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Multimodal travel behaviour, attitudes, and cognitive dissonance

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ABSTRACT

Multimodal travel behaviour, also termed multimodality, refers to as the phenomenon of an individual using more than one mode of transport in a given period. Studies indicate that encouraging multimodality may provide a solution to induce modal shifts towards sustainable transport. In this research, we investigate the distribution of mode-specific attitudes and attitude-mode use incompatibilities across clusters and levels of multimodality using the Netherlands Mobility Panel. We find that the most positive attitude does not necessarily correspond to the mode with the highest level of use. Attitudes towards car use are most positive, independent of the cluster membership and levels of multimodality. We also find that multimodal public transport users (compared with car-dominant users) and those with a higher level of multimodality are more likely to be attitudinally incompatible with frequently-used modes and the composition of their existing mode sets of travelling. This suggests that multimodal individuals may tend to experience cognitive dissonance with their mode use. Our findings also help uncover the psychological mechanism underlying a recent important finding that multimodal individuals are inclined to change their mode use patterns over time.

1. Introduction

In social psychology, an attitude can be defined as a latent disposition to evaluate the degree of an individual's (un)favourableness to an object (Fishbein & Ajzen, 2011). Evidence from diverse multidisciplinary backgrounds suggests that attitudes play a crucial role in the enactment of volitional behaviour (Armitage & Conner, 2001). Since the 1970s, the notion of attitudes has been increasingly invoked in studies on travel behaviour (Kroesen et al., 2017). Attitudes have been applied as, for example, latent variables in hybrid choice models (Chorus & Kroesen, 2014), indicators for market segmentation (Anable, 2005), and variables to account for residential self-selection (Cao et al., 2009).

A plethora of literature to date has investigated the relationship between attitudes and travel behaviour concerning the use of a single mode of transport (Elliott et al., 2007; Heinen et al., 2011; Kaplan et al., 2015). Several studies took into account more than one mode, but exclusively analysed their relation with the corresponding attitudes (Chorus & Kroesen, 2014; Donald et al., 2014; Kroesen et al., 2017).

In the last decade, an increasing number of studies has gone beyond the focus on exclusive mode use and sought to explore how multimodal travel behaviour, also termed multimodality, is associated with attitudes (Große et al., 2018; Hunecke et al., 2020; Mehdizadeh & Ermagun, 2018; Molin et al., 2016; Ramos et al., 2020; Ton et al., 2019). Multimodality refers to the phenomenon of an

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individual using more than one mode of transport during a given period.

Deciphering the relationship between attitudes and multimodality is important for developing sustainable mode-shift interventions. To improve transport sustainability, a desirable multimodal development is to facilitate the replacement of car use with walking, cycling, and the use of public transport in suitable trips. While increasing multimodality does not necessarily contribute to less car use (An et al., 2021b), evidence suggests that multimodal individuals tend to change their mode use over time (Heinen & Ogilvie, 2016; Kroesen, 2014). Also, individuals who are more multimodal are also more inclined to change (Heinen, 2018), more open to adopting emerging transport services (Diana, 2010), and more likely to be influenced by transport interventions (Heinen & Ogilvie, 2016). Encouraging multimodality therefore potentially provides an easier solution to induce modal shifts towards long-term sustainable transport behaviour.

Most existing studies on the attitude-multimodality relationship centre on general attitudes, such as environmental awareness (Groβe et al., 2018), political orientation (Ramos et al., 2020), and social milieus (Hunecke et al., 2020). Two studies analysed mode-specific attitudes and found that individuals in multimodal clusters, compared to monomodal clusters, held more positive or less negative attitudes towards more than one mode (Molin et al., 2016; Ton et al., 2019). A multimodal cluster herein denotes a a collection of individuals identified by latent cluster analysis; individuals in a given multimodal cluster use more than one mode of transport frequently and share a similar mode use pattern.

Applying mode-specific attitudes allowed the researchers to investigate attitude-mode use incompatibilities, which play a crucial role in evoking cognitive dissonance. Drawing on Festinger's (1957) cognitive dissonance theory, such investigations help explore an individual's potential to change their mode use. Cognitive dissonance theory defines dissonance as an unpleasant emotive state evoked by the incompatibility between relevant cognitions, e.g., enacting a behaviour yet having a negative attitude to it (Festinger, 1957; Harmon-Jones et al., 2009). The psychological discomfort experienced in the state of dissonance motivates the person to undertake dissonance reduction strategies, for example, by changing one of the cognitions (Festinger 1957).

While the studies by Ton et al. (2019) and Molin et al. (2016) did not explicitly measure psychological discomfort and cognitive dissonance, they found high levels of attitude-mode use misalignments for multimodal clusters. On this basis, they concluded that multimodal individuals tended to be attitudinally consonant with their mode use. Molin et al. (2016) defined a dissonant cluster as the cluster where the mode with the most positive attitudinal component (e.g., the convenience of driving) did not align with the most frequently-used mode across multimodal clusters. Most multimodal clusters were found to be consonant clusters. Ton et al. (2019) defined 'dissonant individuals' as those who did not use their most-preferred mode, namely, the mode with the most positive attitudinal components on average. They compared the percentage of the dissonant individuals across clusters and found that the share in 'dissonant individuals' was significantly larger for exclusive car users than for multimodal clusters.

Yet, these two studies share three limitations. First, the multimodality measures applied do not sufficiently capture the level of multimodality, which is defined as the extent to which an individual varies their mode use over a given period. The existing studies use an aggregate cluster-level measure of multimodality, i.e., latent cluster analysis. This analysis primarily focuses on which and how many modes are frequently used by individuals in each identified cluster on average, making it intuitive to the cluster-level mode-use composition of multimodality and follow-up interpretations. Nevertheless, such a measure does not provide information on mode use variability or diversity at the individual level (Heinen & Mattioli, 2019). Consequently, the relationship between attitudes and the level of individual multimodality remains unexplored.

Second, these studies apply incomplete frameworks drawn from the TPB to measure attitudes. The TPB elucidates that an attitude to a behaviour is determined by belief-based attitudinal components through their integration. An attitudinal component is the multiplication between two elements, namely, the expectancy and evaluation of behavioural outcomes. The outcome expectancy refers to the belief strength that an outcome will occur as a result of a behaviour, whilst the outcome evaluation denotes the subjective importance attached to such an outcome (Ajzen, 1985). However, the existing studies consider only outcome expectancies in measuring attitudes, which may contribute to biased measurements (Fishbein & Ajzen, 2011). Travel behaviour studies corroborated this and demonstrated that, after data was controlled for outcome expectancies, the perceived importance related to expected outcomes of travelling – the so-called 'transport priority' – was significantly associated with binary mode choices (Egset & Nordfjærn, 2019) and choices to be multimodal (Mehdizadeh & Ermagun, 2018).

