Understanding Correlates of Multimodal Travel Behaviour

：The Role of Age-Period-Cohort, Trip Purposes, and Attitudes

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Abstract

Inducing modal shifts away from car-oriented travel patterns is crucial to the development of a sustainable transport system. Multimodal travel behaviour, which is also termed as multimodality, refers to the behavioural phenomenon of using more than one mode of transport during a given period. Evidence suggests that encouraging individual multimodality may potentially constitute a first step to sustainable mode use change. Understanding correlates of multimodality provides more insights into how multimodality is distributed, how modifiable factors may influence multimodality, and based on these insights, how to support policies to promote multimodality. Recently, increasing scientific attention has been paid to correlates of multimodality. Nevertheless, little is known about the extent to which multimodality, especially the level of multimodality, is correlated with variables beyond socioeconomic, demographic, and residential dimensions. Indicated by studies on the use of single modes, it could be hypothesised that variables in several other dimensions may be linked with multimodality.

This thesis aims at extending the conceptual framework used to analyse correlates of multimodality by exploring variables in the temporal, situational, and attitudinal dimensions. Three elements around each of these dimensions, namely, age-period-cohort, trip purposes, and attitudes, are specifically focused.

This thesis used nationwide multiday travel diary surveys from England and the Netherlands. The results showed that age-period-cohort and trip purposes were significantly associated with multimodality. By contrast, mode-specific attitudes may not necessarily be influential for corresponding mode use decisions when multimodality is involved.

Chapter 2 showed that individuals tended to be less multimodal as they got older. The results do not support the view held by most existing studies, namely, that multimodality has increased in recent decades. Instead, multimodality presented a downward trend for recent (birth) cohorts. The existence of significant cohort-specific variations in multimodality also indicates the important role of early life conditions and formative experience in shaping multimodality.

Chapter 3 found that individuals presented higher levels of multimodality when they made trips that were more variable in departure time and travel distance, but only when sufficient trip stages (at least 3 stages) were made. Moreover, there were cross-purpose disparities in correlates of multimodality in terms of significance and variance explained.

Chapter 4 suggested that for mode use decisions of multimodal travel behaviour, attitudes may not be as influential as they affect decisions of single mode use. Moreover, the results support the view that multimodal travellers may have a high potential for a long-term modal shift due to high-level cognitive dissonance. This may also provide explanations of the psychological mechanism by which multimodal travellers tend to change their mode use over time.

As a whole, this thesis reveals the multifaceted nature of correlates of multimodality. The novel approaches, namely the hierarchical age-period-cohort model and Heckman selection model used in this thesis provided new tools for understanding multimodality. The main implication of this thesis is that policymakers need to take into account the complexity of correlates of multimodality to develop policies aimed at encouraging multimodality and to develop effective mode-shift interventions.

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Abbreviations

A number of abbreviations and acronyms are used throughout this thesis. They are listed here for reference in alphabetical order.

ANCOVA	Analysis of covariance
ANOVA	Analysis of variance
APC	Age-period-cohort
DAL	Dalton index
DSPS	Difference between the share of primary and secondary modes used
HAPC	Hierarchical age-period-cohort
HHI	Herfindahl-Hirschman index
IMR	Inverse Mills ratio
MAUP	Modifiable area unit problem
MPN	Netherlands Mobility Panel
NTS	National Travel Survey
NMU	Number of modes used
OM_PI	Objective mobility personal index
PCA	Principal component analysis
SNK	Student–Newman–Keuls
TPB	Theory of planned behaviour
VIF	Variance inflation factor

Chapter 1

Introduction

1.1. Background

Conventional car-oriented transport in developed countries contributes to negative externalities to public health, the environment, and the development of societies (United Nations Human Settlements Programme, 2013). A sustainable transport system should 'meet society’s economic, social, and environmental needs whilst minimising its undesirable impacts on the economy, society and the environment' (Council of the European Commission 2006, p. 10). In recent decades, as the awareness of climate change has intensified, the need for developing a more sustainable transport system has become increasingly urgent. The Sustainable and Smart Mobility Strategy of the European Commission in 2020 suggested that the biggest challenge to achieve this goal was to reduce transport emissions (European Commission, 2020). This strategy highlighted three 'pillars' that future actions should take upon: (1) reducing vehicles' dependence on fossil fuels; (2) promoting modal shifts towards more sustainable modes of transport; and (3) internalising external costs of transport. It is important to emphasise that these measures should be implemented jointly. For example, the EU-funded TOSCA (Technology Opportunities and Strategies towards Climate-friendly trAnsport) project showed that technical improvements alone might not be sufficient for a remarkable reduction in greenhouse gas emission by 2050; behavioural changes were still required (Schäfer et al., 2011). Nevertheless, evidence has shown that measures aimed at significantly restricting car use may not be effective to drive individuals' modal shifts away from cars (e.g., Wang et al. (2014); Liu et al. (2016); Davis (2017)).

Within this context, the notion of multimodal travel behaviour has been proposed and attracted attention from policymakers (e.g., European Commission (2014)) and the scientific community (e.g., Kuhnimhof et al. (2012a)). Multimodal travel behaviour, which also is termed multimodality and intrapersonal modal variability, can be broadly referred to as the behavioural phenomenon of using more than one mode of transport in a given period (Kuhnimhof et al., 2012a). Multimodality is commonly used to characterise individuals' mode use patterns but can also be applied to a population (Heinen and Mattioli, 2019a). For example, an individual could be considered more multimodal if they use more modes or use various modes in a more balanced way; a population could be considered more multimodal if its aggregate mode share is more balanced across modes. The notion of multimodality is different from that of intermodality, which is referred to as using multiple modes in a given trip (Goletz et al., 2020); as such, being multimodal for an individual does not necessarily require using two or more modes in given trips. The focus of this thesis is multimodality at the individual level. Various measurements of multimodality have been developed; this will be discussed in Section 1.2.

The notion of multimodality aligns well with the classic 'citizen–consumers' framework of environmental policy (Barr et al., 2011; Department of the Environment, Food, and Rural Affairs, 2008; Shove, 2010). This framework positions citizens as consumers and highlights the role of 'citizen-consumers' as primary makers of change. According to this framework, travellers should take the initiative to change their behaviour, whilst policymakers' responsibility is to support them to make sustainable choices. A number of empirical studies have supported this conception, and revealed that an increase in multimodal travel patterns might be closely linked with modal changes (e.g., Diana (2010); Heinen (2018); Kroesen (2014); Heinen et al. (2017)). Therefore, policymakers could focus on diversifying travellers' mode use (i.e., encouraging multimodality) rather than introducing car use restrictions at the expense of travellers' travel demand. Increased multimodality then potentially allows policymakers to induce desirable modal shifts in an easier way, if conditions for a sustainable change can be further provided. This thesis looks into the correlates of individual multimodality in various domains. Uncovering this will provide more insights into how multimodality is distributed across various dimensions (e.g., subpopulations, time, and trips), how modifiable factors may affect multimodality, and based on these insights, how to support policies to promote multimodality.

1.2. Measurements of individual multimodality

The existing literature has applied various measurements of multimodality at the individual level. These measurements broadly fall into three categories: (1) pre-defined classifications; (2) data-driven characterisations; and (3) continuous indicators. The pre-defined classifications and data-driven characterisations are similar by categorising individuals into different clusters according to their mode use patterns. Pre-defined classifications classify travellers based on researchers' subjective criteria, such as how many modes or whether specific modes are used. For example, travellers who rely on only one mode of transport can be defined as monomodal travellers, whilst those who jointly use two or more modes are defined as multimodal travellers (e.g., Blumenberg and Pierce (2014)). Data-driven approaches categorise travellers into different clusters according to individual mode use information (e.g., including but not limited to the share of mode use), using unsupervised clustering characterisations, such as the latent clustering and k-means clustering methods (e.g., Kroesen (2014)). Data-driven methods are therefore more objective than pre-defined methods for classifying travellers' mode use patterns and can fit better with modal intensity (e.g., frequency, distance, and time of mode use).

While pre-defined and data-driven approaches provide useful information on the cluster-level mode use patterns, these two approaches are limited in indicating the individual level of multimodality (Heinen and Mattioli, 2019a). For an individual, the level of multimodality refers to the degree they change their mode use during a given period (Heinen and Chatterjee, 2015). For example, considering one-week mode use patterns of two travellers: Traveller 1 cycles three times and uses private cars five times a week; Traveller 2 cycles once and uses private cars seven times. As both travellers use more than one mode of transport during the week, they can be defined as multimodal travellers if a straightforward definition of multimodality is taken. These two travellers may also be categorised as multimodal car users by using the data-driven approaches. Nevertheless, Traveller 1 has arguably a higher level of multimodality as they use private cars and bicycles in a more balanced way.

Several continuous indicators have been applied to measure the level of multimodality, such as the number of modes used (NMU) (e.g., Heinen and Chatterjee (2015)), the difference between the share of primary and secondary modes used (DSPS) (Scheiner et al., 2016), the objective mobility personal index (OM_PI) (e.g., Diana and Mokhtarian (2009)), and the Herfindahl–Hirschman index (HHI) (e.g., Susilo and Axhausen (2014)). These indicators reflect variations (e.g., NMU and OM_PI) or concentrations (e.g., DSPS and HHI) of individual mode-use patterns. A greater value of indicators of variation indicates a higher level of multimodality, whilst a smaller value of indicators of concentration indicates a lower level of multimodality. Diana and Pirra (2016) assessed the properties of nine existing potential continuous indicators for measuring the level of multimodality. The authors concluded that no indicator outperformed the others in all situations, whilst some indicators showed strengths in specific circumstances. HHm (a modification of the HHI), OM_PI, and OM_MI (a modification of the OM_PI) may be suitable for measuring 'real multimodality' in the situation where some individuals do not have access to specific modes. By applying these indicators, for example, when each individual in question equally uses modes (e.g., Individual 1 uses trains and drives both four times a week; Individual 2 uses trains, drives, and cycles all four times a week), those who use more modes (Individual 2) will be calculated to have a higher level of multimodality. Moreover, DALm (a modification of the Dalton Index) is recommended when the average intensity between uses of modes exhibits a large difference. However, it should be highlighted that as the level of multimodality is *not* necessarily associated with actual mode use, these indicators are thus not indicative of which modes are used.

Measurements of multimodality also depend on data specification. In this vein, two elements should be particularly highlighted: the duration of data collection and the number of modes considered. Firstly, data collected through a longer duration could in general capture the variability of mode use more effectively (Heinen and Mattioli, 2017). However, it is inconclusive how long the data collection should take from a practical standpoint because a longer duration is associated with a higher drop-out rate and, in turn, a smaller sample size (Buehler and Hamre, 2015). Secondly, on the one hand, considering a large variety of modes may help accurately reflect the diversity of travellers' mode use. On the other hand, using choice sets based on more aggregate modes (e.g., public transport, private transport, active modes) may be more robust for measuring multimodality when individuals in question have a low number of trips. The reason is that the number of trips is closely correlated with measured multimodality. For a given individual, aggregate mode choice sets may be less sensitive to measured multimodality when the number of trips changes, which could be largely determined by the duration of data collection.

1.3. Multimodality as a step to sustainable modal shifts

Evidence suggests that promoting multimodality may constitute the first step towards more established sustainable travel behaviour. Studies have revealed that multimodal travel patterns may be significantly associated with mode use change over time. This indicates that policies and interventions aimed at inducing long-term sustainable modal shifts may be more effective when the multimodality of the targeted population increases. Quasi-natural experimental research of Heinen and Ogilvie (2016b) examined the effect of baseline level of multimodality and exposure to transport interventions (distance to a busway) on follow-up changes in commuting mode share. The authors found that people with higher levels of baseline multimodality tended to alter their modal share in active modes, public transport, and cars over time. The authors also observed that the baseline level of multimodality interacted with the exposure to interventions, which strengthened the effect of exposure to interventions on promoting active mode use and reducing the use of cars. Kroesen (2014) investigated the transition probabilities of groups with different mode use patterns over a five-year interval. He found that multimodal groups were more likely to switch their group membership in the follow up than their counterparts who mostly relied on one single mode. Heinen (2018) found that multimodal travellers, compared with monomodal or less multimodal ones, held stronger intentions to alter their future use of cars. Diana (2010) found that the magnitude of multimodal travel habits was positively correlated with the strength of the stated intention to use hypothetically new transport services. There is thus evidence that multimodal travellers may have a relatively high willingness to adopt the non-existing transport services, even if they are not acquainted with the technological background of these services.

