times is given in Table 3.

3.2. Weather data

For this paper objectively measured weather data provided by the Royal Netherlands Meteorological Institute (KNMI) are used. The dataset contains information on 45 different weather attributes, ranging from rainfall to solar radiation, as collected by 50 different weather stations placed throughout the Netherlands. Note that not all the weather stations collect all types of weather data. The data are collected every 10 min. Fig. 2 shows the locations of the weather stations.

The weather variables included in our analysis are the observed levels of temperature, wind speed, precipitation, and solar radiation. These variables are selected because of a series of (count) regression analyses, which showed that no other variables had a significant impact on the use of any of the modes included in this analysis. It is worth pointing out that data is collected during autumn in the relatively mild climate of the Netherlands, and that as such no days with snow were part of the sample.

The weather data needs to be matched to the travel behaviour data based on spatial and temporal dimensions. In doing so, we aimed at assigning weather to trips based on the weather that impacted the mode choice decision of that trip. For this data preparation process the programming language Python is used, mainly relying on the package pandas (McKinney, 2010). Code is written and tested in the JupyterLab IDE (Kluyver et al., 2016). The exact procedure is described in the following section.

The location of the trip origin is used to locate the weather station from which the weather data are read. This location is known up to the postal code area from which the trip departed. The size and spread of these postcode areas are visualized in Fig. 2. Weather data is collected from the closest weather station to the postal code area where the trip originated. If the data were not available for the weather station, the next-closest weather station is used instead. The maximum distance allowed between the trips' origin and the weather station is 30 km: if no weather station is available within this distance the trip is removed from the analysis. The average

Table 2
Questions related to mode attitudes and their factor loadings.

	Factor Loadings			
Questions	Car	Train	BTM	Bicycle
Travelling by (mode) is comfortable	0.859	0.871	0.891	0.828
Travelling by (mode) is relaxing	0.771	0.853	0.876	0.864
Travelling by (mode) saves time	0.765	0.688	0.788	0.662
Travelling by (mode) is safe	0.742	0.576	0.553	0.688
Travelling by (mode) is flexible	0.789	0.735	0.820	0.783
Travelling by (mode) is enjoyable	0.852	0.882	0.897	0.877

Table 3
Descriptive statistics for alternative specific travel times.

	Min.	Max.	Mean	Median	St. D.
Car Travel Time (min)	1	203	11.3	7	13.8
PT Travel Time (min)	1	634	30.2	21	32.5
Bicycle Travel Time (min)	1	1344	28.6	9	63.2
Walking Travel Time (min)	1	7086	124	42.2	278

Fig. 2. The locations of weather stations and the size of postal code areas in the Netherlands.

distance between trips and weather station when a connection is made varies slightly for each type of weather variable and is lowest for wind-related variables at 12.8 km and highest for cloud-related variables at 14.1 km. Daily average values are collected from each weather station, weighted by the overall number of trips made in each hour. This means that weather during the night, which has relatively little impact on travel behaviour, is not influential whilst weather during travel peak-hours is weighted more strongly. To give an indication for the weather in the Netherlands during the sampling period descriptive statistics for the weather variables as connected to the trips in the MPN are given in Table 4. The weather variables are standardized before inclusion in the model.

3.3. Modelling procedure

To analyse the effects of weather on mode choices and the differences of this effect between travellers with varying behavioural profiles a Latent Class Choice Model (LCCM) is estimated (Greene and Hensher, 2003). We only allow the alternative specific constants (ASCs) and weather parameters to vary between classes. The variation of ASC's allows for the capture of different modality styles, while the variation of the weather parameters allows for the identification of different effects that the weather has on the mode choices for each class. Since one of the objectives of this paper is to find heterogeneity specifically with regards to the effects of the weather on travel behaviour, we do not let other parameters vary across classes. This allows the latent classes to capture taste heterogeneity with respect to weather, and not for example heterogeneity with respect to travel times.

The LCCM then enables capturing taste heterogeneity within the population, essentially by estimating separate effects of one

Table 4
Descriptive statistics of weather variables.

	Min.	Max.	Mean	Median	St. D
Temperature (°C)	0.976	20.9	11.4	11.7	3.79
Wind Speed (m/s)	0.284	18.5	4.01	3.61	0.284
Rain Intensity (mm/h)	0	1.96	0.0921	0.00383	0.185
Sunshine (W/m^2)	8.40	301	107	90.4	68.9

explanatory variable on the choice probability for each latent class. These effects can be used to provide more insight into the sensitivity of different modality styles to trip circumstances, highlighting the behavioural predispositions of the different classes. Further information on the latent classes is retrieved by the estimation of class-membership probabilities for each individual respondent based on a certain set of socio-demographic characteristics.

The utility function of all LCCM classes is based on random utility maximization and uses a linear-additive MNL structure. The model varies the parameters of each latent class and the covariates of the class membership function to maximise the likelihood of the data given the model. A difficulty for latent class models in general is that the log-likelihood function is not concave, which means that the maximum likelihood estimation procedure is prone to get stuck in a local optimum. To alleviate this issue multiple sets of starting values for the parameters and covariates are used before estimating the model, which increases the odds of finding the global optimum (Bierlaire et al., 2010).