Third, the adopted definitions of cognitive dissonance are limited in indicating attitude-mode use dissonance. The definitions are made based on misalignments rather than incompatibilities between mode use and attitudes, as these definitions focus on the relative intensity between attitudes, without looking into the direction of attitudes. The misalignment between cognitions corresponds to the concept of cognitive discrepancy (Harmon-Jones and Mills 2019). This concept is theoretically distinct from cognitive dissonance, which highlights the discomfort aroused by experiencing contradictory cognitions. Evidence shows that cognitive discrepancy may not necessarily lead to a strong motivation to adopt dissonance reduction strategies; these strategies may only be triggered when (strong) psychological discomfort exists (Harmon-Jones & Harmon-Jones, 2002; Jean Tsang, 2019);. Findings on cognitive discrepancy by themselves may thus be limited in indicating the potential of behavioural changes. For transport choices, attitude-mode use misalignments may not necessarily contribute to cognitive dissonance. For example, given the positive association between trip satisfaction and attitudes to modes used (De Vos, 2018), one may not sufficiently perceive discomfort for having positive attitudes to two modes, but using the less-preferred one more frequently. Dissonance would rather be awakened by situations where attitude-mode use incompatibilities are present, e.g., one (frequently) uses a mode they have a negative attitude to.

This research aims to investigate the relationship between attitudes and multimodality using the Netherlands Mobility Panel (in Dutch: MobiliteitsPanel Nederland; MPN). Addressing the identified research gaps, we first examine the association between attitudes with the level and clusters of multimodality. Second, we investigate the extent to which attitude-mode use incompatibilities are connected with multimodality. This may provide new insights into the relationship between multimodality and cognitive dissonance.

Our research could contribute to an advanced understanding of the attitudinal formation of multimodality and support developing interventions for sustainable modal shifts.

2. Research design

2.1. Data

This research uses the 2018 MPN data (Hoogendoorn-Lanser et al., 2015). The MPN is an annual household panel survey aimed to study both short- and long-term dynamics in the travel behaviour of the Dutch population. We use three MPN data sets, namely, household, individual, and travel diary data sets. The MPN collects participants' household and individual information through self-administrative questionnaires. The participants' three-day travel information is collected through computer-aided location-based travel diaries. Each participant aged 18 and over is asked to record origin and destination addresses for locations visited in the three survey days as well as the trip information for each origin–destination pair. The MPN's fieldwork lasts for eight weeks from September to November each year, to reduce the disturbance of time-related factors, such as weather conditions and national holidays. Households are assigned with different starting dates for completing the travel diary so that the number of 'starter' households could be relatively evenly distributed over time. We refer our readers to Hoogendoorn-Lanser et al. (2015) for detailed information about the MPN's survey design.

The MPN data is suitable for studying the attitude-multimodality relationship for two reasons. First, the MPN covers a relatively rich set of attitudinal variables that are directly connected with mode use. This enables us to incorporate not only the outcome expectancy but also the outcome evaluation, which has been largely overlooked in the existing literature, into measurements of attitudes. Second, this survey applies a three-day location-based travel dairy. The three-day observation helps to capture individual day-to-day variations in mode choices, whilst simultaneously reducing diary fatigue. This enables us to characterise multimodality more accurately.

Our research is restricted to individuals aged 18 and over for using travel diary data. We include 5326 individuals from 3314 households for our analyses. Our sample has an even age distribution, consisting of 33 %, 35 %, and 32 % of individuals aged 18–39, 40–59, and above 60, respectively. 55 % of the individuals are employed. Most of the individuals own a bicycle (79.7 %) or hold a public transport subscription (47.4 %). While these figures are largely representative of the Dutch population (Ton et al., 2019), our data has an underrepresentation of individuals from low-income households (18.1 %) and an overrepresentation of car owners (76 %).

2.2. Measuring attitudes

We measure individuals' mode-specific attitudes based on the TPB (Ajzen, 1985). For a given mode, we measure seven belief-based attitudinal components, and then *combine* these components as the attitude. An attitudinal component is jointly determined by the expectancy and evaluation of an outcome related to the mode use. The outcome expectancy refers to the belief strength that a given outcome will occur as a result of using the mode; the outcome evaluation denotes the subjective importance attached to the outcome. Each attitudinal component is measured as the multiplication between the expectancy and evaluation of an outcome, following Fishbein and Ajzen (2011).

We measure the outcome expectancy based on the extent to which the participants agree with statements such as 'I find travelling by car comfortable', using a 5-point Likert scale that ranges from 'strongly disagree' to 'strongly agree'. The MPN considers seven outcomes, i.e., comfort, relaxation, pleasure, flexibility, time-saving, safety, and prestige, in affective, instrumental, and symbolic aspects. Belief-based attitudinal components concerning these outcomes are revealed to be closely related to individuals' overall (un) favourability for mode use (Steg, 2005) and have been widely applied in measuring attitudes in travel behaviour studies (Bohte et al., 2009; Heinen et al., 2011). The outcomes are sequentially measured for five modes, i.e., car, walk, bicycle, bus/tram/metro (BTM), and train. The MPN combines bus, tram, and metro when presenting attitudinal questions. Despite this, a report from the Netherlands Ministry of Transport, Public Works, and Water Management (MinV&W) shows that Dutch individuals' satisfaction towards these modes are similar (MinV&W, 2010). This suggests that the integration of bus, tram, and metro services may not severely influence the robustness of our BTM attitude measurements. We measure the outcome evaluation using a 5-point Likert scale that ranges from 'very unimportant' to 'very important', with statements such as 'Travelling must be comfortable'. Following Fishbein and Ajzen (2011, p. 95), we respectively score outcome expectancy and outcome evaluation by bipolar (from -2 to $+2$) and unipolar (from 0 to $+4$) scales. For a given mode, seven belief-based attitudinal components are measured, each of which is calculated by multiplying the expectancy of an outcome by the outcome evaluation as previously explained.

We calculate mode-specific attitudes in two ways, namely, sum scoring and PCA, based on the seven belief-based attitudinal components. The sum scoring method has been applied widely to reflect an individual's overall attitude to an object in the domains of transport and social psychology (Kroesen et al., 2017; McCartan & Elliott, 2018), owing to its conciseness and high validity (Fishbein & Ajzen, 2011). However, this approach implicitly assumes that all attitudinal components carry an equal weight in underpinning an attitude, which is inconsistent with studies on the structure of attitudes (Bagozzi, 1985).

PCA has been extensively used for producing composite indices in various contexts (Nardo et al., 2005). This method maximally preserves the information contained by attitudinal components in the dimensionality reduction, and it uses factor loadings and eigenvalues to differentiate the contribution of these attitudinal components in underpinning an attitude. For each mode, we apply PCA to the seven computed attitudinal components. We extract one PC for attitudes towards car use, cycling, and the use of BTM (**Table S1** in **Supplementary Material**). The method yields two PCs when it is applied to walk- and train-specific attitudinal components. The two PCs for train use attitudes respectively capture affective and instrumental attitudinal components; those for walking attitudes differentiate time cost attitudinal components from the others. This suggests a large interpersonal difference in individuals' perceptions of walking and train use when considering different travelling outcomes. We use a variance-based weighted aggregation method, developed by Nicoletti et al. (2000), to aggregate the attitudinal components into mode-specific attitudes. **Appendix A** explains the aggregation method and the applied weights.