1.4. Research into multimodality

This section provides a short overview of existing studies on multimodality to reveal the research gaps.

1.4.1. Prevalence and trends of multimodality

Existing studies have shown that multimodal travellers are widely present in developed societies. However, only a limited number of studies have considered the level of multimodality, and showed that the level of multimodality is low in developed countries.

When following the definition of whether a traveller uses more than one mode of transport, Heinen and Chatterjee (2015) looked at the week-long National Travel Survey and showed that 69% of travellers in Great Britain were multimodal. Nobis (2007b) used Mobility in Germany surveys with one-week travel diaries and observed that 49% of German travellers were multimodal. Buehler and Hamre (2015) looked into US National Household Travel Survey (NHTS) with one-week travel diaries and found that multimodal car users and walk, bike, or public transport only users accounted for 65% and 7% of sampled US individuals. By contrast, only 28% of individuals were monomodal car users. Olafsson et al. (2016) used a national-representative self-administrative survey and found that 81% of Danish travellers used two or more modes for at least two days during the survey week. **Table 1.1** summarises the data specification and multimodality prevalence of these discussed studies. Very few studies considered the level of multimodality. Heinen and Chatterjee (2015) found that travellers used only 2.2 modes per week in Great Britain, and that the difference in the modal share between the primary and secondary mode use was large (i.e., 0.6). Similarly, Scheiner et al. (2016) observed by using the German Mobility Panel that German travellers used 2.8 modes a week and were highly reliant on their primary mode (modal share: 0.6).

Only a few studies have investigated temporal patterns of multimodality. Most studies have shown that multimodality has increased in recent decades in developed countries, especially amongst young adults (e.g., Kuhnimhof et al. (2012a); Kuhnimhof et al. (2012b); Buehler and Hamre (2014); Streit et al. (2015)). For example. Buehler and Hamre (2014) investigated how the share of multimodal car users, monomodal car users, and travellers who do not use cars changed between 2001 and 2009 using the US NHTS. The authors found the share of monomodal car users decreased from 2001 to 2009, whilst the share of multimodal car users slightly increased between 2001 to 2009. Streit et al. (2015) used the MOP data to examine the change in the level of individual multimodality between two time slices (1998-2002 and 2010-2012) in Germany. The authors found that young adults aged between 18 and 35 showed an increased level of multimodality. For people between 35 and 50 years old and living in big cities, only males showed an increased level of multimodality. These findings are inconsistent with those derived from the English research by Heinen and Mattioli (2019a). Heinen and Mattioli (2019a) studied trends in the level of multimodality in England over 21 consecutive years (1995-2015) by use of the NTS, and found that the level of multimodality decreased in England. Nevertheless, as is explained in Section 1.5, temporal patterns of multimodality may only be revealed when three time-related linear-dependent variables – age, period, and birth cohort – are simultaneously taken into analysis.

Table 1.1 Data specifications and prevalence of multimodality of the discussed studies.

Author(s)	Country	Data (year)	Sample size	Length of the analysis period	Number of modes considered	Prevalence of multimodality
Heinen and Chatterjee (2015)	Great Britain	NTS (2010)	19072	1 week	8 modes (car driver; car passenger; bus; rail; walk; bicycle; taxi; other); 3 modes (private transport; public transport; active transport)	69% (8 modes); 56% (3 modes)
Nobis (2007b)	Germany	MiD (2002)	61729	1 week	3 modes (walk; bicycle; public transport)	49%
Olafsson et al. (2016)	Denmark	Self-administrative survey (2011)	1957	1 week	7 modes (car alone; car together; train; bus; bicycle; walk)	81%
Buehler and Hamre (2015)	US	NHTS (2009)	192575	1 week; 1 day	3 modes (car; walk; bicycle; public transport)	65% (multimodal car users, one-week diaries); 14% (one-day diaries)

Abbreviations: National Travel Survey (NTS); Mobility in Germany, 2002 (MiD); National Household Travel Survey (NHTS);

1.4.2. Correlates of multimodality

A growing body of literature has studied correlates of multimodality. **Table 1.2** summarises the studies on this topic that use multivariate analyses. Chapters 2, 3, and 4 will provide more comprehensive overviews on each topic this thesis focus on.

Existing studies on this topic have predominantly investigated the correlation between multimodality and individual socioeconomic as well as demographic characteristics based on cross-sectional data. While definitions of multimodality are inconsistent across studies, several findings could be drawn. Individuals in multimodal clusters and those with a higher level of multimodality are more prevalent amongst Caucasians (e.g., Buehler and Hamre (2015); Heinen and Chatterjee (2015)), students (as opposed to full-time employees; e.g., Heinen and Mattioli (2019a)), part-time employees (as opposed to full-time employees; e.g., Chatterjee et al. (2016); Heinen and Chatterjee (2015)), people with higher educational attainment (e.g., Diana and Mokhtarian (2009); Buehler and Hamre (2016); Buehler and Hamre (2015)), people who have higher household income (e.g., Blumenberg and Pierce (2014); Heinen and Mattioli (2019a)), and those who do not have a driver's license (e.g., Lee et al. (2020)) as well as have limited car availability (e.g., Nobis (2007b)). The relationships between gender and multimodality and between age and multimodality are inconclusive, which seems to depend on the countries in question largely. For gender, multimodal travellers are more prevalent amongst females in Germany (e.g., Vij et al. (2011)), Great Britain (e.g., Heinen and Chatterjee (2015)), and the Netherlands (e.g., Heinen (2018)), whilst males tend to be more multimodal in the US (e.g., Blumenberg and Pierce (2014); Buehler and Hamre (2016)). For age, German studies showed that there was a U-shaped relationship between age and multimodality (e.g., Nobis (2007b)). British studies suggested that a lower level of multimodality is associated with age (e.g., Heinen and Mattioli (2019a)). Buehler and Hamre (2015) showed no clear pattern about the age-multimodality relation in the US. Moreover, Scheiner et al. (2016) looked into the relationship between life courses and changes in the level of multimodality. This research revealed that long-term changes in personal socioeconomic characteristics could influence the level of individual multimodality over time. Scheiner et al. (2016) found that having a child moving out tended to increase multimodality, whilst entering the labour market, acquiring a driver's license, and increasing access to cars might reduce multimodality.

Several studies have also investigated how residential contexts may be associated with multimodality. Multimodal individuals were found to be more prevalent in areas with greater population density (e.g., Buehler and Hamre (2015)), larger settlements (e.g., Heinen and Chatterjee (2015); Blumenberg and Pierce (2014)), and better access to public transport (e.g., Buehler and Hamre (2016)), and higher activity intensity (e.g., Lee et al. (2020)). A panel study by Klinger (2017) also highlighted the role of residential relocation in shaping multimodality. The author found that individuals tended to become more multimodal after moving to public transport- and cycling-friendly cities.

Nevertheless, existing studies on correlates of multimodality are limited in three ways. First, they largely overlook correlates beyond socioeconomic, demographic, and residential dimensions. Second, these studies mostly apply to cluster-level pre-defined and data-driven approaches to characterise multimodality, whilst little attention has been paid to the level of individual multimodality. Third, existing studies on this topic use data based on undifferentiated trips or exclusive trips; little is known about how (correlates and levels of) multimodality differs by trip purposes.

Table 1.2 Studies on correlates of multimodality.

Author(s)	Study area	Data	Data type; method	Multimodality measurements	Studied trip	Main findings
Heinen and Chatterjee (2015)	Great Britain	NTS	Cross-sectional	Continuous indicators (NMU, DSPS, OM_PI, and HHI)	Undifferentiated trips	Higher levels of multimodality: age under 60, Caucasians, female, working part-time, larger settlements, higher household income, limited access to cars, and having public transport seasonal ticket.
Heinen and Mattioli (2019a)	England	NTS	Repeated cross-sectional	Continuous indicators (OM_PI and HHI)	Undifferentiated trips	Higher levels of multimodality: female, higher household income, no walking difficulties, owning a house, better access to bicycles.
Nobis (2007b)	Germany	MiD and MOP	Cross-sectional	Pre-defined groups (monomodal, car-bike, car-public transport, bike-public transport, and car-bike-public transport)	Undifferentiated trips	Higher likelihoods of being in multimodal groups: lower car availability, a smaller number of household cars, no children in the household, the employed. There is a U-shaped relation between age and the likelihood of being in multimodal groups.
Buehler and Hamre (2015)	US	NHTS	Cross-sectional	Pre-defined groups (car users with a maximum of 6 trips per week, multimodal car users, walk, bicycle, public transport only users)	Undifferentiated trips	Higher likelihoods of being multimodal car users: male, Caucasians, higher educational attainment, no household car, a greater population density of settlements, better access to rail.
Buehler and Hamre (2016)	US	NHTS	Cross-sectional	Pre-defined groups (monomodal motorists and multimodal motorists)	Undifferentiated trips	Higher likelihoods of being multimodal car users: male, age between 16-24, higher educational attainment, the unemployed, fewer cars in the household, a greater population density of settlements, better access to rail
Vij et al. (2011)	Germany	MOBIDRIVE	Cross-sectional	Pre-defined groups (quasi-unimodal auto, multimodal green, multimodal all)	Work and non-work trips	Higher likelihoods of being 'multimodal all': female, less travel time, less transit access and egress time, and having a transit season pass. Higher likelihoods of being 'multimodal green': less travel time, a smaller number of cars in the household.

Scheiner et al. (2016)	Germany	MOP	Two-wave panel	Continuous indicators (NMU, Entropy, HHI, share of primary mode)	Undifferentiated trips	Increased levels of multimodality (baseline variables): students, better access to public transport, limited parking conditions, better public transport quality, limited car availability, a child moving out, improved public transport quality, worsened parking conditions, decreased car availability, gaining a driver's license. Decreased levels of multimodality (change variables): entry into the labour market, increased parking conditions, decreased public transport quality, and increased car availability.
Heinen (2018)	Utrecht, the Netherlands	Author's own survey	Cross-sectional	Pre-defined groups and data-driven groups	Commuting trips	Higher likelihoods of being multimodal travellers: female, the unemployed, students, lower household income, occasional access to cars.
Lee et al. (2020)	California, US	California Millennials Dataset	Cross-sectional	Data-driven groups (monomodal driver, carpooler, transit rider, active traveller)	Undifferentiated trips	Higher likelihoods of being multimodal travellers: not having a driver's license and fewer cars in the household, and settlements with high activity intensity.
Blumenberg and Pierce (2014)	US	NHTS	Cross-sectional	Pre-defined groups (multimodal, unimodal, non-travellers)	Undifferentiated trips	Higher likelihoods of being multimodal travellers: male, higher household income, a smaller number of cars in the household, larger settlements.
Chatterjee et al. (2016)	Bristol, UK	North Bristol Commuter Panel	Cross-sectional	Pre-defined groups (car alone, partial car alone, no car alone)	Commuting trips	Higher likelihoods of being partial car alone users: working part-time, having access to a bicycle for work, and working in multiple locations.
Klinger (2017)	Bremen, Hamburg, and the Ruhr area, Germany	Author's own survey	Two-wave panel	Pre-defined groups (multimodal, monomodal)	Undifferentiated trips	Increased likelihoods of being multimodal travellers: the unemployed, younger adults, increased urban centrality, moving to a public transport or cycling-friendly city

Abbreviations: NHTS (National Household Travel Survey); National Travel Survey (NTS); Mobility in Germany, 2002 (MiD); Number of modes used (NMU); Herfindahl–Hirschman index (HHI); objective mobility personal index (OM_PI);

1.5. Research gaps

To develop sound policies aimed at encouraging multimodality, it is essential that we understand its correlates from diverse standpoints. Despite increasing attention on correlates of multimodality in the scientific literature, little is known about the extent to which multimodality, especially the level of multimodality, is correlated with variables beyond socioeconomic, demographic, and residential dimensions. Indicated by studies on the use of a single mode, it could be hypothesised that factors in several other dimensions may be linked with multimodality. Based on the literature review, this thesis identifies three research gaps in terms of variables in three largely overlooked dimensions, namely, temporal (age-period-cohort), situational (trip purposes), and attitudinal (attitudes) dimensions.