The number of classes is exogenous to the utility maximization and thus needs to be determined by the modeller. To find the optimal number of classes two criteria are used: statistical performance and behavioural interpretability. Multiple models are estimated with an increasing number of classes. After estimating the four-class model we found that it was statistically better performing than the three-class model (based on AIC, BIC, and the Likelihood Ratio Test), but that the four classes were difficult to interpret. For this reason, the three-class model has been selected.

In revealed preference data the chosen alternative is observed directly, but the other considered alternatives are not. This is a well-known problem when using revealed preference data to estimate choice models, which revolves around the fact that choice sets by their nature are mental processes, and are thus latent: it is impossible to determine the actual considered choice set using this type of survey data (Ben-Akiva and Lerman, 1985). This problem necessitates the approximation of the true considered choice set (Ton et al., 2020). This choice set is approximated using deterministic constraints, which are based on availability and consideration of a travel mode (Calastri et al., 2019). Mode availability depends on whether a traveller has access to some travel mode, irrespective of the context of a specific trip. People that do not have access to a bicycle will not have the bicycle as an available alternative for any trip. Consideration of a travel mode in contrast is trip-specific, and consideration set formation stipulates that some alternatives might not be considered for a specific trip. Despite having access to a bicycle, a traveller will not actually consider using a bicycle for a 100 km round trip for example.

One type of availability constraint is imposed on the bicycle and the car, which are only part of the choice set if at least one bicycle or car respectively is owned within the household of the respondent. There are two main consideration constraints. The first sets a maximum distance for the bicycle and for walking. These modes are not part of the choice set for trips longer than this imposed maximum distance. The maximum distance is based on the 97.5th percentile of the travelled distance using these modes rounded upwards, resulting in maximum distances of 10 km and 20 km for walking and the bicycle, respectively. The second rule looks at whether public transport is a reasonable alternative compared to the car and bicycle. Public transport is excluded for trips where it was not available (which for example is often the case for trips made during the night). It is also excluded for people who own a car if it takes either 90 min longer than the car or takes more than three times as long as the car, with a minimum of a 30-minute difference.

Finally, this research only uses trips that originate at the residence of the traveller. In almost all cases this is the location where the mode choice is made: if one travels to work by car then the decision to travel back by car is also often already made. This decision is supported by the data, which show that in a large majority of cases the mode used to depart the home is also used for all subsequent trips until one arrives back at the residence. In total, 46.259 unique trips (all departing from the residential location of the traveller) are used to estimate the choice model.

The choice model is estimated using the Apollo package (Hess and Palma, 2019a; Hess and Palma, 2019b) for the programming language R (R Core Team, 2017). We estimated MNL models with and without weather variables and 3-class LC models, both with and without weather variables. The models are specified in increasing order of complexity, where we test both in-sample and out-of-sample performance of the models. All four models are first estimated on data from waves 1 through 4 of the MPN and then tested out-of-sample on wave 5. The performance of these models is presented in Table 5 below.

Table 5
Goodness-of-fit statistics for four models, increasing in order of complexity.

	MNL (no weather)	MNL (incl. weather)	LC (no weather)	LC (incl. weather)
Within-sample fit statistics				
N	6434 individuals; 37,896 trips			
LL_0	−43421			
LL_β	−28278	−28102	−23822	−23662
LL_β per obs.	−0.746	−0.742	−0.629	−0.624
Nr. of parameters	15	27	47	83
Rho-square	0.348	0.353	0.451	0.455
AIC	56,586	56,258	47,745	47,491
BIC	56,714	56,488	48,172	48,200
Out-of-sample fit statistics				
N	2548 individuals; 8363 trips			
Hit rate	0.667	0.679	0.707	0.708
Mean(chosen)	0.571	0.574	0.591	0.594
LL_β	−6109	−6089	−5713	−5694
LL_β per obs.	−0.730	−0.728	−0.683	−0.680

We see a small, but significant improvement within-sample for the models using weather variables, both for the MNL and LC models (based on likelihood-ratio tests, p-values 0.000 for both). We also see an improvement in model performance out-of-sample for the LC models compared to the MNL models, which is important as LC models can be prone to overfitting. Finally, the LC model including weather variables performs slightly better out-of-sample than the model not including weather variables. We conclude here that the LC model including weather provides the best fit both within- and out-of sample. Since this model also allows for further behavioural insight, we think this is the preferable model. We report on the findings with this model fitted to data from all 5 MPN waves in the results section below.

4. Results

The results from the latent class choice model estimation with three latent classes are described in this section. First, the classes will be interpreted, followed by an interpretation of the effects of the weather variables on the mode choices for each latent class.