2.3. Characterising multimodality

We apply both data-driven approaches and continuous indices to characterise multimodality. First, we use a k-means clustering approach to distinguish clusters of multimodality. A Silhouette method is used to determine the optimal number of clusters (Rousseeuw, 1987). A higher average value of Silhouette coefficients for all objects in question indicates a higher level of intra-cluster cohesion and inter-cluster separation, and in turn, a more appropriate configuration of clusters. The input variables are the share in trip segments made by car, foot, bicycle, BTM, and train as well as the total number of trip segments travelled during the survey days. In the MPN, a trip may consist of several trip segments, which are differentiated by transfers that potentially involve modal change. In the 2018 MPN, an individual makes 9.0 trips (10.4 segments) on average. 5.5 %, 1.8 %, and 0.6 % of trips involve using more than two, three, and four modes. We consider all trip segments made by each individual, since the MPN does not collect information on mode-specific attitudes for different trip purposes.

Second, we use two continuous indices – the Objective Mobility Personal Index (OM_PI) and the Herfindahl–Hirschman Index (HHI) – to measure the level of individual multimodality, following existing studies on the level of multimodality (An et al., 2021a; Susilo & Axhausen, 2014). The OM_PI is developed based on Shannon's Entropy index, which is a well-tested index to reflect inequality (Diana & Mokhtarian, 2007). The OM_PI is an index for measuring 'real' multimodality (Diana & Pirra, 2016). Unlike some other indices, such as the Gini index and Dalton index, a higher level of multimodality will be indicated by the OM_PI when replicating modes with their corresponding intensities (i.e., replication variance) (Diana & Pirra, 2016). Consider an example of two individuals' one-week travel patterns: Individual 1 cycles ten times a day; Individual 2 cycles and drives both ten times a week. Individual 2 will be calculated to have a higher level of multimodality. The HHI is an extensively accepted measure of market concentration (Matsumoto et al., 2012). The HHI also holds the quality of replication variance and it places more wights on the concentration of modes with larger shares. This allows us to highlight habitual travel behaviour and capture the existence of a regular pattern of an individual's multimodality (Susilo & Axhausen, 2014). A higher level of multimodality can be indicated by a greater value of the OM_PI and a smaller value of the HHI. These two indices were measured as follows:

$$OM\_PI_i = \sum_{j=1}^{N} \left(S_{ij} \ln\left(1/S_{ij}\right)\left(1/\ln N\right) \right) \tag{1}$$

$$HHI_i = \sum_{j=1}^{N} \left(S_{ij}\right)^2 \tag{2}$$

where OM_PI_i and HHI_i refer to the value of OM_PI and HHI for individual *i*, respectively. *N* denotes the number of modes we considered (i.e., 5). S_{ij} is the share of trip segments made by specific mode *j*.

2.4. Analytical approaches

We use the one-way analysis of variance (ANOVA) to examine whether there are statistical differences in the mean value of mode-specific attitudes across clusters and levels of multimodality. We also examine the cross-cluster and cross-level difference in the mean value of intrapersonal variance in the attitudes between modes, using the one-way ANOVA. This allows us to look into the association between the balance of the magnitude of attitudes to various modes and multimodality. We apply the Newman-Keuls test for posthoc comparisons of the one-way ANOVA.

We then look into how clusters and levels of multimodality are associated with attitude-mode use incompatibilities. We consider individuals with three types of attitude-mode use incompatibilities: attitudinally incompatible individuals with the (i) primary mode; (ii) primary/secondary mode (iii) existing mode set. In the order we present, individuals with the former type of incompatibilities are a subset of individuals with the latter type.

An a*ttitudinally incompatible individual with the primary mode* refers to an individual who holds negative attitudes to at least one mode they used most frequently. An individual's most frequently modes are the modes accounting for the largest share in trip segments made by the individual in question. An individual may have more than one most frequently-used mode (with the same mode share). An *attitudinally incompatible individual with the primary/secondary mode* denotes the individual who holds a negative attitude to at least one mode they used most or second most frequently (unused modes are not included). An *attitudinally incompatible individual with the existing mode set* refers to the individual who has negative attitudes to at least one mode they used during the survey days. The reason for such a labelling method is that independent of mode shares, this type of incompatibilities is partially shaped by the composition of an individual's existing mode set of travelling. Following these definitions, we conduct comparisons on the percentage of individuals with attitude-mode use incompatibilities between clusters and levels of multimodality.

Finally, we adopt multivariate analyses to explore the extent to which clusters and levels of multimodality may affect the likelihood of attitude-mode use incompatibilities. For this, we apply binary logit models and set the status of incompatibility or compatibility (the reference category) as the dependent variable. For the independent variables, the clusters or levels of multimodality, which are separately included in the models, are our variables of interest. The control variables are individual socioeconomic characteristics, i.e., age, gender, household income, employment status, residential population density, the ownership of cars and bicycles, and public transport subscription status (see, **Section 3.2**). O.

Our main analyses are conducted using the sum scoring method and the OM_PI to measure attitudes and the level of multimodality, respectively. We also conduct sensitivity analyses to ensure the robustness of our results. The aforementioned analyses are repeated by using (1) PCA-based measures of attitudes; and (2) the HHI as a measure of the level of multimodality.

3. Results

3.1. Descriptive analyses

Car use accounts for the largest share of trip segments on average (0.49), followed by cycling (0.24), walking (0.21), and the use of train (0.02) and BTM (0.02) (Table 1). This suggests that Dutch people use cars and intra-city public transport less but cycle more than their counterparts in some other European countries, such as Germany (Nobis & Kuhnimhof, 2018), the UK (An et al., 2021b), and Sweden (Liu et al., 2015). Overall, 68 % of individuals use more than one mode of transport and thus are multimodal.

Attitudes towards car use are most positive on average (sum scoring-based attitudes: 20.96), followed by attitudes towards cycling (14.58), walking (12.22), train (4.06), and BTM (-1.97) (Table 1). Most individuals hold positive attitudes towards the use of cars (94 %), cycling (85 %), and walking (83 %). By contrast, only 59 % and 37 % of individuals have positive attitudes towards train and BTM use, respectively. These patterns are highly consistent for the PCA-based attitudes. Individuals are most positive for car use-specific attitudinal components (Fig. 1). Walking- and cycling-specific attitudinal components are relatively similar, although individuals are less positive for walking when considering only time-saving. Attitudinal components for the use of train and BTM are less positive than those for the other modes. BTM use-specific attitudes are least positive for pleasure, relaxation, and comfort outcomes. We refer our readers to Tables 2 and 3 in **Supplementary Material** for the detailed descriptive statistics of PCA-based attitudes and attitudinal components.

3.6 %, 8.7 %, and 12.6 % of individuals are attitudinally incompatible with the primary mode, the primary/secondary mode, and the existing mode set, respectively. Table 2 shows the share of individuals (out of all individuals) who jointly present two types of attitude-mode use incompatibilities.

3.2. Profile of multimodal individuals

We generate five clusters of multimodality using k-means clustering: (1) CAR MOSTLY; (2) BICYCLE MOSTLY; (3) WALK + CAR + BICYCLE (WCB); (4) MM BTM; and (5) MM TRAIN (Table 3). The prefix ’MM’ refers to ’multimodal’.

The *CAR MOSTLY* cluster is the largest cluster (43.9 %). Members in this cluster almost exclusively use the car, using the car on average for 86 % of trip segments. The CAR MOSTLY individuals rarely travel on foot (6 %) and by bicycle (6 %), and hardly use public transport during the survey days. The CAR MOSTLY individuals thus have the lowest level of multimodality (OM_PI: 0.16; HHI:0.83). This cluster has, compared with the other clusters, a higher percentage of males, middle-aged adults (40–59), people who are employed, people with medium household income, car owners, and individuals who live in low-density areas. Individuals in this cluster also have the smallest number of trip segments on average (8.4).