- **Gap G1: Correlates of multimodality in temporal dimensions**

  Existing studies on correlates of multimodality have been mostly conducted based on a cross-sectional design looking at one point in time. Only a few studies have looked into the long-term temporal patterns of multimodality. More importantly, these studies are limited in simultaneously considering three time-related variables, namely, age, period, and (birth) cohort in the temporal analysis. Because these three variables are linearly dependent on one another (e.g., age plus cohort equals period), overlooking any one of these variables may contribute to biased results and misguidance on policies aimed at encouraging multimodality. For example, since period and cohort succession move through time together, it is important to decipher whether period or cohort successions explain the observed trend of multimodality. Moreover, at a specific point of time, individuals who have the same age must be in the same cohort. Therefore, it would be infeasible to differentiate the effects of age and cohort if period is not considered.

- **Gap G2: Correlates of multimodality in situational dimensions**

  The existing empirical knowledge of multimodality is predominantly derived based on undifferentiated or a single trip purpose. No study has compared the difference in correlates of multimodality between trip purposes. Since variability in departure time and destination/origin depend on trip purposes (Ås, 1978), it is reasonable to hypothesise that multimodality is closely connected with trip purposes.

- **Gap G3: Correlates of multimodality in attitudinal dimensions**

  Many studies have revealed that attitudes may play an important role in decisions to use transport modes. These studies generally focus on the use of one single mode. However, it remains largely unknown how attitudes towards different modes affect decisions regarding multiple mode use. Moreover, according to Festinger's (1957) cognitive dissonance theory, a state of cognitive dissonance – a state where a behaviour and an attitude towards this behaviour is not aligned – may result in a change in such a behaviour or an attitude. Insights into whether the actual use of various modes match corresponding attitudes allows the research to explore the potential of travellers with various mode use patterns to change their mode use over time.

1.6. Research aims and questions

This thesis aims to extend the conceptual framework used to analyse correlates of multimodality. The central research question of the thesis is: *to what extent are individuals' levels of multimodality affected by temporal, situational, and attitudinal variables?* Three elements around each of these dimensions are specifically focused on, namely age-period-cohort (**RQ1**), trip purposes (**RQ2**), and attitudes (**RQ3**).

This research aims to answer three research questions. These will be successively addressed in Chapters 2 to 4 (**Figure 1.2**):

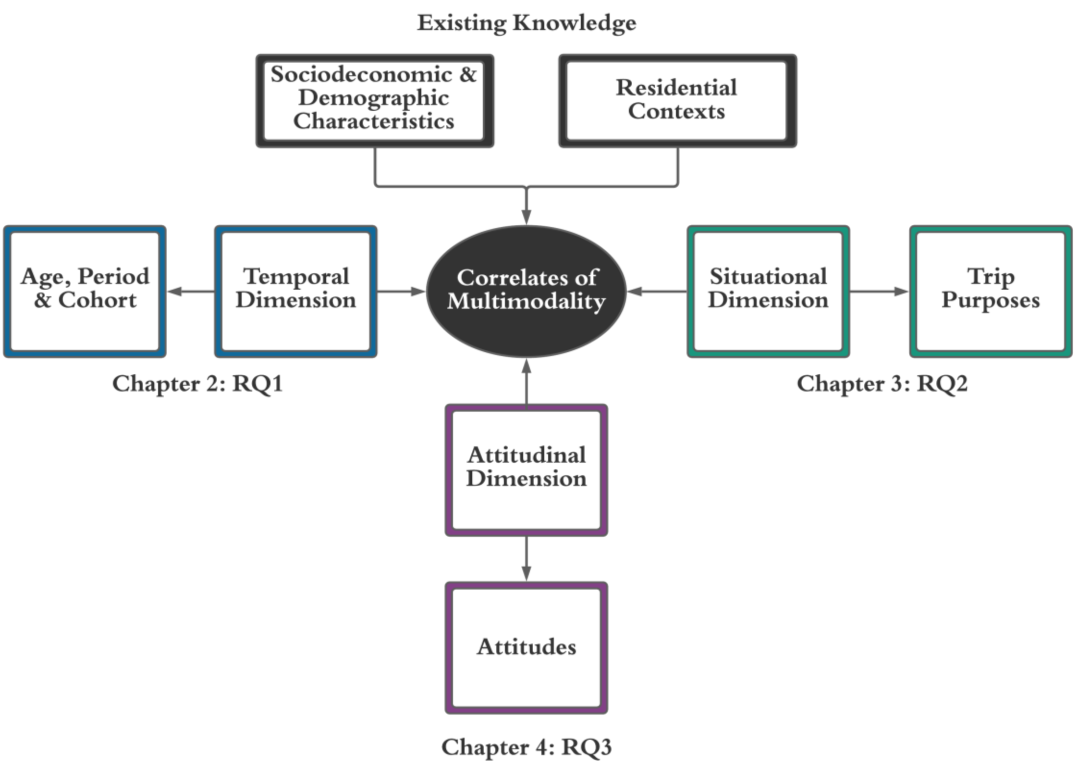

Figure 1.1 Connections between correlates of multimodality, research questions, and chapters.

***RQ1**: How does multimodality change over time? More specifically: to what extent does multimodality change across age, period, and (birth) cohort?*

Research question RQ1 focuses on the temporal pattern of multimodality and is addressed in Chapter 2. Understanding the temporal patterns of multimodality may help policymakers to forecast the future trend of population-level multimodality and to target specific groups (e.g., groups with specific ages and birth cohorts) that are less multimodal.

RQ2: *To what extent do the level and correlates of multimodality differ between trip purposes?*

Research question RQ2 explores the differences in the level and correlates of across trip purposes, and it is addressed in Chapter 3. This will help to target trips with a low level of multimodality. Moreover, since travel demand for participating in different types of activities may differ by individual characteristics, understanding how multimodal travel patterns are different across trip purposes could help support purpose-specific policies to encourage multimodality over a wide population.

RQ3: *To what extent are mode-specific attitudes associated with multimodality, and how are multimodal travellers attitudinally dissonant/consonant with their actual mode use?*

Research question RQ3 investigates the relationship between attitudes and multimodality. Chapter 4 addresses RQ3 and analyses the distribution of mode-specific attitudes across levels and clusters of multimodality as well as how the degree of mode use-attitude dissonance differs by levels and clusters of multimodality. Since a high level of cognitive dissonance may contribute to behavioural change, addressing RQ3 may help policymakers identify travellers with a high potential to change their mode use over time.

1.7. Outline of the thesis

This thesis is a collection of three empirical papers. Each chapter of the thesis is organised based on one paper that is either published in or under reviewed for peer-reviewed journals. Chapter 2 focuses on the extent to which the level of multimodality changes across age, periods, and cohorts. Chapter 3 investigates how the level and correlates of multimodality differ by trip purpose. Chapter 4 looks into the distribution of mode-specific attitudes and the degree of mode use-attitude dissonance across levels and clusters of multimodality. Chapter 5 summarises the principal findings of the thesis, highlights the methodological contributions, reflects on the limitations, and suggests the outlook for future studies. This thesis ends by discussing its policy implications.

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Chapter 2

When you are born matters: An age-period-cohort analysis of multimodality

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Abstract

Multimodality – the behavioural phenomenon of using multiple modes of transport – has been suggested to be a useful indicator of an individual's willingness to adopt more sustainable transport alternatives. Analysing temporal patterns in multimodality provides the opportunity to understand the formation of multimodal practices. Yet the existing studies on this topic share one limitation: they fail to simultaneously incorporate into their analysis the three interconnected temporal dimensions: age, period, and (birth) cohort. Given that age, period, and cohort are mathematically intertwined, the omission of any of these three variables may lead to biased explanations.

Using the National Travel Survey in England, from 2001 to 2017, this research explored the extent to which individual multimodality varied by age, period, and cohort. We adopted the hierarchical age-period-cohort model to estimate the net effects of age, period, and cohort on multimodality. Our analyses showed that travellers tend to be less multimodal as they get older. The age effects may be moderated by work or physical mobility constraints, which accelerate the decrease in multimodality before or after reaching 30 years old, respectively. Individual multimodality exhibited significant variation across periods and cohorts. The total variance in multimodality accounted for by cohorts was larger than that explained by periods. Multimodality reached the lowest level for cohorts born between 1945 and 1969. This may be partially explained by the joint influence of multiple spatial mobility constraints as well as by the distinctive early life conditions and formative experience of baby boomers in terms of driving during the post-war economic expansion.

Keywords: Multimodality; Intrapersonal modal variability; Age-period-cohort analysis; Generation; Temporal Pattern; Travel behaviour

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2.1. Introduction

Making transport more sustainable has been on the policy agenda for decades and is gaining momentum in light of current climate change awareness and the link with transport emissions. To achieve this, multimodality – the behavioural phenomenon of using multiple modes of transport – has recently emerged in academic discourses (e.g., Nobis (2007b); Heinen and Chatterjee (2015); Klinger (2017)). Although being multimodal does not necessarily result in less car use, indications of the nexus between multimodality and more sustainable transport could be drawn from the existing literature. Studies revealed that individuals with more multimodal travel behaviour patterns are more likely to change their travel behaviour over time (e.g., Heinen (2018); Heinen and Ogilvie (2016a); Kroesen (2014)), which allows an easier transition to sustainable transport if the right conditions are provided (e.g., Heinen and Ogilvie (2016a)). It has also been highlighted that a higher level of multimodality may be conducive to reducing CO2 emissions if travel distance remains constant (e.g., Heinen and Mattioli (2019b)).

The majority of the literature on multimodality has shed light on its correlates. It has been demonstrated that multimodality is unequally distributed across subpopulations in terms of their sociodemographic characteristics and residential environments (e.g., Heinen and Mattioli (2019a); Lee et al. (2019); Mehdizadeh and Ermagun (2018); Scheiner et al. (2016); Heinen and Chatterjee (2015); Diana and Mokhtarian (2009); Nobis (2007b)). Briefly, multimodal travellers are more prevalent white ethnic groups, young people, students, part-time employees, people with limited car availability, people who do not hold a car license, individuals with higher income, individuals living in urban areas, and individuals who travel more often. Nevertheless, these findings have been primarily drawn from cross-sectional studies (see Heinen and Mattioli (2019a) and Scheiner et al. (2016) for exceptions). Less is known about how multimodality is distributed across different points in time. The understanding of temporal patterns in multimodality could provide useful information for policy-making to encourage multimodal transport. Recently, several longitudinal works have sought to fill this gap. Most of these studies have found that travellers/car users were more multimodal over past decades in developed countries (e.g., Kuhnimhof et al. (2012a); Kuhnimhof et al. (2012b); Streit et al. (2015); Buehler and Hamre (2016)), the exception being Heinen and Mattioli (2019a) who observed a shift towards more monomodal daily travel between 1995 and 2015 in England.