The modality styles can be interpreted straightforwardly by using the estimated choice probabilities for each mode in average weather conditions. These choice probabilities are based on alternative specific constants, which are varied across classes, and travel time parameters, which are fixed across classes. There are also variables for the purposes of work and education which offset the alternative specific constants for these specific purposes. The alternative specific constants for each class, as well travel time and trip purpose parameters are given in Table 6.

The estimated parameters regarding travel time, given in Table 6, seem plausible, especially when taking into account that they are estimated on revealed-preference data where travel times across modes are highly correlated. The combination of the square-root and linear component create non-linear utility functions with respect to travel time. For the car and public transport the initial slope of this function is positive, which changes to a negative slope after 10 min and 34 min respectively. This can be explained given an otherwise unobserved preference to use these modes to travel greater distances. Use of both modes for example is associated with time spent getting the vehicle ready and parking it (in the case of the car) or with getting to the transit stop and potential lay-overs (in the case of public transport). Since the model does not otherwise capture this phenomenon, it is ingrained in the function with respect to travel time (by including both the linear and square-root component).

To obtain a more intuitive picture as to how the different classes are affected by travel time and trip purpose, we calculated the choice probabilities for certain trips. Table 7presents the choice probabilities for leisure, work, and educational trips at both the mean and median travel distances and travel times (see Table 3 for these values). The weather conditions here are assumed to be average, meaning that the standardised values are set to 0 and the weather parameters thus have no effect on the estimated probabilities. These choice probabilities under average weather conditions are used for a first interpretation of the modality style of each class.

The estimated probabilities are given in Table 7 and show three distinct patterns. The estimated probabilities for class 1 point to the use of either car or bicycle for almost all trips during average weather circumstances. Depending on the travel distance (and associated travel times) and travel purpose, either the car or the bicycle is most likely to be used. Class 2 is the most unimodal, with remarkably high estimated probabilities for the use of car under all circumstances. Only educational trips are relatively multimodal for this group, although the estimated probability for car is still very high compared to the other two classes. The choice probability estimated for Class 3 are much more mixed and vary more across the travel distances and travel purposes. This class is the most multimodal. When travel times are smaller, this class shows sizeable shares of walking, whereas both other classes' walking share is close to zero for nearly all trips. PT share is also higher than for the other two classes, especially for non-leisure trips.

These findings are complemented by an interpretation of the class-membership model, which shows how mode attitudes and socio-demographics impact the likelihood of being a part of a class. The class-membership parameter estimates are given in Table 8.

These class-membership parameter estimates show us a couple of interesting things. First, one can see that there are more people in classes 1 and 2 compared to class 3 based on the delta values. In total, 45% of people are assigned to class 1, whereas 39% and 16% are assigned to classes 2 and 3, respectively.

Second, mode ownership and mode attitudes have a significant effect on the class-membership probabilities. This result is to be expected, if the latent classes are to be identified as modality styles. People who own a car or a driver's license are much more likely to be part of class 2, whereas people who own an e-bike are more likely to be part of class 1. More positive bicycle and car attitudes

Table 6
Estimated non-weather parameters.

<table>
<tr><th></th><th>Car</th><th>PT</th><th>Bike[a]</th><th>Walk[a]</th></tr>
<tr><td>Constant across classes</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Square Root Travel Time</td><td>1.108***</td><td>1.371***</td><td colspan="2">−0.865***</td></tr>
<tr><td>Travel Time</td><td>−0.1788***</td><td>−0.118***</td><td colspan="2">0.0140***</td></tr>
<tr><td>Purpose (work)</td><td></td><td>1.218***</td><td>1.508***</td><td>−0.008</td></tr>
<tr><td>Purpose (education)</td><td></td><td>3.318***</td><td>3.249***</td><td>1.361***</td></tr>
<tr><td>Alternative Specific Constants</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Class 1</td><td></td><td>−5.62***</td><td>4.72***</td><td>4.52***</td></tr>
<tr><td>Class 2</td><td></td><td>−7.80***</td><td>1.39***</td><td>3.12***</td></tr>
<tr><td>Class 3</td><td></td><td>−3.69***</td><td>3.09***</td><td>6.04***</td></tr>
</table>

Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001.

a. One parameter per travel time component is estimated for bike and walk simultaneously.

Table 7
Estimated choice probabilities of travel modes in average weather conditions.

	Class 1				Class 2				Class 3			
	Car	PT	Bike	Walk	Car	PT	Bike	Walk	Car	PT	Bike	Walk
Trip Purpose	Median values (travel distance = 3 km)											
Leisure	0.35	0.01	0.62	0.02	0.91	0	0.06	0.03	0.48	0.1	0.17	0.25
Work	0.11	0.01	0.87	0.01	0.75	0.01	0.22	0.02	0.26	0.19	0.41	0.13
Education	0.02	0.02	0.96	0.01	0.35	0.03	0.58	0.04	0.06	0.33	0.5	0.11
	Mean values (travel distance = 9.1 km)											
Leisure	0.75	0.03	0.22	0	0.98	0	0.02	0	0.75	0.18	0.04	0.02
Work	0.41	0.05	0.54	0	0.94	0.01	0.05	0	0.47	0.39	0.13	0.01
Education	0.1	0.1	0.8	0.	0.72	0.08	0.2	0	0.11	0.72	0.16	0.01

Table 8
Class-membership parameter estimates.