The *BICYCLE MOSTLY* cluster is the second largest cluster (23.7 %). The BICYCLE MOSTLY individuals primarily rely on the bicycle for daily transport (76 %). Members of this cluster use mostly the car and walk for the remaining trips. The BICYCLE MOSTLY cluster has the second-lowest level of multimodality (OM_PI: 0.31; HHI: 0.68). Females and bike owners are more prevalent in this cluster than

Table 1
Descriptive statistics of individuals’ mode shares and mode-specific attitudes.

	Mode shares			
	Min	Max	Mean	S.D.
Car	0.00	1.00	0.49	0.38
Walk	0.00	1.00	0.21	0.25
Bicycle	0.00	1.00	0.24	0.32
BTM	0.00	0.60	0.02	0.07
Train	0.00	0.50	0.02	0.06
Other	0.00	0.91	0.02	0.10
	Sum scoring-based mode-specific attitudes			
	Min	Max	Mean	S.D.
Car	−42.00	56.00	20.96	12.71
Walk	−52.00	56.00	12.22	12.81
Bicycle	−56.00	56.00	14.58	13.61
BTM	−56.00	56.00	−1.97	13.44
Train	−56.00	56.00	4.06	13.77

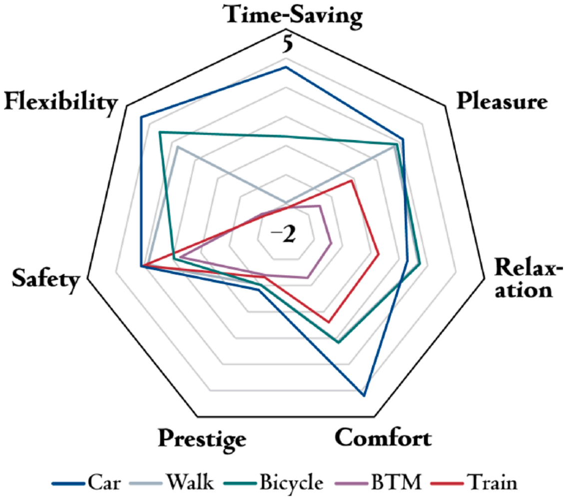

Fig. 1. Comparison of mean values of belief-based attitudinal components.

Table 2
Percentages of individuals with two types of attitude-mode use incompatibilities.

Attitudinally incompatible individuals with	Attitudinally incompatible individuals with		
	Primary mode	Primary/secondary mode	Existing mode set
Primary mode	3.6 %		
Primary/secondary mode	3.6 %	8.7 %	
Existing mode set	3.6 %	8.7 %	12.6 %

those in the other clusters.

The *WCB* cluster contains 18.8 % of the respondents. The CWB cluster largely differs from the three clusters mentioned above in that it has a higher-level mixture of walking (57 %), car use (28 %), and cycling (11 %) shares, and in turn, a higher level of multimodality (OM_PI: 0.40; HHI: 0.58). The CWB cluster contains a high share of females, the retired, the unemployed, and car owners.

The *MM BTM* cluster is relatively small (6.3 %). This cluster uses BTM the most (share: 33 %) of all clusters, but despite this, >50 % of trip segments are made by walking, cycling, or car. The MM BTM is second highest only to MM TRAIN cluster in terms of multimodality. The MM BTM cluster consists of a relatively high percentage of females, students, people living in the high-density area, individuals who do not own a car, and individuals who have a public transport subscription.

The *MM TRAIN* cluster has a share of 7.6 %. About one fifth (19 %) of trip segments are made by train. Members in this cluster also frequently use other modes, with segments made by walking, cycling, and using of the car accounting for 34 %, 25 %, 16 %, respectively. This cluster has the highest level of multimodality (OM_PI: 0.71; HHI: 0.37). The MM TRAIN cluster contains a high percentage of young adults, students, people who have a public transport subscription, residents living in a high-density area, and bike owners. Individuals in this cluster also have the largest number of trip segments on average (17.0).

3.3. Attitudes and multimodality clusters

Table 4 shows the distribution of mode-specific (sum scoring-based) attitudes across clusters of multimodality. For most clusters, individuals' attitudes towards car use are most positive. In contrast, attitudes to BTM use are the lowest in all the clusters and are only positive in the MM BTM cluster. These patterns are similar to the distribution of the individuals who have positive attitudes to given modes (results are not reported for brevity). Posthoc comparisons show that, of all clusters, mode-specific attitudes are the most positive in the cluster with the highest level of use. However, for the MM BTM and MM TRAIN clusters, modes with higher levels of use do not correspond to more positive attitudes. We also find that the variance in attitudes across modes is significantly smaller for the MM BTM, MM TRAIN, and WCB clusters than for the other clusters.

The MM BTM and MM TRAIN clusters have a larger share of attitudinally incompatible individuals with the primary mode, the primary/secondary mode, and the existing mode set (Fig. 2). By contrast, the CAR MOSTLY cluster has the smallest share of individuals with all three types of attitude-mode use incompatibilities. Binary logit models corroborate these results and show that MM BTM and MM TRAIN individuals have a higher likelihood of being attitudinally incompatible with the use of primary modes, the use of primary/secondary modes, and the composition of the existing mode set than CAR MOSTLY individuals (ORs: 5.82 to 10.48; Table 5), controlling for socioeconomic characteristics.

For attitudinal incompatibilities with primary modes, most incompatible MM BTM and MM TRAIN individuals have a negative

Table 3
Characteristics of clusters identified by k-means clustering.

	CAR MOSTLY	BIKE MOSTLY	WCB	MM BTM	MM TRAIN	Overall
N	2336	1239	1011	337	403	5326
Level of multimodality						
OM_PI	0.16	0.31	0.40	0.63	**0.71**	0.31
HHI	**0.83**	0.68	0.58	0.41	0.37	0.69
Mode share						
Car	**0.86**	0.17	0.28	0.15	0.16	0.49
Walk	0.06	0.08	**0.57**	0.46	0.34	0.21
Bicycle	0.06	**0.73**	0.11	0.11	0.25	0.24
BTM	0.00	0.00	0.00	**0.24**	0.06	0.02
Train	0.00	0.00	0.00	0.02	**0.19**	0.02
Other	0.02	0.01	**0.04**	0.02	0.01	0.02
No. trip segments	8.42	9.46	11.30	16.30	**17.00**	10.35
Age (%)						
18–39	32.6 %	28.5 %	23.8 %	50.7 %	**62.0 %**	33.4 %
40–59	**38.0 %**	35.8 %	33.7 %	24.6 %	25.1 %	34.8 %
60 and over	29.4 %	35.8 %	**42.4 %**	24.6 %	12.9 %	31.8 %
Gender (%)						
Female	48.0 %	**58.5 %**	58.3 %	57.9 %	52.1 %	53.3 %
Male	**52.0 %**	41.5 %	41.7 %	42.1 %	47.9 %	46.7 %
Employment status						
Employed	**64.0 %**	50.1 %	44.0 %	44.8 %	59.8 %	55.4 %
Student	2.0 %	6.5 %	3.4 %	24.3 %	**25.8 %**	6.5 %
Retired	17.9 %	22.7 %	**28.5 %**	15.4 %	9.4 %	20.2 %
Unemployed	16.2 %	20.7 %	**24.1 %**	15.4 %	5.0 %	17.8 %
Household income[a]						
Low	14.6 %	20.0 %	21.8 %	**23.1 %**	19.6 %	18.1 %
Medium	**51.6 %**	50.1 %	50.0 %	45.7 %	50.1 %	50.5 %
High	18.0 %	16.2 %	13.2 %	**20.8 %**	18.1 %	16.9 %
Unknown	**15.8 %**	13.6 %	15.0 %	10.4 %	12.2 %	14.5 %
Ownership						
Car	**90.9 %**	69.2 %	73.3 %	45.1 %	46.2 %	76.2 %
Bicycle	74.0 %	**89.1 %**	79.2 %	76.9 %	88.1 %	79.7 %
PT subscription	35.7 %	52.5 %	45.9 %	68.8 %	**85.1 %**	47.4 %
Residential density[b]						
Low	**36.3 %**	27.6 %	28.5 %	16.3 %	19.6 %	30.2 %
Medium	17.8 %	**19.9 %**	18.4 %	12.2 %	17.4 %	18.0 %
High	45.9 %	52.5 %	53.1 %	**71.5 %**	63.0 %	51.7 %