Yet, the existing studies on temporal patterns in multimodality share one limitation: they fail to *simultaneously* incorporate three interconnected temporal dimensions, namely, age, period, and (birth) cohort into the temporal analysis. The existing literature has explicitly associated multimodality with age (e.g., Nobis (2007b); Scheiner et al. (2016);

Buehler and Hamre (2014)) or period (e.g., Kuhnimhof et al. (2012b); Streit et al. (2015); Heinen and Mattioli (2019a)), whilst the nexus between cohort and multimodality still remains unclear. Evidence has suggested that cohort effects could contribute to the intergenerational disparity in multimodality-associated factors, such as levels of daily mobility (e.g., Frändberg and Vilhelmson (2011)), driver license acquisition (e.g., Delbosc and Currie (2013)), and availability/use of cars (e.g., Kuhnimhof et al. (2011)). It is, therefore, reasonable to hypothesise that multimodality may vary between cohorts. Given that age, period, and cohort are mathematically intertwined (e.g., age plus cohort is equal to period), the omission of any of these three variables may lead to biased explanations (Yang and Land, 2016). For instance, changes in historical contexts are inevitably accompanied by generational membership replacement. The variations in multimodality reported by previous studies could, therefore, potentially be attributable to cohort rather than period effects.

This paper aims to explore the extent to which individual multimodality varies by age, period, and cohort. To this end, we adopted the hierarchical age-period-cohort (HAPC) model, which allows us to estimate the net effects of age, period, and cohort on multimodality. We used data from the National Travel Survey (NTS) for England that spans 17 consecutive years, from 2001 to 2017. The consistency of the travel surveys over the years of observation, the large sample size, and the collection of a 7-day travel diary are three elements of the NTS that allow us to infer a relatively comprehensive picture of the levels of multimodality over time in England. The research findings and methods may be used to help policymakers monitor temporal patterns in multimodality, make ex-post evaluations of policies, and, thereby, craft targeted strategies for promoting multimodal transport.

The remainder of the paper is organised as follows. Section 2.2 clarifies the definitions of the effects of age, period, and cohort, followed by the review of the studies on the nexus between multimodality and these three time-related variables. The data source and analytical approaches are expounded in Section 2.3. Section 2.4 is dedicated to the findings drawn from the HAPC models, followed by Section 2.5 in which these findings are further discussed.

2.2. Definitions and interrelationships between age, period and cohort effects and their relationship with multimodality

Age effects, also called life-course effects (Robinson and Jackson, 2001), refer to the changes in individuals during ageing in any given length of time period, regardless of which (birth) cohort groups they appertain to (Blanchard et al., 1977). These changes subsume a series of social and biological transformation processes (Yang and Land, 2016). Some of them are deemed to be associated with the variability in individual mode choices, such as the occurrence of key age-associated life events (e.g., driving license acquisition, education-to-employment transition, new household formation, and childbirth) (e.g., Scheiner et al. (2016)) and the decline in physical mobility (e.g., Heinen and Chatterjee (2015); Heinen and Mattioli (2019a)).

Period effects refer to the consequences of changes in contextual factors over time that simultaneously influence individuals with different age and cohort groups (Yang and Land, 2016). The changes in contextual factors contain a complex set of economic, social, and environmental dimensions, within which individuals are embedded, such as economic fluctuations, expansions and contractions of the labour market, urban growth and shrinkage, and in recent decades, the introduction of new mobilities. Against this backdrop, individuals correspondingly respond to these changes in terms of their income, employment status, size/density of residential settlement, and mode choice set, which in turn potentially contribute to variations in individual multimodality (e.g., Blumenberg and Pierce (2013); Buehler and Hamre (2014); Heinen and Mattioli (2019a); Heinen and Chatterjee (2015)).

(Birth) cohort effects represent temporal variations across groups of individuals whose births fall in the same interval (Blanchard et al., 1977). In demography, a cohort is defined as a collection of people who experience a certain event in a given time period (Newell, 1990). Individuals with the same birth cohort move through life together and are confronted by the same historical, social, and economic events at the same age and same point in time. Accordingly, cohort effects are deemed to reflect the effects of formative experience acquired via the influence of early life conditions and via the continuous exposure to these events in the remainder of the lifespan (Yang, 2008). Because older cohorts die off and are replaced by younger cohorts with different birth background and life trajectories – a phenomenon termed 'demographic metabolism' by Ryder (1965) – society continuously renews its population composition, and thereby maintains its flexibility, and may, on these bases, experience induced changes (Ryder, 1965). Along this line, insights into cohort effects help to understand not only current pictures of different subpopulations but also future trends in society. The substantive influence of cohorts largely underlines the necessity of an age-period-cohort (APC) analysis. To date, very little is known about how multimodality varies by cohort, yet as we explain later in Section 2.2.3, variations in some of the correlates of multimodality could be strongly embedded in cohort succession.

Figure 2.1 illustrates the structural relationship between the effects of age, period, and cohort. The vertical and horizontal axes represent a series of cohorts and periods, respectively. At each point on the same diagonal line (i.e., the pink line), same-aged individuals may belong to different periods and cohorts. The shaded area bounded by pink lines reflects the 18-19 age group, and the pink arrow, therefore, indicates the effect of age from 18 to 19 averaged over periods and cohorts (supposing our diagram could be extended indefinitely). Likewise, the effects of period and cohort can be depicted by changing the vertical and horizontal axes.

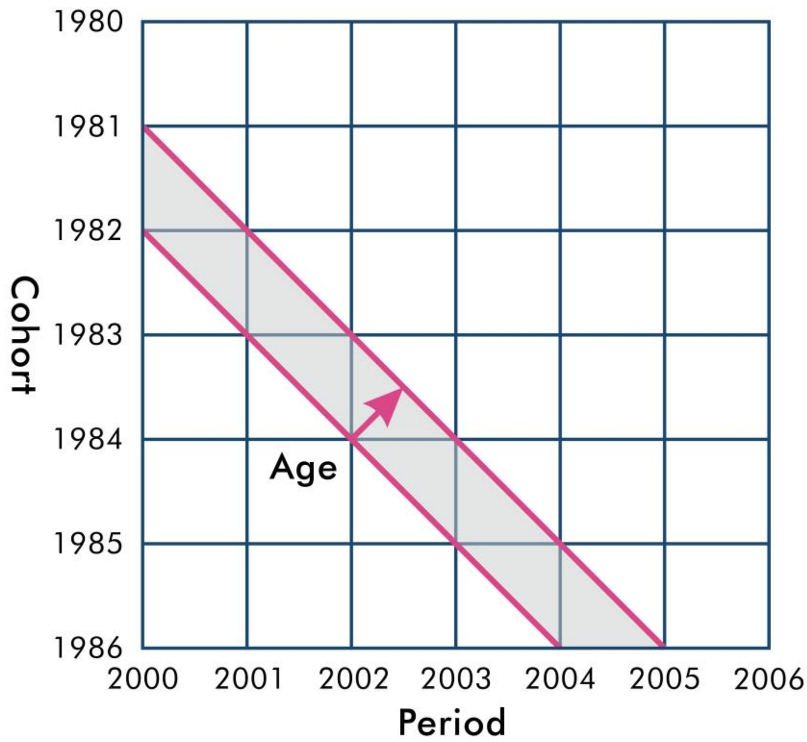

Figure 2.1 Nexus between age, period, and cohort (based on Yang and Land (2016)).

2.2.1. Age

A plethora of studies has observed the significant association between age and multimodality. The majority of the studies found evidence that was supportive of the belief that younger travellers tend to be more multimodal (e.g., Heinen and Mattioli (2019a); Heinen (2018); Klinger (2017); Molin et al. (2016); Buehler and Hamre (2016); Circella et al. (2019)). Yet the age-multimodality relation appears to be more complicated; it may not be depicted by linear or even monotonic relationships. The findings on this topic also seem to vary by countries. For example, Heinen and Mattioli (2019a) categorised individuals into three groups according to their age (i.e., 16 to 30, 31 to 64, and over 65 years old) and found that individuals in the older age group were associated with a lower level of multimodality in England. Moreover, the difference in multimodality between the 16-30 and 31-64 age groups was more pronounced than that between the 31-64 and over 65 age groups. Buehler and Hamre (2014)'s research in the US observed that, compared with their older counterparts (aged over 65), younger travellers were more likely to be multimodal car users than monomodal car users. However, they also showed that there were no regularities within the younger age groups in terms of the relation between age and the propensity of being multimodal or monomodal car users. Moreover, using the data from Mobility in Germany (MiD) and German Mobility Panel (MOP), Nobis (2007b) investigated the prevalence of various predefined multimodal groups in different life stages in Germany and found a steep decline in the percentage of multimodal travellers during the education-to-employment transition. Nevertheless, it was also shown that this trend was largely reversed in older adults, even amongst those with a high car availability. This research is partially in line with the research by Streit et al. (2015), which observed that multimodality was the lowest for 26-35, 36-50, and 51-60 age groups. Thus, multimodality may not necessarily decrease with age. Nobis (2007b) and Streit et al. (2015) suggested that there is a U-shaped association between age and multimodality, while some studies did not find a relationship (for example, Blumenberg and Pierce (2013), reported an insignificant correlation between age and the probability of multimodal travel in the US).

2.2.2. Period

Limited studies to date have focused on the temporal trends in multimodality over time. Two studies, which we describe in detail below, have looked into trends in the modal share shift from car use to other modes over the decades. On this basis, they made a conclusion as to whether there had been changes in multimodality over a long period, yet the degree of such changes remained relatively unclear. The multi-country research by Kuhnimhof et al. (2012a) analysed trends in the travel behaviour amongst young adults in six developed countries (i.e., Germany, France, Great Britain, Japan, Norway, and the US) by use of national travel surveys. Four years extracted from each of the 1970s, 1980s, 1990s, and middle 2000s were compared. The authors concluded that all countries except Japan had experienced a slight shift in the modal share from the car to public transport since the 1990s, which may have been indicative of an increase in multimodality in those countries. However, for young adults with car availability, the long-term upward trends in multimodality were only observed in Germany and Great Britain. Kuhnimhof et al. (2012b) explored travel trends among young German adults (18 to 29 years) using the Kontiv (i.e., Kontinuierliche Verkehrserhebung) 1976 survey and the MOP 1999-2008. They compared three discontinuous years, i.e., 1976, 1997, and 2007. For travellers with a car available, a dramatic decline was observed in the share of trips made by driving, whilst the use of public transport and non-motorised modes escalated, albeit to varying degrees. Nevertheless, only the share in car passengers showed a stable downward trend for those without car access. On this basis, the authors concluded that multimodality had increased among young adults with car availability in Germany.

Another three studies have shed light on the trends in multimodality characterised by predefined groups or indices. Indicated by the changes in the indices and shares of groups, these studies reveal the extent to which the level of multimodality has changed over time.

However, due to data restrictions, the time span and waves of the data are limited (exception: Heinen and Mattioli (2019a)). Buehler and Hamre (2014) looked into the differences in shares of multimodal/monomodal groups between 2001 and 2009 using the US National Household Travel Surveys. Three groups, namely, multimodal car users, monomodal car users, and travellers who do not use cars, were differentiated at the chained trip, day, and week levels. The authors found that monomodal car users accounted for a smaller share at all three levels in 2009 relative to 2001; the share in travellers who do not use cars and multimodal car users increased between 2001 and 2009, yet the magnitude of changes was fairly small. Streit et al. (2015) used the MOP data to study variability in individual travel behaviour between two time slices (1998-2002 and 2010-2012) in Germany. Indicated by the changes in customised multimodal indicators (MM), they concluded that multimodality increased for young adults aged between 18 and 35, regardless of their gender. For travellers between 35 and 50 years old and living in big cities, men tended to be become multimodal, whereas women showed an inverse trend. Heinen and Mattioli (2019a) made a substantial contribution to this topic by looking at a relatively large number of years and adopting various multimodality indices. They investigated trends in multimodality across various socioeconomic groups in England over 21 consecutive years (1995-2015) by use of the NTS. Looking at changes in multimodality indicators and estimating multivariate models (with year treated as a continuous variable), they concluded that multimodality decreased in England between 1995 and 2015.