	Class 2	Class 3
Delta	−1.18***	−3.30***
Male	−0.09	−0.06
Age	0.13***	0.17***
Employed	0.62***	0.03
Education	−0.02	0.11**
Urban Density	−0.08*	0.25***
Owns E-bike	−0.41**	−0.40
Owns Car	0.96***	0.19
Owns Driver's License	1.76***	0.12
Car Attitude	0.51***	0.10
Train Attitude	−0.28***	−0.10
BTM Attitude	0.17**	0.41***
Bike Attitude	−1.07***	−0.73***

Class 1 is the reference alternative. The parameters for this class are fixed to zero.
Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001.

increase the likelihood of the respondent being part of classes 1 and 2, respectively. Attitudes towards public transport are a bit more ambivalent, with local transport (Bus, Tram and Metro) attitudes leading to increased probability of being part of class 3 while train attitudes mostly result in an increased probability of being part of class 1. In summary, the mode attitudes and ownership variables are congruent with the observed mode choice behaviours as given in Table 7.

The above analyses lead to the conclusion that the latent classes identified by the model can be described as modality styles, conform the expectations set out in the conceptual model. The classes are all a different modality style. The interpretations given to the classes in the remainder of this paper are as follows: class 1 is 'bike + car', class 2 is 'car mostly', and class 3 is multimodal.

The objective set out in the introduction of this paper is to find whether these modality styles moderate the effect of the weather on travel behaviour. To meet this objective, the weather parameters need to be analysed. These weather parameters are given in Table 9.

Two different methods are used to illustrate the effects of the parameter estimates. First, the model-level elasticities of travel time and weather are given. This serves to illustrate the relative effect of weather variables compared to travel time according to the model. Afterwards, we show the estimated choice probabilities for each class under various weather conditions to interpret the different

Table 9
Parameter estimates for the effect of weather on travel mode utility.

Class		PT	Bike	Walk
1: Multimodal	Temperature	0.068	0.101**	0.049
	Wind	0.010	−0.044	0.062
	Rain	0.157**	−0.134***	−0.089*
	Solar Radiation	0.152*	0.110**	0.091
2: Bike + Car	Temperature	0.101	0.123***	−0.111
	Wind	0.106	−0.089	−0.084
	Rain	−0.048	−0.073	0.018
	Solar Radiation	−0.119	0.053	0.138
3: Car mostly	Temperature	−0.132	0.389**	0.162
	Wind	0.109	−0.394***	−0.276***
	Rain	−0.153*	−0.142*	−0.109
	Solar Radiation	0.057	0.033	−0.174*

The car is the reference alternative. The parameters for this mode are fixed to zero.
Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001.

effects of weather for each class. The model-level elasticities for travel time for each of the four modes and for the four weather variables are given in Table 10. These elasticities are calculated by separately increasing the respective values of each variable by 10% and then letting the model estimate new predictions. The natural log of the summed difference between the predicted likelihoods of choosing an alternative before and after changing these values by 10% are then divided by the natural log of 1.10 to get the elasticities presented in Table 10.

A few conclusions can be drawn based on the elasticities. First, the elasticities of travel time look relatively good and are generally compatible with values often found in the literature. There is one exception, namely the travel time elasticity of car. The effects of car travel time on mode choice for the active modes is in the wrong direction, and the elasticity of car-use on car travel time is relatively low. The model is unable to effectively disentangle the effects of these travel times because of the high correlations between car and active mode travel time in the revealed preference data we used. Second, most weather elasticities seem to be about one order of magnitude smaller than the travel time elasticities. There are some exceptions, namely the elasticity of bicycle w.r.t. temperature (0.15) and the elasticity of public transport use w.r.t. wind (0.17). These values indicate that the effects of the weather are comparatively small compared to the effects of travel time, which is in-line with general expectations.

Now the varying effects of the weather on mode use for the three different modality styles can be analysed, which is done by showing the estimated choice probabilities for each class under various weather conditions. This allows for an easy interpretation of the effect of the weather on the mode choice behaviour of each latent class. Reference weather scenarios are used to calculate these choice probabilities. The weather scenarios are realistic (if for some scenarios extreme) weather patterns for the weeks in which the data were collected, namely late Summer – Autumn in the Netherlands. The reference weather scenarios and the choice probabilities in these scenarios are given for a commute trip with median travel times in Table 11. When interpreting this table, one should keep in mind that this is a relatively short trip and thus that bicycle and walking mode shares are relatively high.

Interpreting Table 11, one can first see that the weather can have a sizeable effect on predicted travel demand, especially for the active modes. However, the effects of travel time and travel purpose variations on predicted choice probabilities, as seen in Table 7, were larger and more varied. This is in-line with the elasticities reported earlier in Table 10. Second, on a general level the results show that temperature and solar radiation have a positive effect on the use of active modes, whilst wind and rain negatively affect the shares of these modes, again mostly congruent with the elasticities.