Note. Figures reported are mean values and percentages. Figures in bold denotes the largest value of a given variable across all clusters.
[a] Household income is categorised based on the national benchmark income (NBI): Low (<NBI (<27000 €)); Medium (1-2X NBI (27000–65000 €)); High (>2X NBI (>65000 €)). [b] Residential density: Low (<1000 inhabitants/km^2); Medium (1000–1500 inhabitants/km^2); High (>1500 inhabitants/km^2).

Table 4
Comparison of mode-specific attitudes between multimodality clusters.

Variable	CAR MOSTLY	BICYCLE MOSTLY	WCB	MM BTM	MM TRAIN	Overall
Average sum scoring-based mode-specific attitudes						
Car	**23.96**	18.10	19.49	18.23	18.27	20.96
Walk	11.03	12.65	**15.00**	10.91	11.86	12.22
Bicycle	12.11	**19.97**	14.34	10.37	16.49	14.58
BTM	−4.37	−0.74	−1.41	**5.21**	0.74	−1.97
Train	1.45	5.66	4.19	8.55	**10.18**	4.06
Average intrapersonal variance in attitudes between modes						
Variance	**159.52**	117.94	127.92	85.01	100.40	133.63

Note. One-way ANOVA shows that there are differences for each cross-cluster comparison in mode-specific attitudes at the level of 0.001. Figures in bold denote the largest value of a given variable across all clusters.

attitude to walking (shares: 63 %-73 %) (**Appendix B**). For attitudinal incompatibilities with primary/secondary modes and existing mode sets, a relatively large share of incompatible MM BTM (69 %-74 %) and MM TRAIN (46–47 %) individuals involve negative attitudes towards the use of BTM and trains, respectively.

For the sensitivity analyses, our findings remain fairly similar for the cross-cluster comparisons of attitudes, distribution of individuals with attitude-mode use incompatibilities, and results of multivariate analyses when we use PCA-based attitudes (Tables 4 and

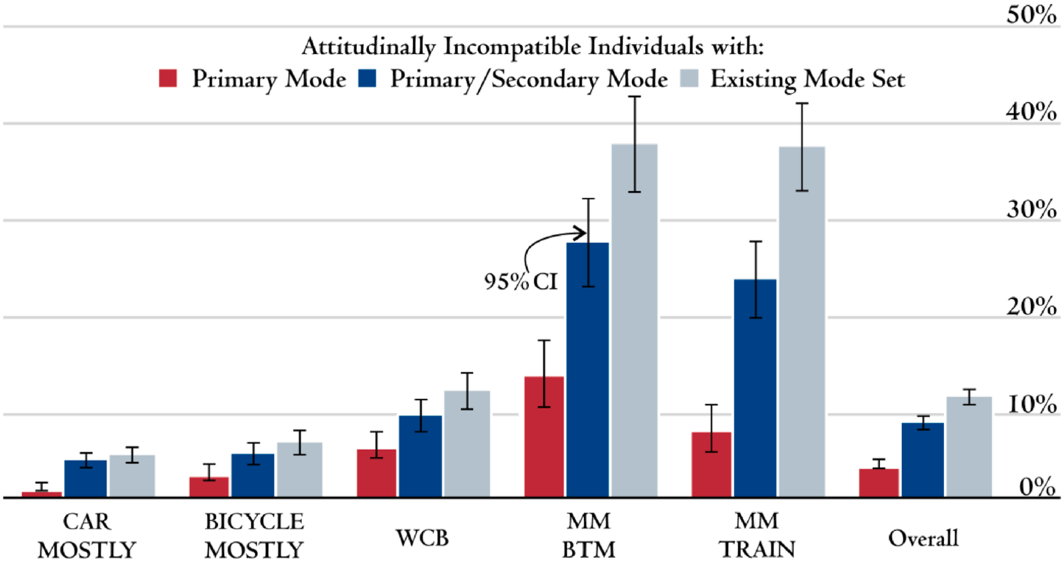

Fig. 2. Comparison of percentages of individuals with attitude-mode use incompatibilities between multimodality clusters.

Table 5
Binary logit models for effects of multimodality clusters and levels on the likelihood of attitude-mode use incompatibilities.

	Attitudinal incompatibilities with the primary mode			Attitudinal incompatibilities with the primary/secondary mode			Attitudinal incompatibilities with the existing mode set		
Multimodality	Coef	S.E.	OR	Coef	S.E.	OR	Coef	S.E.	OR
Clusters									
BICYCLE MOSTLY	0.826 **	0.274	2.284	0.110	0.177	1.116	0.212	0.161	1.236
WCB	1.529 ***	0.247	4.614	0.758 ***	0.158	2.134	0.945 ***	0.144	2.572
MM BTM	2.320 ***	0.279	10.177	2.014 ***	0.178	7.495	2.349 ***	0.264	10.475
MM TRAIN	1.761 ***	0.305	5.817	1.830 ***	0.180	6.233	2.337 ***	0.161	10.347
CAR MOSTLY (ref)									
Nagelkerke R-squared		0.133			0.142			0.208	
Levels									
OM_PI	1.320 ***	0.296	3.745	2.413 ***	0.215	11.164	3.583 ***	0.210	35.971
Nagelkerke R-squared		0.087			0.120			0.208	

Note. The dependent variable is the status of attitudinal incompatibilities or compatibilities (the reference category). Clusters/levels of multimodality are the independent variables of interest. The models are controlled for age, gender, household income, employment status, residential population density, the ownership of cars and bicycles, and public transport subscription status (see, Table 3).
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 6
Comparison of mode-specific attitudes between levels of multimodality.