2.2.3. Cohort

To the best of our knowledge, the notion of a cohort had been largely untouched in relation to the topic of multimodality until the recent research by Lee et al. (2019). They looked into the discrepancies in daily travel patterns between millennials and GenXers using the California Millennials Dataset 2015. Treating age as an inactive covariate in their latent analysis, the authors analysed the estimated distributions of travel patterns across ages, *ceteris paribus*. It was observed that monomodal drivers were disproportionately prevalent in the 46–50 age group, whilst the share of transit riders and active travellers peaked before reaching an age of 40 years and then decreased. On this basis, a conclusion was drawn that millennials tend to be, on average, more multimodal than GenXers. Nevertheless, this research used cross-sectional data, and thus it was unable to distinguish whether the findings were attributable to a generational shift or ageing *itself*.

The existing literature has also shed light on the intergenerational differences in general travel behaviour, particularly in availability and the use of a car (see, e.g., Goodwin and Van Dender (2013) and Van Wee (2015) for the review and discussion on peak car). In light of the dominant role of the car in daily travel in developed societies, studies on this topic may provide us with a deeper understanding of the cohort-multimodality nexus.

For example, Kuhnimhof et al. (2011) observed that young Germans born in the late 60s, 70s, and early 80s were, relative to the earliest cohort (born 1955-1964), associated with a higher level of car ownership, more intensive car use, and a greater growth rate in car travel before reaching their middle adulthood (i.e., 30 years old). In contrast, the post-1985 cohort noticeably lagged behind the older cohorts in terms of car ownership and car travel distance. Similarly, Garikapati et al. (2016) found that, in early adulthood (18-24 years old), 'younger' American millennials (born 1988-1994), compared to the 'older' millennials (born 1979-1985), spent considerably less time on car travel and outdoor activities. Although millennials exhibited increasing similarities as they aged with their same-aged predecessors (i.e., GenXers) in terms of their activity-time use patterns, millennials remained less car-oriented. The generational decline in car use was also recognised in the non-western context. Zhou and Wang (2019) used a propensity score matching method to compare the daily travel patterns of similar-aged individuals between 2002 and 2011 in Hong Kong. The authors found that younger generations, compared to the older counterparts with similar socioeconomic characteristics, undertook fewer car trips and spent less time on travel. Some studies have tried to shed light on the causes behind these observations. For example, Grimal (2020) looked into the potential mechanism by which French millennials became less car-oriented (characterised by more regular transit use and less car ownership) and found that the generational differences in cars could be mainly attributed to the shift in residential patterns and to some extent to increasing work pressure, degraded transport conditions, and changes in desired lifestyles over recent decades.

It is not only in car use and ownership that we may see evidence of such patterns, but also in the acquisition of a driving license, with this tending to become less prevalent for more recent generations. Delbosc and Currie (2013) summarised the existing empirical evidence on international trends in driver license acquisition amongst same-aged young adults (18-30 years old) over time (1983-2010). It was found that the percentage of youth licensing universally decreased in nine out of fourteen analysed countries – Australia, the US, Canada, Norway, Sweden, Great Britain, Germany, France, and Japan – with an average annual rate of decline of 0.6%.

It appears that recent generations, particularly millennials and subsequent generations, have seen a decline in car availability and car use. Nevertheless, recent research by Krueger et al. (2019) suggested that cohort succession (or the replacement of generations) may not play a critical role in explaining the observed downward trend in car use in young Germans. Using a hierarchical Bayesian model, Krueger et al. (2019) analysed the trend in frequencies of using different modes, from 1996 to 2016, whilst simultaneously taking into account both period and cohort effects. Though in line with most studies, in that young

Germans were found to make fewer daily trips by car in 2016 than their counterparts 20 years ago, they found that only one-sixth of such a decline could be ascribed to cohort effects. By contrast, period effects explained two-thirds of the decline in car use between 1996 and 2016.

Finally, going beyond car use, Frändberg and Vilhelmson (2011) explored spatial mobility across cohorts over a period of 28 years (i.e., 1976-2008) using data from the Swedish National Travel Survey. Since the level of daily mobility is closely connected with opportunities to use different modes, their research potentially provides a novel perspective into the understanding of the cohort-multimodality relation. The authors found that the more recent cohorts of young males showed a substantial decline in the daily travelled distance. The authors discussed that the reduction in daily mobility for new-cohort young males might be attributed to their distinct life trajectory (e.g., a longer study time before entering into the labour market) and increased 'virtualisation' (i.e., spending more time on activities conducted through the internet).

2.2.4. Research gaps

In summary, it appears that multimodality increased in most developed countries over the last decades, especially for young travellers. England seems to be an exception. Nevertheless, limitations exist in the methodology and data used by most of the aforementioned studies on temporal patterns in multimodality. The majority of these studies are descriptive, focusing on the temporal patterns across the population or specific subpopulations. Given the mathematical coupling between age, period, and cohort, it follows that the conclusions of these studies may not be robust. Moreover, although some look at a relatively long-time span, the majority of studies were conducted based on longitudinal data with limited waves of observations, which limits the ability to investigate cohort effects.

2.3. Research design

2.3.1. Data

The research reported in this paper was based on data extracted from the special licensed National Travel Survey (NTS) for England, 2001 to 2017 (Department for Transport, 2019a, b). The NTS is a nationwide repeated cross-sectional survey designed to monitor trends in travel behaviour within England2 (NatCen Social Research, 2018). The NTS was firstly conducted in 1965/1966, and it became an annual survey in 1988. From 2002 onwards, the NTS used weights to offset the influence of non-response bias; the weighting methodology was retrospectively applied to data back to 1995.

[2] The NTS only covers England for the full-time span (2001-2017) we studied.

The NTS has several strengths for investigating temporal patterns in multimodality across age, periods, and cohorts. Firstly, the data structure of the NTS is well-suited for our purpose. The repeated cross-sectional survey, owing to its high representativeness, can be applied to the synthetic cohort approach that traces essentially the life trajectories of groups of people born in the same year or range of years (Preston and Guillot, 2000). Compared to a panel survey, such a survey also has the advantage that it spans a longer period with more waves, due to its robustness against drop-out of samples (Crossley and Ostrovsky, 2003). These advantages enabled us to disentangle the confounding effects of age, period, and cohort. Secondly, this survey has adopted a relatively consistent sampling method and survey technique since 1995 (see NatCen Social Research (2018) for detailed information). Thirdly, the NTS uses high-quality seven-day travel diaries to collect personal travel information that covers a wide range of modes and the intensity of using these modes, which allows us to accurately capture individual multimodality. Fourthly, the NTS is highly representative of the population of England, allowing us to draw conclusions for the entire country.

We limited our analyses to the years 2001 to 2017 in order to ensure the consistency of weighting methodologies and the considered variables[3]. Our research was restricted to the individuals living in England, as Scotland and Wales were no longer covered by the NTS from 2013 onwards. We restricted our main analyses to the individuals aged 16 and over (n=203,329). Alternative sample sets with different age groups were also used for our sensitivity analyses (see Section 2.3.4).

2.3.2. Multimodality measurements

We used a continuous index, namely, the objective mobility personal index (OM_PI), to measure multimodality. The existing literature has developed a relatively wide range of multimodality measurements, which can be generally distinguished into several categories of individual multimodality: (1) predefined categorisations (e.g., Klinger (2017)); (2) data-driven classifications (e.g., Kroesen (2014)); and (3) continuous indices (e.g., Heinen and Mattioli (2019a)). The former two measurements provide intuitive results by categorising individuals into distinct groups regarding multimodality. However, they overlook, to a certain extent, the intragroup differences and the levels of variability. The continuous indices, while not explicitly able to describe the use of a specific mode, are more effective in gauging the level of individual multimodality (Heinen, 2018). This is well-suited to the

[3] Several potential correlates of multimodality, e.g., ethnicity, bicycle ownership, and locations of work, are not consistently available for the 1995-2000 NTS data.

aim of our research by enabling us to capture the changes in the level of multimodality at the individual level.

The **OM_PI**, as proposed by Diana and Mokhtarian (2007), is regarded as one of the potentially desirable continuous indices for measuring multimodality. This index is developed based on the Shannon entropy formula, which has been extensively acknowledged as a reliable measure of diversity and inequality. Moreover, Diana and Pirra (2016) suggested that the **OM_PI** is preferable in depicting multimodality in cases where individuals in question are not equally accessible to specific modes. The **OM_PI** ranges from 0 to 1; a value of 0 indicates the exclusive use of only one mode, whilst a value of 1 stands for the circumstance where all modes in the considered mode choice set are equally used at the same intensity. The **OM_PI** is calculated based on the modal share by considered modes.

$$OM\_PI = \sum_{i=1}^{n}\left[\frac{f_i}{\sum_{j=1}^{n} f_j}\ln\left(\frac{\sum_{j=1}^{n} f_j}{f_i}\right)\frac{1}{\ln n}\right] \tag{2.1}$$

In **Eq. (2.1)** *n* stands for the total number of modes considered, and f_i denotes the number of trip stages made by mode *i* by a given individual during the travel diary week.

In the NTS, a *trip* refers to a one-way course of travel with one main purpose. A trip can be constituted of several trip stages, for example, for one commute trip, someone could cycle to the train station, use the train, and walk to work from the train station. To include the full individual modal mix, we use the mode choice data at a *trip stage* level.

Following the existing studies on multimodality using the NTS (e.g., Heinen and Mattioli (2019b); Heinen and Chatterjee (2015)), we considered a total of eight modes for measuring the OM_PI: (1) walk; (2) bicycle; (3) car driver; (4) car passenger; (5) bus[4]; (6) railway[5]; (7) taxi; and (8) other[6]. Since the calculated level of multimodality is connected with the definition of the mode choice set, a more aggregated three-mode-based choice set was also considered for the purpose of sensitivity analysis, with the composite modes defined as: car transport (car driver and car passenger), and public transport (bus, railway, taxi, and other) and active travel (walk and bicycle). As suggested by the NTS Data Extract User Guide (Department for Transport, 2018b), we applied weights to calibrate the number of trip stages made by different modes. For short walks (i.e., walking trip stages of less than one mile) a weight known as SSXSC was used to adjust for the fact that such trips were only recorded on the last day of the survey week. Also, a trip/stage weight known as W5 was applied to offset the 'drop-off' phenomenon of the recorded number of trips/stages

[4] 'Bus' covers bus in London as well as other local and non-local (coach) services.

[5] 'Railway' covers London Underground and surface rail.

[6] 'Other' covers motorcycle, other private (mostly private hire bus) and other public transport (mostly light rail).

declining over time during the week[7]. These weighting methodologies have been applied consistently across the NTS surveys from 1995 onwards (NatCen Social Research, 2018).

In the 2001-2017 NTS data, individuals made on average 23.3 (S.D.=16.6) trips stages during the travel diary week. Car driver trip stages accounted for the largest share 45%, whilst walk (20%), car passenger (19%), and bus (8%) trip stages made up most of the remainder. We examined the correlations between the (eight-modal-based) OM_PI and the shares in mode choice. Car diver modal share was negatively correlated (r=-0.393) with OM_PI at a significance level of 0.01. By contrast, significantly positive correlations were observed between OM_PI and the shares in trip stages made by walking (r=0.328), cycling (r=0.102), bus (r=0.117), rail (r=0.248), taxi (r=0.069), and other modes (r=0.044). Car passenger modal share was not significantly correlated with OM_PI ($|r|$<0.001; p=0.909). Our examinations indicated that travellers with a higher level of multimodality, *on average*, drove less; this is in the context of England, where driving is the dominant mode of transport.