Finally, we can see that the effect sizes of the weather variables vary markedly across the classes. The effect on public transport use is greatest by far for the multimodal class, which makes sense given the fact that this class uses public transport (much) more frequently than the other classes. In general, the relative stability of predicted choice probabilities for both the 'bike + car' and 'car mostly' classes contrast sharply to the variation that can be seen for the multimodal class. The effect is clearest for the two most extreme days given here. For the rainstorm day, the predicted use of the bicycle is reduced from 0.41 to 0.04 for the multimodal class, which is accompanied by an increase of the car share from 0.26 to 0.66. The bike + car segment also sees a decrease of the bike share, but it is relatively much smaller (from 0.87 to 0.63). On the other end of the weather spectrum, warm and sunny weather induces multimodal travellers to use the bicycle more often (0.41–0.74), an effect that is decidedly smaller for both the 'bike + car' (0.87–0.92) and the 'car mostly' (0.22–0.31) modality styles. The latent classes, earlier identified as modality styles, thus clearly moderate the effect of the weather on travel behaviour. The more multimodal third class is most sensitive to weather effects, whereas the least multimodal second class is least sensitive to weather effects.

5. Conclusion & discussion

This paper set out to investigate whether travellers with a more multimodal modality style are more sensitive to changes in the weather circumstances of their travels. This idea is investigated using a latent class choice model, which estimates separate effects of the weather for different parts of the population, segmented by modality style.

The results show that the effects of weather conditions on mode choices do indeed differ between three identified modality styles, that is, (1) bike + car; (2) car mostly and (3) multimodal. For the more multimodal third class, the use of the sustainable modes is more strongly affected by weather conditions when compared to the first, less multimodal class. Inclement weather (wind, rain) has a much greater impact on the use of the bicycle for the third class. Simultaneously, the least sustainable second modality style, which mostly consists of car use, is also affected to a lesser extent by weather conditions. More pleasant weather conditions are for the most part

Table 10
Model-level elasticities of mode shares with respect to travel times and weather variables.

	Car	PT	Bike	Walk
Travel Time				
Car	−0.049	0.72	−0.0033	−0.073
PT	0.048	−0.50	0.000	−0.011
Bike	0.18	0.28	−0.40	0.16
Walk	0.093	0.10	0.016	−0.90
Weather				
Temperature	−0.06	−0.17	0.15	−0.041
Wind	0.038	0.17	−0.069	−0.023
Rain	0.010	0.017	−0.018	0.0020
Solar Radiation	−0.027	0.053	0.037	−0.017

Table 11
Estimated choice probabilities for a median distance commute trip under various weather conditions.

	Weather				Class 1: Bike + Car				Class 2: Car Mostly				Class 3: Multimodal			
	Temp (°C)	Wind (m/s)	Rain (mm/h)	Sun (W/m^2)	CR[1]	PT[1]	BC[1]	WK[1]	CR[1]	PT[1]	BC[1]	WK[1]	CR[1]	PT[1]	BC[1]	WK[1]
Mean	11.4	4.01	0.092	107	0.11	0.01	0.87	0.01	0.75	0.01	0.22	0.02	0.26	0.19	0.41	0.13
Rainstorm	10	15	1.5	25	0.35	0.01	0.63	0.01	0.89	0.01	0.08	0.02	0.66	0.26	0.04	0.04
Overcast	10	3	0	10	0.12	0.01	0.86	0.01	0.76	0.01	0.21	0.02	0.24	0.17	0.41	0.18
Wind, Rain	10	7	1	100	0.22	0.01	0.76	0.01	0.83	0.01	0.14	0.02	0.5	0.21	0.19	0.1
Near freezing	2	4	0	100	0.13	0.01	0.85	0.01	0.79	0.01	0.17	0.03	0.33	0.35	0.21	0.12
Mild, clear	15	2	0	150	0.09	0.01	0.9	0.01	0.71	0.01	0.27	0.02	0.17	0.11	0.6	0.12
Warm, sunny	20	2	0	250	0.06	0.01	0.92	0.01	0.66	0.01	0.31	0.02	0.12	0.07	0.74	0.08

1: CR = Car, PT = Public Transport, BC = Bicycle, WK = walk.

unable to entice people within this segment to use more sustainable modes.

These findings have several research implications, both for the literature on weather and travel behaviour and for the literature on multimodality. This paper has uncovered heterogeneity with respect to the effect of weather on travel behaviour on the level of the individual traveller using revealed preference data. This is to the best of our knowledge the first paper to do so, complementing similar findings on stated preference data by Heinen et al. (2011) and Motoaki and Daziano (2015). Simultaneously we are able to effectively capture modality styles using latent class choice models, which has only rarely been done before (for example by Vij et al., 2013). This approach enables us to provide more behavioural insight into the modality styles compared to the more often used clustering approaches, as behavioural parameters can be estimated for each group. This allows us to not only use the mode choices as indicators of modality styles, but also to see (and ideally, understand) how these mode choices came to be. In other words, the ability to capture modality styles in choice models allows us to show and explain intra-personal heterogeneity in mode choice behaviour and link that heterogeneity to the modality style.