Variable	Q1 (0.00)	Q2 (0.00–0.36)	Q3 (0.36–0.43)	Q4 (0.43–0.62)	Q5 (0.62–1.00)	Overall
Average sum scoring-based mode-specific attitudes						
Car	**22.55**	21.03	20.22	19.63	19.56	20.96
Walk	10.14	13.16	12.98	**14.14**	13.04	12.22
Bicycle	11.71	15.26	15.45	16.37	**17.38**	14.58
BTM	−3.72	−2.47	−1.68	−1.49	**1.45**	−1.97
Train	2.13	3.57	4.13	5.00	**7.66**	4.06
Average intrapersonal variance in attitudes between modes						
Variance	**153.76**	142.32	130.64	120.12	102.01	133.63

One-way ANOVA shows that there are differences for each cross-quintile comparison in mode-specific attitudes at the level of 0.001.
Note. Figures in bold denotes the largest value of a given variable across all clusters. Figures in parentheses denotes ranges of the OM_PI of each quintile.

5 and Fig. 1 in **Supplementary Material**). The major difference is that the percentage of the identified incompatible individuals increases slightly.

3.4. Attitudes and multimodality levels

Table 6 shows the distribution of mode-specific attitudes between levels of multimodality. Q1 to Q5 denote quintiles of the level of multimodality, with Q5 being the highest level of multimodality.

Independent of levels of multimodality, car-use attitudes are most positive. Posthoc comparisons show that individuals in the highest multimodality quintile (Q5) hold the most positive attitudes towards the use of bicycles, BTM, and train. This is in contrast to the pattern for the car-use attitude, which is the most positive in the least multimodality quintile (Q1). While walking attitude is least positive in the Q1, no significant difference is tested between higher quintiles (Q2-Q5). Our results also show that higher quintiles correlate with smaller across-mode variance in attitudes.

Higher levels of multimodality quintiles tend to have a higher share of attitudinal incompatible individuals with the primary mode, the primary/secondary mode, and the existing mode set (Fig. 3). Multivariate analyses corroborate this and show that individuals with a higher level of multimodality have a higher likelihood of being attitudinally incompatible with the use of primary modes, the use of primary or secondary modes, and the composition of the existing mode set (ORs: 3.75–35.97; Table 5).

In the two highest quintiles, a relatively large share of the individuals with attitude-mode use incompatibilities is accounted for by those who have negative attitudes to walking (34 %-60 %) or using BTM (33 %-49 %; for attitudinal incompatibilities with the primary/secondary mode and the existing mode set) (**Appendix B**). Our results are robust against different measurements of attitudes and the level of multimodality (Tables 5-8 and Figs. 1-2 in **Supplementary Material**).

4. Discussions

4.1. Discussions on principal findings

This research investigates the relationship between multimodality and attitudes. We provide insights into the distribution of mode-specific attitudes in multimodality. Of all clusters, mode-specific attitudes are the most positive in the cluster with the highest level of use of corresponding modes. For a given cluster, especially a multimodal public transport cluster, nevertheless, the most positive attitude does *not* necessarily correlate with the mode with a higher level of use. That is, there are larger attitude-behaviour gaps for individuals in the multimodal clusters. While we still need to be cautious about such a finding, as our measurement of attitudes may not comprehensively capture how attitudes are underpinned, our research indicates that the distribution of attitudes in multimodality may present a different pattern from the case when only one mode is considered.

Our findings suggest that attitudes may have an impact on mode use decisions when multimodal travel behaviour is involved, but such an impact may not be necessarily decisive. According to the TPB, attitudes, perceived behavioural control, and social norms jointly influence mode use decisions (Ajzen, 1985). The other two elements, perceived behavioural control in particular, may be more influential in determining such decisions than attitudes (Norstedt & Sjölinder, 2021), which in turn contributes to a large attitude-

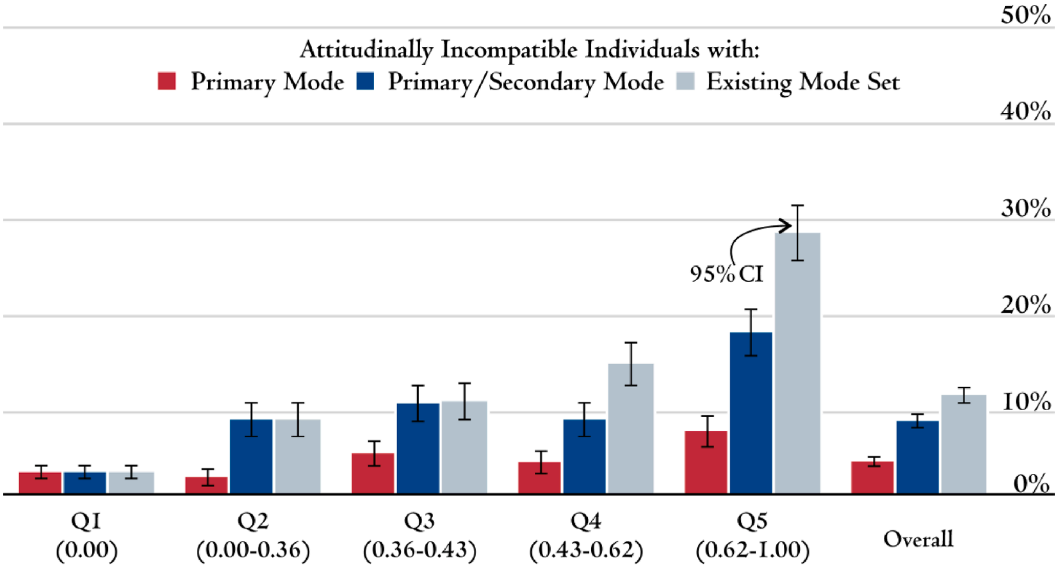

Fig. 3. Comparison of percentages of individuals with attitude-mode use incompatibilities between multimodality levels. Note. Figures in parentheses denote ranges of the OM_PI of each quintile.

behaviour gap. Several studies on attitudes focusing on one mode have indeed found that the effect magnitude of perceived behavioural control is larger than that of attitudes for the intention to use cars (Donald et al., 2014) and public transport (Zailani et al., 2016). Our data also supports this point. 25 % of members in multimodal transport clusters are students. They have pro-driving attitudes (PCA-based attitudes to the use of cars, BTM, and trains: 5.7, 0.5, and 2.9). However, these people are less likely to afford private cars, and they generally have free or subsidised public transport for daily travelling.

The difference in attitudes between modes is smaller for individuals in multimodal clusters and those with a higher level of multimodality. This means that multimodal individuals tend to have more balanced attitudes towards different modes than monomodal and less multimodal individuals. Our finding may be ascribed to the single mode-dominant individuals' prejudice to other modes of transport. For example, Pedersen et al. (2011) find that car-dominant users tend to have low predicted satisfaction with public transport options by overestimating the travel time and costs. However, their satisfaction increases substantially after a one-month use of public transport.

Moreover, we looked into the extent to which attitude-mode use incompatibilities vary by multimodality. We found that multimodal public transport users (compared with car-dominant users) and those with a higher level of multimodality are more likely to be attitudinally incompatible with the frequently-used modes and the composition of their existing mode sets of travelling. These findings suggest that multimodal individuals in general use modes they dislike. Our research is in contrast with existing studies, which indicate that individuals in multimodal clusters tend to be attitudinally consonant with their mode use (Molin et al., 2016; Ton et al., 2019). Considering that the incompatibility between cognitions is a crucial ground for awakening cognitive dissonance, our results suggest that multimodal individuals, compared with monomodal or less multimodal individuals, may be *more likely* to present cognitive dissonance with their mode use.