2.3.3. Correlates

Heinen and Chatterjee (2015) applied a systematic framework of correlates of individual multimodality, derived from the perspective of spatial mobility constraints of Hägerstraand (1970), and found that multimodality can be simultaneously shaped by multiple types of such constraints. Drawing on their conceptual framework, we focused on the correlates of multimodality that covered six dimensions of mobility constraints as follows: (1) social role constraints; (2) physical mobility constraints; (3) work constraints; (4) economic constraints; (5) accessibility constraints; and (6) mobility resource constraints. The descriptive statistics for these variables in different age, period, and cohort groups is provided in **Appendix A.1**.

2.3.4. Statistical analyses

This research adopted a contextual approach – the HAPC model (Yang and Land, 2006) – to explore the age, period, and cohort effects on multimodality. The principle of the

[7] Short walks weight (SSXSC) multiplies the number of short walk trip stages by seven to ensure a representative weekly report. This is to control for the fact that such trip stages are only asked to be reported in the last day of the survey week to reduce the burden for the respondents (NatCen Social Research, 2018). Similar to other multiday travel diary surveys, in the NTS, there is a gradual reduction in the number of trips reported during the travel diary week. To reduce the drop-off bias, the trip/stage weight (W5) is developed. The drop-off rates differ slightly across the survey years; detailed information on this issue can be found in the NTS technical report of each year.

APC analysis is to statistically partition age, period, and cohort, and estimate the net effects of these three variables (Smith, 2008). Nevertheless, there exists a well-known 'identification problem' that these three time-related variables necessarily fall in perfect multicollinearity, e.g., cohort plus age equals period, which makes it impossible to use classic linear regression in the estimation. Yang and Land (2016) systematically summarise conventional approaches to this identification problem that have been developed since the 1970s, such as the reduced two-factor models, constrained generalised linear models, nonlinear parametric transformations, and proxy variable approaches (see, e.g., Kupper et al. (1983), Fienberg and Mason (1979), and O'Brien et al. (1999) for applications and reviews). Yang and Land (2016) argue that each of these approaches has its own drawbacks. Most importantly, they note, such approaches fail to conceptualise and quantify the contextual effects of social-historical transformations embedded in the changes of time periods and birth cohorts.

The HAPC method can be seen as an extension of the mixed effects model to the APC analysis. In light of the multihierarchical nature of such a method, it does not trigger the identification problem, and so is able to explicitly distinguish in the estimation the contextual (random) effects of periods/cohorts from the (fixed) effects of individual attributes. Specifically, the HAPC herein consists of two levels as follows:

Level 1, namely the within-group model, which is adopted for the fixed effect estimation of all individual-level correlates:

$$Y_{ijk} = \alpha_{jk} + \beta_1 AGE_{ijk} + \beta_2 AGE_{ijk}^2 + \sum_{n \geq 3} \beta_n X_{nijk} + e_{ijk} \quad (2.2)$$

where Y_{ijk} denotes the level of multimodality (measured by the OM-PI) for individual i within the jth period and kth cohort. AGE and AGE^2 represent the age and age squared, respectively. Following Bell (2014), we centred the age of each individual around the grand mean (i.e., 48.3 years old) to reduce potential multicollinearity. As AGE and AGE^2 can be disproportionally large in relation to the other correlates, the original value of centred age was divided by 10 to calculate these two variables. X_{nijk} stands for the other correlates of multimodality. α_{jk} is the intercept at level one; it reflects the average level of multimodality in the jth period and kth birth cohort when the values of all correlates are zero. β_n is the coefficient of the corresponding correlate X_{nijk}. e_{ijk} stands for the random error at level 1.

Level 2 is the between-group model, wherein the level-1 intercept is assumed to vary across periods and cohorts:

$$\alpha_{jk} = \gamma_0 + u_{0j} + v_{0k} \quad (2.3)$$

$$u_{0j} \sim N(0, \tau^2),\ v_{0k} \sim N(0, \varphi^2) \quad (2.4)$$

In **Eq. (2.3)**, γ_0 is the grand mean of the level of individual multimodality across all periods and birth cohorts when the values of all level-1 correlates are zero. Periods are defined by the seventeen waves of the NTS between 2001 to 2017; cohorts are defined by five-year intervals (except the pre-1930 and post-1990 cohorts based on the consideration of the sample size of each cohort) of the birth year. u_{0j} is the slope of the jth period that explains the residual random effect of the *j*th period averaged over all cohorts. v_{0k} is the slope of the *k*th cohort that explains the residual random effect of the *k*th cohort averaged over all periods. u_{nj} and v_{nk} follow a normal distribution with variance τ^2 and φ^2, respectively (**Eq. (2.4)**).

According to **Eqs. (2.3)-(2.4)**, the combined model is established as follows:

$$Y_{ijk} = \gamma_0 + \beta_1 AGE_{ijk} + \beta_2 AGE_{ijk}^2 + \sum_{n\geq 3} \beta_n X_{nijk} + u_{0j} + v_{0k} + e_{ijk} \qquad (2.5)$$

A multistep estimation strategy was used to improve the interpretability of our results. We changed level-1 components (spatial mobility constraints except for social role constraints) for different estimations, yet kept the level-2 components (period and cohort) constant. The social role constraints (i.e., age, gender, and ethnicity) were retained in each estimation, as these constraints (except for age) are relatively stable over the life course for most individuals. First, we estimated the maximally adjusted model with all spatial mobility constraints accounted for. Second, five models – with the spatial mobility constraints excluded one type at a time from the maximally adjusted model – were tested. Third, the spatial mobility constraints (except for social role constraints) were removed one at a time from the maximally adjusted model. As such, a total of 26 (i.e., $C_5^2 + C_5^3 + C_5^4 + C_5^5$) models were examined in this step. We report the maximally adjusted model as the main model to interpret the changes in multimodality across ages, periods, and cohorts. By comparing all models, we looked into the extent to which the age-, period-, and cohort-specific changes in multimodality could be moderated by spatial mobility constraints. Given the richness of the potential input variables, we assessed the multicollinearity of the HAPC models using the classic variance inflation factors (VIFs). The VIF values of all variables lay within an acceptable range (VIF<4; see, e.g., Hair et al. (2010)), indicating the absence of problematic multicollinearity.

Sensitivity analyses were conducted to ensure the interpretability and robustness of the results. First, we included the number of trip stages in the main model as an explanatory variable (**Sensitivity test 1**)), as more trip stages travelled potentially offer more opportunities to use different modes (Heinen, 2018). Second, we repeated the analyses adopting the three-mode-based OM_PI as the dependent variable (**Sensitivity test 2**). Third, the HAPC models were separately estimated using three additional sets of samples aged 30 and over (Alternative Sample Set A), 35 and over (Alternative Sample Set B), and between 30 and 70 (Alternative Sample Set C) (**Sensitivity tests 3-5**). The reason is that repeated cross-sectional data are necessarily unbalanced in the age-by-cohort (or cohort-by-period) distribution. Therefore, individuals in some recent cohorts, such as 1980-1984, 1985-1989, and post-1990 cohorts, are associated with younger-than-average ages. In light of the correlations between multimodality and age and between multimodality and some age-related attributes, the estimated effects of these cohorts could be potentially overstated, despite the fact that the HAPC model is able to peel the age effect off the cohort effect effectively.

2.4. Results

The HAPC models were applied to examine the net effects of age, period, and cohort on multimodality. We first examined the fixed effects (**Table 2.1**). In the maximally adjusted model (main Model, **Model 1)**, age was negatively associated with multimodality, whilst age squared has only an insignificant effect on multimodality. As the ageing process involves a wide range of social and biological changes, we then examined the extent to which spatial mobility constraints may impact the age-multimodality relation. The age effects were, therefore, tested by removing one type of these constraints at a time from the main model. As indicated by the changes in coefficients of age and age squared (**Model 2-6**), we found that all types of spatial mobility constraints might potentially moderate the association between age and multimodality, albeit to a varying extent. In particular, the negative effect of age squared turned to be significant after the physical mobility, work, and economic constraints were excluded. This is similar to the examination of the extent to which the combinations of these constraints were related to the temporal patterns in multimodality across ages. It was found that after the data were simultaneously uncontrolled for physical mobility, work, and economic constraints, the age-squared variable became significant (results were not shown for brevity).

To illustrate the degree of age-specific changes in multimodality, we calculated the predicted mean value of OM_PI according to the aforementioned models[8]. The OM_PI predicted by Model 1 dropped from 0.276 to 0.183 from the age of 16 to 80, *ceteris paribus*. To intuitively illustrate this, consider a traveller who makes 100 trips a week, with driving, walking, and the use of public transport accounting for 50, 25, and 25 trips, respectively. The decrease of 0.093 in the OM_PI indicates roughly 10 trips made by either walking or public transport will turn to driving trips, and such a 10% mode change would be a considerable effect if replicated across the population[9]. We then successively compared the temporal patterns in the predicted OM_PI across ages between Model 1 and Models 2-6 (**Figure 2.2**). **Figure 2.2** contains five subfigures (A-E), each of which

[8] The predicted OM_PI for specific age *i* averaged over periods and cohorts is calculated based on Eq. (2.5), when other variables are set to zero: $\hat{y} = \widehat{\gamma_0} + \widehat{\beta_1}\left((Age_i - 48.3)/10\right) + \widehat{\beta_2}\left((Age_i - 48.3)/10\right)^2$

[9] This hypothetical case was posed considering the average level of modal shares in England. It should be noted that a lower level of multimodality does not necessarily mean more car trips/use. For example, the decrease of 0.093 in the OM_PI can also indicate roughly 10 trips made by either walking or driving will turn to public transport trips for an individual who had 50, 25, and 25 trips that are respectively made by public transport, driving, and walking.

successively displays the comparison between the OM_PIs predicted by Models 2-6 (purple-to-pink lines) and Model 1 (blue lines). By examining the slope of these predicted lines, it was suggested that physical mobility and work constraints, compared to other constraints, might have a stronger influence in moderating the age-multimodality nexus, particularly in specific age groups (work constraints for age under 30 and above 60; physical mobility constraints for age above 30). **Figure 2.3** shows the difference in the predicted value of OM_PI between the maximally adjusted model and the model with only physical mobility and work constraints excluded. The value of OM_PI predicted by the latter model is greater yet decreases faster than that predicted by the former one, before the two predicted lines intersect at the age of 30. After the age of 30, the two predicted lines diverge at first and then converge. Combining these findings, it appears that changes in work constraints (e.g., the change from student to full-time employee) and physical mobility constraints (e.g., developing walking difficulties) has accelerated the decline in multimodality before and after reaching middle adulthood, respectively.