The findings reported in this paper shed a new light on the concept of multimodality, as they suggest that multimodality should not be the primary goal of transport policies. More multimodal travellers are less likely to keep using sustainable modes after exogenous variation has decreased the utility of these modes, in contrast to less multimodal travellers. On the other hand, more multimodal travellers are more likely to use sustainable modes if exogenous variation increases the utility of these modes. To make matters more concrete, from the perspective of sustainability, the less multimodal 'bike + car' group can be preferable compared to the multimodal segment, especially for people who travel relatively shorter distances. In our view, policy makers should thus not focus as much on the concept of multimodality. Rather, they should make more sustainable travel modes more attractive and focus on decreasing unimodal car use. The concept of multimodality thus can still be useful, but it should be applied with more reference to the actual sustainability of the modes in question and the behavioural change that leads to the more multimodal travel pattern.

There are two other, slightly more speculative practical implications of this paper. First, we find that more experienced cyclists are less susceptible to adverse weather conditions, as are people who own an e-bicycle. These results would suggest that policy makers could increase bicycle use in adverse conditions both by getting people to ride bicycles in more welcoming weather conditions first and by increasing electronic bicycle adoption. An important disclaimer here is that the direction of causality could realistically (partly) run in the opposite direction: more weather-resistant people are more likely to cycle more often and to buy an electronic bicycle. Second, our finding that the weathers effects are heterogeneous in the population could lead to more detailed forecasts of how climate change will alter travel demand. The effects of the weather are very much specific to the geographical region at hand and the specific effects of climate change are also to some extent region dependent. Our findings do however confirm once again that climate change will not only affect travel infrastructure, but also travel demand and that policy makers are advised to take this into account in planning infrastructure investments.

There are several limitations of this paper, which could be inspiration for future research. First, all choices were observed for trips during late Summer and Autumn in the Netherlands. This means that no seasonal variation was observed and that the weather range is relatively limited. Future research into inter-individual heterogeneity of the effect of weather on travel behaviour might use data from regions with more extreme climates or data from an entire year to fill this remaining research gap. Second, research could try to enumerate the effects of the weather in terms of travel costs. This would enable policy makers to understand the effects of climate change on travel demand in monetary terms, which could be useful for example in travel infrastructure appraisal. Third, this paper uses the weather as one example of exogenous variation. To further substantiate our conclusions, that certain modality styles are more sensitive to exogenous variation, other examples of exogenous variation might be used instead. Future research could use the ability to identify modality styles using latent class choice models to give more behavioural insight into the modality styles. A useful approach would be to investigate the sensitivity of different modality styles to other (not weather-related) exogenous variation in travel circumstances. Finally, future research might cross-validate findings from different methods to identify modality styles (latent class cluster analysis, latent class choice models, other clustering techniques) on a similar data set. This would provide additional robustness to findings pertaining to modality styles with any of the cross-validated methods.

Research funding

The authors received no specific funding for this work.

CRediT authorship contribution statement

R.M. Faber: Conceptualization, Data curation, Methodology, Software, Visualization, Writing – original draft. **O. Jonkeren:** Conceptualization, Supervision, Writing – review & editing. **M.C. de Haas:** Conceptualization, Data curation, Supervision, Writing – review & editing. **E.J.E. Molin:** Conceptualization, Supervision, Writing – review & editing. **M. Kroesen:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ben-Akiva, M.E., Lerman, S.R., 1985. Discrete choice analysis: theory and application to travel demand, 1st ed. MIT Press, Cambridge, Massachussets. Retrieved from https://trid.trb.org/view/274564.

Bierlaire, M., Themans, M., Zufferey, N., 2010. A heuristic for nonlinear global optimization. INFORMS J. Comput. 22 (1), 59–70. https://doi.org/10.1287/ijoc.1090.0343.

Böcker, L., Dijst, M., Faber, J., 2016. Weather, transport mode choices and emotional travel experiences. Transport. Res. Part A 94, 360–373. https://doi.org/10.1016/j.tra.2016.09.021.

Böcker, L., Dijst, M., Prillwitz, J., 2013a. Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review. Transp. Rev. 33 (1), 71–91. https://doi.org/10.1080/01441647.2012.747114.

Böcker, L., Prillwitz, J., Dijst, M., 2013b. Climate change impacts on mode choices and travelled distances: a comparison of present with 2050 weather conditions for the Randstad Holland. J. Transp. Geogr. 28, 176–185. https://doi.org/10.1016/j.jtrangeo.2012.11.004.

Calastri, C., Hess, S., Choudhury, C., Daly, A., Gabrielli, L., 2019. Mode choice with latent availability and consideration: Theory and a case study. Transport. Res. Part B 123, 374–385. https://doi.org/10.1016/j.trb.2017.06.016.