A large share of multimodal individuals with attitude-mode use incompatibilities is accounted for by those who have negative attitudes towards the use of BTM and trains as well as walking. A potential explanation is that although a proportion of multimodal individuals have negative perceptions of travelling by BTM and trains in terms of the sense of pleasure, relaxation, comfort, and flexibility provided (Fig. 1), they have to use these modes for reasons like cost considerations (Forward, 2019). Also, compared with the overall level (share: 10.9 %), the MM BTM (13.9 %) and MM TRAIN (11.6 %) clusters as well as the two highest multimodality level quintiles (6.7 % and 10.0 %) do not contain a substantially higher share of individuals who have a negative attitude to walking. However, as an access and egress mode of public transport, frequent walking is highly required amongst multimodal individuals (Table 2). In contrast, monomodal or less multimodal individuals, especially those who heavily rely on cars, are more flexible to (largely) reduce walking frequency if they have a negative attitude to walking.

Our research findings on attitude-mode use incompatibilities may contribute to an advanced understanding of the relationship between multimodality and travel behaviour change. Existing evidence has shown that baseline mode use patterns are closely related to modal shifts over time (Diana, 2010; Heinen, 2018; Heinen & Ogilvie, 2016; Kroesen, 2014); several hypotheses have been proposed to explain the potential mechanism underlying such evidence. Heinen and Ogilvie (2016) hypothesised that being multimodal may constitute an experimental phase that lays the groundwork for enacting more established travel behaviour. Kroesen (2014) proposed three potential mechanisms. First, multimodal individuals may have less biased perceptions of the available options compared with monomodal individuals, and therefore they may update their mode use profile more readily. Second, multimodality may be seen as a characteristic reflecting the extent to which individuals deliberately make their mode use decision. Individuals who are more multimodal may thus be more likely to respond to changes in environmental conditions. Third, multimodal individuals may be more familiar with modes (e.g., cycling) that complement others, and on this basis, these individuals may switch their main mode use more feasibly.

Our research findings may support an uncovered mechanism. We suggest that the potential cognitive dissonance between mode use and corresponding mode use may be one important reason that drives multimodal individuals to change their mode use patterns over time. Cognitive dissonance theory suggests that people hold an inner drive to keep relevant cognitions compatible, thereby avoiding psychological discomfort (Festinger, 1957). When dissonance is present, people do their best to restore the compatibility between cognition pairs (Festinger, 1957); in our case, dissonant individuals change either mode use or corresponding attitudes. Given the potential association between multimodal individuals and the cognitive dissonance for mode use, these people may, once conditions are suitable, substitute frequently-used modes with their liked but less frequently-used ones, or replace their disliked modes with ones they like but have no chance to use, if their mode-specific attitudes and travel demand are maintained at the current level. Against this backdrop, changes in the use of such modes would result in a reshaping of overall mode use patterns.

4.2. Limitations

This research uses a high-quality three-day travel diary to characterise multimodality. We measure mode-specific attitudes based on a complete framework of the TPB. A rich set of sensitivity analyses are also conducted to ensure the robustness of our findings. Our research has, nevertheless, several limitations. First, we use Dutch data. Our findings may thus not be generalisable to contexts with different transport, social, and cultural backgrounds. For example, in countries like Northern Ireland, where individuals are more satisfied with bus use than cycling and walking (DfI, 2020), public transport users may be less likely to experience the attitude-mode use incompatibility. The transferability of our findings to other contexts therefore needs to be examined. Second, the MPN includes seven attitudinal components for each mode to avoid imposing respondents' burdens. The data may not allow us to entirely capture individuals' full attitudes towards given modes, as some attitudinal components, such as those related to environmental awareness (Hopkins, 2016), health benefits (Acharjee & Sarkar, 2021), and privacy considerations (Heinen et al., 2011), are not included in the MPN. Incorporating these components into the attitude measurements may result in a change in the direction of mode-specific attitudes and the differentiation between the status of incompatibility and compatibility. Future studies could benefit from using more components to measure attitudes. Third, the incompatibility between cognitions does not necessarily result in cognitive dissonance (Taylor, 1998). Similar to existing studies, we do not explicitly examine psychological discomfort, and thus we cannot make a strong conclusion that multimodal individuals tend to experience cognitive dissonance. Alternative interpretations of our findings cannot be ruled out. For example, individuals with attitude-mode use incompatibilities may have regulated their discomfort (and thus cognitive dissonance) by increasing their attitude towards the used modes. Further research applying the measure of mode use-led discomfort would be important for understanding the interrelationship between multimodality, attitudes, and cognitive dissonance.

4.3. Policy implications

We argue that an increase in multimodality may offer not only an opportunity but also a challenge for inducing long-term sustainable modal shifts. Our findings suggest that multimodal public transport users (compared with car-dominant users) and individuals who have a higher level of multimodality may have a higher potential for changing frequently-used modes and the composition of existing mode sets over time. Nevertheless, multimodal individuals are found to have strong pro-car attitudes, and a large share of multimodal individuals with attitude-mode use incompatibilities is accounted for by those who have negative attitudes towards the use of BTM and trains as well as walking. Therefore, voluntary modal changes for multimodal individuals may not occur towards a more sustainable direction; in the worst-case scenario, the dominant role of cars in daily travelling could increase in the long term. This inference is in line with empirical evidence. For example, Kroesen (2014) showed that when no explicit intervention was implemented, there was no clear pattern as to which direction multimodal individuals would shift towards. These individuals were found to have a similar likelihood of becoming strict car or bicycle users. Lehtonen et al. (2021) found that individuals who were more multimodal had a higher intention to use Level 3 automated vehicles. Individuals with medium-to-high levels of multimodality were more prone to reduce the use of public transport. Thus, Level 3 automated vehicles may replace part of trips currently travelled by sustainable modes for multimodal individuals.

The effectiveness of encouraging multimodality when it is expected as a tool to induce sustainable modal shifts could also be vulnerable to unpredictable disruptions of transport systems. For example, recent studies showed that people have reduced the use of public transport and increased car use after the outbreak of the COVID-19 pandemic (Almlöf et al., 2021; Zhang et al., 2021). These changes potentially contribute to the restoration of attitude-mode use compatibilities amongst multimodal public transport users. The modified mode use patterns of these individuals may thus persist, and efforts before the pandemic aimed at achieving long-term transport sustainability through increasing multimodality may fail.

Against these backdrops, policymakers should be aware that an increase in multimodality is only the *first step* towards the development of more established sustainable travel behaviour. Long-term supporting policies, such as those that focus on promoting the use of active modes and public transport and positive attitudes towards these modes, are highly required and should be planned to steer the direction of modal shifts for multimodal individuals. It is encouraged to conduct regular monitoring during the process of planned modal shifts. Otherwise, the transport system may shift towards an undesirable direction.

5. Conclusion

This research investigates how attitudes and attitude-mode use incompatibilities are distributed across clusters and levels of multimodal travel behaviour. Individuals in multimodal clusters and those who are more multimodal have more balanced attitudes to different modes. However, the most positive attitude does not necessarily correspond to the mode with the highest level of use. Independent of the cluster membership and level of multimodality, attitudes to car use are most positive. Moreover, our results show that multimodal public transport users (compared with car-dominant users) and those with a higher level of multimodality are more likely to be attitudinally incompatible with the frequently-used modes and the composition of their existing mode sets of travelling. This indicates that multimodal individuals may be more likely to experience cognitive dissonance with their mode use. Our findings may also help understand the psychological mechanism underlying a recent important finding that multimodal individuals are more likely to change their mode use over time.