Table 2.1 Results from hierarchical age-period-cohort model of multimodality (fixed-effect parts).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Social Role Constraints							
Age	-1.460E-02 (1.132E-03) ***	-1.783E-02 (1.184E-03) ***	-1.155E-02 (1.108E-03) ***	-1.365E-02 (9.540E-04) ***	-1.532E-02 (1.282E-03) ***	-1.355E-02 (9.490E-04) ***	-8.290E-03 (1.096E-03) ***
Age squared	-3.000E-04 (2.540E-04)	-5.400E-04 (2.580E-04) *	1.701E-03 (2.450E-04) ***	-5.600E-04 (2.490E-04) *	-1.500E-04 (2.590E-04)	1.170E-04 (2.470E-04)	6.350E-04 (2.440E-04) **
Gender							
Female	3.778E-02 (9.020E-04) ***	3.851E-02 (9.060E-04) ***	4.436E-02 (8.580E-04) ***	3.842E-02 (9.040E-04) ***	3.829E-02 (9.080E-04) ***	3.589E-02 (8.950E-04) ***	3.664E-02 (8.650E-04) ***
Male (ref)							
Ethnicity							
White	-1.304E-02 (4.399E-03) **	-1.198E-02 (4.418E-03) **	-1.143E-02 (4.412E-03) **	-1.343E-02 (4.411E-03) **	3.490E-04 (4.422E-03)	-1.170E-02 (4.440E-03) **	-1.304E-02 (4.219E-03) **
Mixed Multiple Ethnic Groups	-5.476E-02 (1.996E-03) ***	-5.324E-02 (2.004E-03) ***	-5.344E-02 (1.996E-03) ***	-5.518E-02 (2.001E-03) ***	-3.089E-02 (1.956E-03) ***	-6.496E-02 (2.000E-03) ***	-4.686E-02 (1.915E-03) ***
Asian/Asian British (ref)							
Black/African/Caribbean/Black British	-2.394E-02 (2.869E-03) ***	-2.197E-02 (2.881E-03) ***	-2.268E-02 (2.875E-03) ***	-2.631E-02 (2.875E-03) ***	2.032E-03 (2.823E-03)	-2.545E-02 (2.890E-03) ***	-1.843E-02 (2.752E-03) ***
Other Ethnic Group	-3.090E-02 (4.107E-03) ***	-2.927E-02 (4.125E-03) ***	-2.978E-02 (4.118E-03) ***	-3.239E-02 (4.118E-03) ***	-1.173E-02 (4.112E-03) **	-3.360E-02 (4.145E-03) ***	-2.614E-02 (3.940E-03) ***
Physical Mobility Constraints							
Having Walking Difficulties							
Yes	-6.300E-02 (1.485E-03) ***		-6.534E-02 (1.464E-03) ***	-6.397E-02 (1.489E-03) ***	-6.603E-02 (1.495E-03) ***	-6.348E-02 (1.494E-03) ***	-5.100E-02 (1.428E-03) ***
No (ref)							
Work Constraints							
Economic Status							
Full-time (ref)							
Part-time	3.066E-02 (1.329E-03) ***	3.065E-02 (1.335E-03) ***		2.513E-02 (1.322E-03) ***	3.021E-02 (1.340E-03) ***	3.105E-02 (1.340E-03) ***	2.205E-02 (1.277E-03) ***
Unemployed	1.770E-02 (2.834E-03) ***	1.804E-02 (2.846E-03) ***		6.865E-03 (2.819E-03) *	1.474E-02 (2.855E-03) ***	2.450E-02 (2.854E-03) ***	2.312E-02 (2.719E-03) ***
Retired	4.193E-02 (1.887E-03) ***	3.861E-02 (1.895E-03) ***		3.289E-02 (1.867E-03) ***	4.184E-02 (1.903E-03) ***	4.285E-02 (1.901E-03) ***	4.392E-02 (1.810E-03) ***
Student	3.635E-02 (2.579E-03) ***	3.551E-02 (2.592E-03) ***		2.915E-02 (2.572E-03) ***	3.999E-02 (2.600E-03) ***	4.380E-02 (2.588E-03) ***	3.743E-02 (2.474E-03) ***
Other inactive employment	-3.980E-03 (1.594E-03) *	-1.581E-02 (1.576E-03) ***		-1.347E-02 (1.567E-03) ***	-7.510E-03 (1.602E-03) ***	-1.950E-03 (1.597E-03)	5.095E-03 (1.530E-03) ***
Multiple Work Locations							
Yes (ref)							
No	-2.079E-02 (1.575E-03) ***	-2.047E-02 (1.582E-03) ***		-2.155E-02 (1.579E-03) ***	-1.991E-02 (1.587E-03) ***	-2.381E-02 (1.588E-03) ***	-1.006E-02 (1.513E-03) ***
Work from Home							
Yes	-1.520E-03 (2.700E-03)	-2.110E-03 (2.712E-03)		-1.700E-04 (2.707E-03)	-1.710E-03 (2.719E-03)	-1.950E-03 (2.726E-03)	4.731E-03 (2.590E-03)
No (ref)							

Economic Constraints							
Household Income							
£50,000 and over (ref)							
£25,000 to £49,999	-4.317E-02 (1.295E-03) ***	-4.424E-02 (1.300E-03) ***	-3.806E-02 (1.264E-03) ***		-5.596E-02 (1.280E-03) ***	-3.185E-02 (1.243E-03) ***	-3.275E-02 (1.245E-03) ***
£24,999 and less	-2.315E-02 (1.145E-03) ***	-2.303E-02 (1.150E-03) ***	-2.117E-02 (1.146E-03) ***		-2.999E-02 (1.147E-03) ***	-2.122E-02 (1.142E-03) ***	-1.779E-02 (1.099E-03) ***
Accessibility Constraints							
Settlement Type							
London Boroughs	6.853E-02 (2.230E-03) ***	6.972E-02 (2.239E-03) ***	6.834E-02 (2.237E-03) ***	7.433E-02 (2.229E-03) ***		7.252E-02 (2.239E-03) ***	5.244E-02 (2.143E-03) ***
Metropolitan Built-up Areas	1.226E-02 (2.076E-03) ***	1.196E-02 (2.084E-03) ***	1.239E-02 (2.082E-03) ***	1.193E-02 (2.081E-03) ***		1.283E-02 (2.088E-03) ***	5.106E-03 (1.992E-03) *
Urban over 250 population	1.760E-02 (2.005E-03) ***	1.731E-02 (2.013E-03) ***	1.764E-02 (2.011E-03) ***	1.812E-02 (2.010E-03) ***		1.907E-02 (2.023E-03) ***	7.733E-03 (1.925E-03) ***
Urban with 25k to 250k population	9.867E-03 (1.821E-03) ***	9.689E-03 (1.828E-03) ***	9.618E-03 (1.826E-03) ***	9.816E-03 (1.825E-03) ***		1.201E-02 (1.836E-03) ***	3.641E-03 (1.747E-03) *
Urban with 3k to 25k population	6.933E-03 (1.647E-03) ***	6.832E-03 (1.654E-03) ***	6.777E-03 (1.652E-03) ***	6.484E-03 (1.651E-03) ***		8.665E-03 (1.662E-03) ***	4.045E-03 (1.580E-03) *
Rural (ref)							
Population Density (Persons/ha)							
40 and over	1.392E-02 (1.779E-03) ***	1.349E-02 (1.787E-03) ***	1.365E-02 (1.785E-03) ***	1.350E-02 (1.784E-03) ***		1.970E-02 (1.786E-03) ***	8.148E-03 (1.708E-03) ***
20 to 39.99	7.866E-03 (1.592E-03) ***	7.467E-03 (1.599E-03) ***	7.756E-03 (1.598E-03) ***	7.207E-03 (1.596E-03) ***		9.943E-03 (1.604E-03) ***	5.505E-03 (1.528E-03) ***
5 to 19.99	3.754E-03 (1.451E-03) **	3.305E-03 (1.457E-03) *	3.734E-03 (1.456E-03) *	3.392E-03 (1.455E-03) *		4.264E-03 (1.464E-03) **	2.108E-03 (1.392E-03)
4.99 and less (ref)							
Housing Tenure							
Owns/Buying	2.831E-02 (1.107E-03) ***	3.058E-02 (1.111E-03) ***	3.028E-02 (1.106E-03) ***	3.385E-02 (1.097E-03) ***		1.629E-02 (1.054E-03) ***	3.002E-02 (1.062E-03) ***
Rents and other (ref)							
Mobility Resources Constraints							
Number of Household Vehicles							
2 and over	-6.520E-02 (1.661E-03) ***	-6.427E-02 (1.668E-03) ***	-6.435E-02 (1.662E-03) ***	-5.224E-02 (1.613E-03) ***	-7.032E-02 (1.571E-03) ***		-5.680E-02 (1.594E-03) ***
1	-4.154E-02 (1.426E-03) ***	-4.078E-02 (1.432E-03) ***	-4.003E-02 (1.429E-03) ***	-3.808E-02 (1.421E-03) ***	-4.225E-02 (1.388E-03) ***		-3.609E-02 (1.368E-03) ***
0 (ref)							
Owning a Bicycle							
Yes	4.220E-02 (9.460E-04) ***	4.437E-02 (9.490E-04) ***	4.365E-02 (9.470E-04) ***	4.365E-02 (9.480E-04) ***	4.009E-02 (9.440E-04) ***		3.711E-02 (9.080E-04) ***
No (ref)							
Holding Full Car License							
Yes	-8.340E-03 (1.229E-03) ***	-5.750E-03 (1.233E-03) ***	-9.610E-03 (1.222E-03) ***	-9.010E-03 (1.232E-03) ***	-6.210E-03 (1.237E-03) ***		-2.350E-02 (1.185E-03) ***
No (ref)							

Number of Trip Stages							3.399E-03 (2.600E-05) ***
Intercept	2.318E-01 (3.954E-03) ***	2.228E-01 (4.327E-03) ***	2.319E-01 (3.908E-03) ***	1.997E-01 (3.259E-03) ***	2.836E-01 (4.355E-03) ***	1.955E-01 (3.097E-03) ***	1.556E-01 (3.855E-03) ***
Number of observations	203329	203329	203329	203329	203329	203329	203329

Note: Model 1: the maximally adjusted model. Model 2-6: the models that respectively excluded physical mobility, work, economic, accessibility, and mobility resources constraints from the maximally adjusted model. Model 7: sensitivity analysis 1 (including the number of trip stages).

OM_PI-8 was used as the dependent variables.

*, **, and *** denotes significant at the significance level of 0.05, 0.01, and 0.001, respectively.

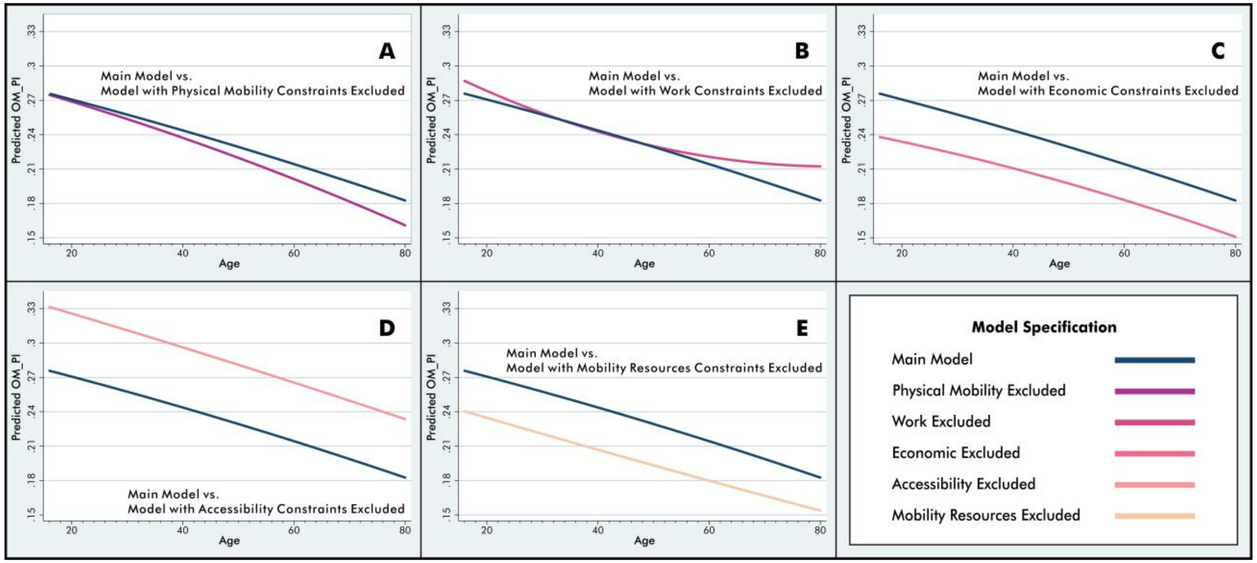

Figure 2.2 The extent to which a specific type of spatial mobility constraint moderates the age-multimodality relation.

Note: subfigures A-E successively display the comparison between OM_PI predicted by Model 1 (the maximally adjusted model; blue lines) and Model 2-6 (the models that respectively excluded physical mobility, work, economic, accessibility, and mobility resources constraints from the maximally adjusted model; purple-to-pink lines).