Cools, M., Creemers, L., 2013. The dual role of weather forecasts on changes in activity-travel behavior. J. Transp. Geogr. 28, 167–175. https://doi.org/10.1016/j.jtrangeo.2012.11.002.

Crainic, T.G., Kim, K.H., 2007. Chapter 8 Intermodal Transportation. In: Handbooks in Operations Research and Management Science. https://doi.org/10.1016/S0927-0507(06)14008-6.

Diana, M., Mokhtarian, P.L., 2009. Grouping travelers on the basis of their different car and transit levels of use. Transportation 36 (4), 455–467. https://doi.org/10.1007/s11116-009-9207-y.

Gallop, C., Tse, C., Zhao, J. (2018). A Seasonal Autoregressive Model Of Vancouver Bicycle Traffic Using Weather Variables. *I-Manager's Journal on Civil Engineering, 1* (4), 9–18. 10.26634/jce.1.4.1694.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: Contrasts with mixed logit. Transport. Res. Part B 37 (8), 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2.

Heinen, E., Chatterjee, K., 2015. The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. Transport. Res. Part A 78, 266–282. https://doi.org/10.1016/j.tra.2015.05.015.

Heinen, E., Maat, K., Van Wee, B., 2011. Day-to-Day Choice to Commute or Not by Bicycle. Transport. Res. Rec.: J. Transport. Res. Board 2230 (1), 9–18. https://doi.org/10.3141/2230-02.

Heinen, E., Mattioli, G., 2019a. Does a high level of multimodality mean less car use? An exploration of multimodality trends in England. Transportation 46 (4), 1093–1126. https://doi.org/10.1007/s11116-017-9810-2.

Heinen, E., Mattioli, G., 2019b. Multimodality and CO2 emissions: A relationship moderated by distance. Transport. Res. Part D 75, 179–196. https://doi.org/10.1016/j.trd.2019.08.022.

Helbich, M., Böcker, L., Dijst, M., 2014. Geographic heterogeneity in cycling under various weather conditions: Evidence from Greater Rotterdam. J. Transp. Geogr. 38, 38–47. https://doi.org/10.1016/j.jtrangeo.2014.05.009.

Hess, S., Palma, D., 2019a. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application (in press). J. Choice Modell. 32, 100170. https://doi.org/10.1016/j.jocm.2019.100170.

Hess, S., & Palma, D. (2019b). *Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application version 0.0.7 User manual*. Retrieved from www.ApolloChoiceModelling.com.

Hoogendoorn-Lanser, S., Schaap, N.T.W., OldeKalter, M.-J., 2015. The Netherlands Mobility Panel: An Innovative Design Approach for Web-based Longitudinal Travel Data Collection. Transp. Res. Procedia 11, 311–329.

Hyland, M., Frei, C., Frei, A., Mahmassani, H.S., 2018. Riders on the storm: Exploring weather and seasonality effects on commute mode choice in Chicago. Travel Behav. Soc. 13, 44–60. https://doi.org/10.1016/j.tbs.2018.05.001.

Keskisaari, V., Ottelin, J., Heinonen, J., 2017. Greenhouse gas impacts of different modality style classes using latent class travel behavior model. J. Transp. Geogr. 65, 155–164. https://doi.org/10.1016/j.jtrangeo.2017.10.018.

Khattak, A.J., De Palma, A., 1997. The impact of adverse weather conditions on the propensity to change travel decisions: A survey of Brussels commuters. Transport. Res. Part A 31 (3), 181–203. https://doi.org/10.1016/S0965-8564(96)00025-0.

Kluyver, T., Ragan-kelley, B., Pérez, F., Granger, B., Bussonnier, M., Frederic, J., … Willing, C., 2016. Jupyter Notebooks—a publishing format for reproducible computational workflows. Positioning and Power in Academic Publishing: Players, Agents and Agendas. 10.3233/978-1-61499-649-1-87.

Liu, C., Susilo, Y. O., Karlström, A., 2015. The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in Sweden. Transport Policy, 41, 147–158. 10.1016/j.tranpol.2015.01.001.

Liu, C., Susilo, Y.O., Karlström, A., 2017. Weather variability and travel behaviour–what we know and what we do not know. Transport Rev. 37 (6), 715–741. https://doi.org/10.1080/01441647.2017.1293188.

Markolf, S.A., Hoehne, C., Fraser, A., Chester, M.V., Underwood, B.S., 2018. Transportation resilience to climate change and extreme weather events – Beyond risk and robustness. Transp. Policy 74, 174–186. https://doi.org/10.1016/j.tranpol.2018.11.003.

Mathisen, T.A., Annema, J.A., Kroesen, M., 2015. The effects of weather and climate change on cycling in northern Norway. Retrieved from EJTIR Issue 15 (2), 261–273. https://brage.bibsys.no/xmlui/bitstream/handle/11250/278946/Mathisen.pdf?sequence=5.

McKinney, W., 2010. Data Structures for Statistical Computing in Python. Retrieved from. http://conference.scipy.org/proceedings/scipy2010/mckinney.html.