CRediT authorship contribution statement

Zihao An: Conceptualization, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Eva Heinen:** Conceptualization, Supervision, Writing – review & editing. **David Watling:** Conceptualization, 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.

Data availability

The authors do not have permission to share data.

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Appendix A. Variance-weighted aggregation methods.

We use a variance-based weighted aggregation method, developed by Nicoletti et al. (2000), to compute mode-specific attitudes as follows:

$$A_{im} = \sum_{k=1}^{k=n}\left(PC_{imk}\left(e_{mk}/\sum_{k=1}^{k=n}e_{mk}\right)\right) \tag{1}$$

$$PC_{imk} = \sum_{j=1}^{j=7}\left(w_{mkj}b_{imjk}\right) \tag{2}$$

$$w_{mkj} = \left(l_{mkj}\right)^2/\sum_{j=1}^{j=7}\left(l_{mkj}\right)^2 \tag{3}$$

where A_{im} denotes individual i's attitude towards mode m and e_{mk} is the eigenvalue of the kth principal component PC_{imk}. The calculation of A_{im} takes into account the extent to which different PCs explain information contained by belief-based attitudinal components in underpinning an attitude, as e_{mk} represents the variance explained by PC_{imk}, Similarly, the score of PC_{imk} is determined by an aggregation method according to the variance explained by the absolute value of belief-based attitudinal component j (b_{imkj}) (**Eqs. (2)-(3)**). The weight of b_{imkj} (w_{mkj}) is derived by standardising the squared factor loading (l_{mkj}) of b_{imkj}; a squared loading value represents the variance explained by a given belief-based attitudinal component in a given PC.

The final equations to compute individual i's attitudes to walking (**Eq. (4)**), cycling (**Eq. (5)**), and the use of cars (**Eq.(6)**), BTM (**Eq. (7)**), and train (**Eq.(8)**) are shown as follows:

$$A_{Walk} = 0.117{*}C + 0.108{*}\mathrm{R} + 0.114{*}Pl + 0.089{*}F + 0.064{*}S + 0.449{*}T + 0.059{*}\mathrm{Pr} \tag{4}$$

$$A_{Bicycle} = 0.195{*}C + 0.193{*}\mathrm{R} + 0.198{*}Pl + 0.142{*}F + 0.124{*}S + 0.117{*}T + 0.031{*}\mathrm{Pr} \tag{5}$$

$$A_{Car} = 0.166{*}C + 0.171{*}\mathrm{R} + 0.191{*}Pl + 0.146{*}F + 0.158{*}S + 0.142{*}T + 0.026{*}\mathrm{Pr} \tag{6}$$

$$A_{BTM} = 0.191{*}C + 0.192{*}\mathrm{R} + 0.169{*}Pl + 0.191{*}F + 0.065{*}S + 0.157{*}T + 0.035{*}\mathrm{Pr} \tag{7}$$

$$A_{Train} = 0.106{*}C + 0.109{*}\mathrm{R} + 0.084{*}Pl + 0.224{*}F + 0.224{*}S + 0.239{*}T + 0.013{*}\mathrm{Pr} \tag{8}$$

where C, R, Pl, F, S, T, and Pr respectively denotes the individual i's belief-based attitudinal components concerning comfort, relaxation, pleasure, flexibility, safety, time-saving, and prestige.

Appendix B. Percentage of individuals who have an attitudinal incompatibility with a given mode.

Multimodality Clusters/Levels	Modes				
	Car	Walk	Bicycle	BTM	Train
	Altitudinal incompatibilities with the primary mode				
CAR MOSTLY	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %
BICYCLE MOSTLY	6.1 %	0.0 %	97.0 %	0.0 %	0.0 %
WCB	10.5 %	89.5 %	1.8 %	0.0 %	0.0 %
MM BTM	2.2 %	73.3 %	13.3 %	22.2 %	0.0 %
MM TRAIN	3.3 %	63.3 %	20.0 %	10.0 %	16.7 %
Q1	26.7 %	46.7 %	26.7 %	0.0 %	0.0 %
Q2	31.3 %	31.3 %	37.5 %	0.0 %	0.0 %
Q3	27.5 %	60.0 %	12.5 %	0.0 %	0.0 %
Q4	16.7 %	56.7 %	23.3 %	13.3 %	0.0 %
Q5	5.0 %	60.0 %	25.0 %	15.0 %	8.3 %

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(*continued*)

Multimodality Clusters/Levels	Modes				
	Car	Walk	Bicycle	BTM	Train
	Altitudinal incompatibilities with the primary and secondary mode				
CAR MOSTLY	28.0 %	52.7 %	20.4 %	0.0 %	0.0 %
BICYCLE MOSTLY	19.0 %	29.3 %	56.9 %	1.7 %	0.0 %
WCB	16.9 %	79.8 %	5.6 %	1.1 %	1.1 %
MM BTM	1.1 %	46.2 %	6.5 %	69.9 %	0.0 %
MM TRAIN	3.2 %	40.0 %	9.5 %	23.2 %	46.3 %
Q1	26.7 %	46.7 %	26.7 %	0.0 %	0.0 %
Q2	14.3 %	60.0 %	18.6 %	4.3 %	4.3 %
Q3	19.1 %	62.9 %	13.5 %	12.4 %	4.5 %
Q4	14.3 %	37.1 %	17.1 %	32.9 %	12.9 %
Q5	4.5 %	47.4 %	14.9 %	33.8 %	18.8 %
	Altitudinal incompatibilities with the mode set				
CAR MOSTLY	24.5 %	56.6 %	19.8 %	1.9 %	0.0 %
BICYCLE MOSTLY	17.8 %	35.6 %	45.2 %	8.2 %	2.7 %
WCB	19.8 %	61.2 %	9.5 %	13.8 %	4.3 %
MM BTM	1.6 %	36.4 %	12.4 %	74.4 %	14.0 %
MM TRAIN	7.2 %	28.8 %	5.9 %	41.2 %	47.7 %
Q1	26.7 %	46.7 %	26.7 %	0.0 %	0.0 %
Q2	14.3 %	60.0 %	18.6 %	4.3 %	4.3 %
Q3	18.7 %	62.6 %	14.3 %	12.1 %	4.4 %
Q4	13.1 %	33.6 %	15.6 %	37.7 %	14.8 %
Q5	8.0 %	34.9 %	13.3 %	49.4 %	29.3 %

Note. This table reports the percentage of individuals who present an attitudinal incompatibility with a given mode. Consider an example of the ***incompatibility between attitudes and primary modes***, all (100%) attitudinally incompatible CAR MOSTLY individuals use cars most frequently but have a negative attitude to car use. In contrast, none (0%) of these individuals present attitudinal incompatibilities with the other modes following the definition of attitudinal incompatibilities with the primary mode. The mentioned information can be found in the first row of the table body. It should be noted that the summation of all figures in each row may exceed 100%. The reason is that some individuals may present attitudinal incompatibilities with more than one mode.

Appendix C. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2022.10.007.

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