McNally, M. G. (2000). The Four Step Model, Handbook of Transport Modeling. In Institute of Transportation Studies and Department of Civil & Environmental Engineering. Retrieved from https://escholarship.org/uc/item/7j0003j0.

Miao, Q., Welch, E.W., Sriraj, P.S., 2019. Extreme weather, public transport ridership and moderating effect of bus stop shelters. J. Transp. Geogr. 74, 125–133. https://doi.org/10.1016/J.JTRANGEO.2018.11.007.

Miranda-Moreno, L., Nosal, T., 2011. Weather or Not to Cycle. Transport. Res. Rec.: J. Transport. Res. Board 2247 (1), 42–52. https://doi.org/10.3141/2247-06.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. Transport. Res. Part A 83, 14–29. https://doi.org/10.1016/j.tra.2015.11.001.

Motoaki, Y., Daziano, R.A., 2015. A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. Transport. Res. Part A 75, 217–230. https://doi.org/10.1016/j.tra.2015.03.017.

Nkurunziza, A., Zuidgeest, M., Brussel, M., Van Maarseveen, M., 2012. Examining the potential for modal change: Motivators and barriers for bicycle commuting in Dar-es-salaam. Transp. Policy 24, 249–259. https://doi.org/10.1016/j.tranpol.2012.09.002.

Nobis, C., 2007. Multimodality: Facets and causes of sustainable mobility behavior. Transp. Res. Rec. 2010 (1), 35–44. https://doi.org/10.3141/2010-05.

Nordbakke, S.T.D., Olsen, S., 2019. Who are most likely to adapt their travel behaviour to changes in weather conditions? A study of weather tolerance and travel behaviour in Norway. Retrieved from Eur. J. Sustain. Dev. 8 (1), 69–81. http://ojs.ecsdev.org/index.php/ejsd/article/view/766.

Olafsson, A.S., Nielsen, T.S., Carstensen, T.A., 2016. Cycling in multimodal transport behaviours: Exploring modality styles in the Danish population. J. Transp. Geogr. 52, 123–130. https://doi.org/10.1016/j.jtrangeo.2016.03.010.

Prato, C.G., Halldórsdóttir, K., Nielsen, O.A., 2017. Latent lifestyle and mode choice decisions when travelling short distances. Transportation 44 (6), 1343–1363. https://doi.org/10.1007/s11116-016-9703-9.

R Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.r-project.org/.

Rérat, P., 2018. Cycling to work: Meanings and experiences of a sustainable practice. Transport. Res. Part A. https://doi.org/10.1016/j.tra.2018.10.017.

Sabir, M., Ommeren, J. van, Koetse, M. J., & Rietveld, P. (2010). *Impact of weather on daily travel demand. Working paper, CROW Fietsberaad*. Retrieved from http://www.fietsberaad.nl/library/repository/bestanden/Sabir et al (2010a).Pdf.
Tao, S., Corcoran, J., Rowe, F., Hickman, M., 2018. To travel or not to travel: 'Weather' is the question. Modelling the effect of local weather conditions on bus ridership. Transport. Res. Part C 86, 147–167. https://doi.org/10.1016/j.trc.2017.11.005.
Ton, D., Bekhor, S., Cats, O., Duives, D.C., Hoogendoorn-Lanser, S., Hoogendoorn, S.P., 2020. The experienced mode choice set and its determinants: Commuting trips in the Netherlands. Transport. Res. Part A 132, 744–758. https://doi.org/10.1016/j.tra.2019.12.027.
Ton, D., Zomer, L.B., Schneider, F., Hoogendoorn-Lanser, S., Duives, D., Cats, O., Hoogendoorn, S., 2019. Latent classes of daily mobility patterns: the relationship with attitudes towards modes. Transportation. https://doi.org/10.1007/s11116-019-09975-9.
van Stralen, W. J. H., Calvert, S. C., Molin, E. J. E., 2015. The influence of adverse weather conditions on probability of congestion on dutch motorways. Eur. J. Transport Infrastruct. Res., 15(4), 482–500. 10.18757/ejtir.2015.15.4.3093.
Vij, A., Carrel, A., Walker, J.L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. Transport. Res. Part A 54, 164–178. https://doi.org/10.1016/j.tra.2013.07.008.
Vovsha, P., Vyas, G., Givon, D., Birotker, Y., 2013. Individual mobility attributes and their impact on modality style. Transp. Res. Rec. 2382 (2382), 132–141. https://doi.org/10.3141/2382-15.
Wadud, Z., 2014. Cycling in a changed climate. J. Transp. Geogr. 35, 12–20. https://doi.org/10.1016/j.jtrangeo.2014.01.001.
Zhao, J., Wang, J., Xing, Z., Luan, X., Jiang, Y., 2018. Weather and cycling: Mining big data to have an in-depth understanding of the association of weather variability with cycling on an off-road trail and an on-road bike lane. Transport. Res. Part A 111, 119–135. https://doi.org/10.1016/j.tra.2018.03.001.