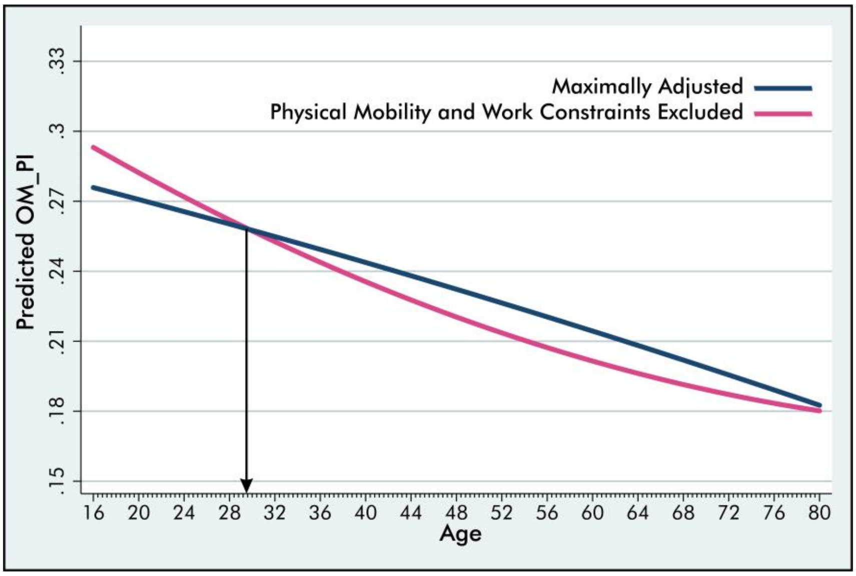

Figure 2.3 The extent to which physical mobility and work constraints moderate the age-multimodality relation.

Note: the predicted mean value of OM_PI-8 was calculated according to Model 1 (the blue line) and the model that excluded physical mobility and work constraints from the maximally adjusted model (the purple line).

In addition to age, we also found that multimodality was associated with the vast majority of the variables we considered, at a significance level of 0.05 (**Model 1**). These identified correlates belong to different domains of mobility constraints. In summary, it was observed that females, Asian/Asian British, students, people who do not have walking difficulties, do not have a full-time job, work at one location, do not work at home, have higher household income, live in self-owned housing, live in a densely populated urban area, and those who do not have access to a vehicle in the household, own a bicycle, and do not hold a full car license, tended to be more multimodal.

We then focused on the random effects. It was found that individual multimodality exhibited significant variation ($p<0.05$) across periods and cohorts (**Table 2.2**). It was also observed that the variance for the cohort was larger than that for the period, regardless of models, 0.000121 and 0.000016, respectively. This implies that the total variance in individual multimodality accounted for by differences in cohort is more than six times of that accounted for by differences in period. Therefore, the cohort effects, compared to the period effects, more effectively explain the observed changes in multimodality over time.

Table 2.2 Results from hierarchical age-period-cohort model of multimodality (random-effect parts).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variance Components	Variance	Variance	Variance	Variance	Variance	Variance	Variance
Period	0.000016 **	0.000012 *	0.000020 ψ	0.000013 *	0.000019 *	0.000018 *	0.000016 **
Cohort	0.000121 *	0.000167 *	0.000116 ***	0.000067 *	0.000192 ψ	0.000062 *	0.000113 *
Random Effects	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Period							
2001	6.600E-04 (2.365E-03)	-5.500E-04 (2.235E-03)	5.260E-04 (2.496E-03)	-1.040E-03 (2.247E-03)	1.944E-03 (2.486E-03)	9.320E-04 (2.419E-03)	-1.430E-03 (2.308E-03)
2002	2.244E-03 (1.952E-03)	5.990E-04 (1.863E-03)	1.680E-03 (2.054E-03)	-2.200E-04 (1.850E-03)	3.103E-03 (2.057E-03)	2.744E-03 (1.981E-03)	-3.500E-03 (1.903E-03)
2003	-1.800E-04 (1.870E-03)	-1.970E-03 (1.783E-03)	-6.500E-04 (1.969E-03)	-2.470E-03 (1.777E-03)	-8.060E-06 (1.961E-03)	4.820E-04 (1.904E-03)	-2.700E-03 (1.823E-03)
2004	-3.150E-03 (1.847E-03)	-4.290E-03 (1.759E-03) *	-3.690E-03 (1.945E-03)	-4.700E-03 (1.762E-03) **	-2.510E-03 (1.937E-03)	-3.020E-03 (1.887E-03)	-5.730E-03 (1.800E-03) **
2005	2.849E-03 (1.808E-03)	1.277E-03 (1.720E-03)	2.897E-03 (1.906E-03)	1.737E-03 (1.731E-03)	3.355E-03 (1.892E-03)	3.297E-03 (1.854E-03)	-7.200E-04 (1.762E-03)
2006	1.776E-03 (1.795E-03)	5.330E-04 (1.706E-03)	1.348E-03 (1.892E-03)	8.410E-04 (1.724E-03)	2.630E-03 (1.874E-03)	2.015E-03 (1.847E-03)	-1.780E-03 (1.750E-03)
2007	4.176E-03 (1.780E-03) *	3.704E-03 (1.690E-03) *	3.975E-03 (1.877E-03) *	3.733E-03 (1.713E-03) *	5.112E-03 (1.855E-03) **	4.802E-03 (1.835E-03) **	4.747E-03 (1.734E-03) **
2008	6.445E-03 (1.786E-03) ***	5.840E-03 (1.696E-03) ***	6.595E-03 (1.883E-03) ***	6.382E-03 (1.721E-03) ***	5.977E-03 (1.858E-03) **	6.734E-03 (1.844E-03) ***	5.945E-03 (1.740E-03) ***
2009	7.047E-03 (1.760E-03) ***	6.735E-03 (1.670E-03) ***	7.298E-03 (1.856E-03) ***	6.931E-03 (1.696E-03) ***	6.894E-03 (1.832E-03) ***	7.119E-03 (1.818E-03) ***	9.127E-03 (1.715E-03) ***
2010	-2.010E-03 (1.784E-03)	-1.780E-03 (1.693E-03)	-1.700E-03 (1.880E-03)	-1.310E-03 (1.718E-03)	-2.160E-03 (1.857E-03)	-2.010E-03 (1.842E-03)	-3.400E-04 (1.738E-03)
2011	-1.140E-03 (1.810E-03)	-9.400E-04 (1.719E-03)	-6.300E-04 (1.907E-03)	-5.700E-04 (1.742E-03)	-1.520E-03 (1.886E-03)	-1.100E-03 (1.866E-03)	1.648E-03 (1.763E-03)
2012	-4.090E-03 (1.790E-03) *	-3.740E-03 (1.700E-03) *	-3.580E-03 (1.887E-03)	-3.160E-03 (1.718E-03)	-5.650E-03 (1.868E-03) **	-4.010E-03 (1.841E-03) *	-1.940E-03 (1.744E-03)
2013	-3.500E-03 (1.826E-03)	-1.630E-03 (1.736E-03)	-3.170E-03 (1.924E-03)	-2.730E-03 (1.749E-03)	-4.230E-03 (1.910E-03) *	-3.680E-03 (1.874E-03) *	-4.000E-05 (1.780E-03)
2014	-3.390E-03 (1.839E-03)	-1.540E-03 (1.750E-03)	-3.370E-03 (1.938E-03)	-1.950E-03 (1.756E-03)	-4.070E-03 (1.928E-03) *	-3.670E-03 (1.881E-03)	-1.000E-05 (1.793E-03)
2015	-4.290E-03 (1.884E-03) *	-2.380E-03 (1.795E-03)	-4.000E-03 (1.985E-03) *	-2.100E-03 (1.793E-03)	-4.730E-03 (1.980E-03) *	-4.890E-03 (1.921E-03) *	-3.400E-04 (1.837E-03)
2016	-3.070E-03 (1.907E-03)	-1.130E-03 (1.819E-03)	-3.280E-03 (2.008E-03)	-9.800E-04 (1.807E-03)	-3.300E-03 (2.011E-03)	-4.220E-03 (1.934E-03) *	-1.810E-03 (1.859E-03)
2017	-3.700E-04 (1.973E-03)	1.258E-03 (1.883E-03)	-2.400E-04 (2.077E-03)	1.588E-03 (1.864E-03)	-8.500E-04 (2.085E-03)	-1.520E-03 (1.995E-03)	-1.110E-03 (1.924E-03)
Cohort							
Pre-1930	-6.060E-03 (5.200E-03)	-1.130E-02 (5.655E-03) *	-9.350E-03 (5.189E-03)	-9.760E-03 (4.298E-03) *	-2.620E-03 (6.056E-03)	-5.900E-03 (4.246E-03)	-1.174E-02 (5.023E-03) *
1930-1934	1.469E-03 (4.547E-03)	1.487E-03 (5.005E-03)	7.482E-03 (4.514E-03)	-3.550E-03 (3.729E-03)	5.482E-03 (5.345E-03)	-3.260E-03 (3.672E-03)	-1.670E-03 (4.389E-03)
1935-1939	1.049E-02 (4.137E-03) *	1.260E-02 (4.597E-03) **	2.063E-02 (4.085E-03) ***	4.866E-03 (3.362E-03)	1.418E-02 (4.908E-03) **	4.663E-03 (3.304E-03)	7.932E-03 (3.992E-03) *
1940-1944	1.535E-02 (3.828E-03) ***	1.825E-02 (4.290E-03) ***	2.486E-02 (3.772E-03) ***	1.010E-02 (3.097E-03) **	1.885E-02 (4.572E-03) ***	9.361E-03 (3.038E-03) **	1.658E-02 (3.692E-03) ***
1945-1949	1.895E-02 (3.567E-03) ***	2.175E-02 (4.033E-03) ***	2.415E-02 (3.513E-03) ***	1.525E-02 (2.867E-03) ***	2.171E-02 (4.293E-03) ***	1.409E-02 (2.804E-03) ***	2.015E-02 (3.439E-03) ***
1950-1954	9.545E-03 (3.474E-03) **	1.173E-02 (3.936E-03) **	8.622E-03 (3.414E-03) *	7.672E-03 (2.814E-03) **	1.143E-02 (4.176E-03) **	6.803E-03 (2.752E-03) *	9.950E-03 (3.347E-03) **
1955-1959	4.941E-03 (3.410E-03)	6.406E-03 (3.872E-03)	4.690E-04 (3.343E-03)	4.666E-03 (2.769E-03)	6.125E-03 (4.100E-03)	4.525E-03 (2.706E-03)	4.207E-03 (3.285E-03)
1960-1964	-2.110E-03 (3.366E-03)	-1.390E-03 (3.833E-03)	-6.480E-03 (3.303E-03) *	-1.510E-03 (2.718E-03)	-1.340E-03 (4.062E-03)	5.580E-04 (2.653E-03)	-1.620E-03 (3.242E-03)
1965-1969	-9.740E-03 (3.405E-03) **	-9.610E-03 (3.874E-03) *	-1.365E-02 (3.349E-03) ***	-8.290E-03 (2.736E-03) **	-9.960E-03 (4.114E-03) *	-5.330E-03 (2.670E-03) *	-1.126E-02 (3.281E-03) ***

1970-1974	-8.290E-03 (3.542E-03) *	-8.690E-03 (4.011E-03) *	-1.234E-02 (3.489E-03) ***	-5.910E-03 (2.841E-03) *	-9.760E-03 (4.270E-03) *	-3.600E-03 (2.776E-03)	-9.140E-03 (3.414E-03) **
1975-1979	-5.440E-03 (3.795E-03)	-6.190E-03 (4.260E-03)	-1.050E-02 (3.745E-03) **	-1.760E-03 (3.058E-03)	-7.850E-03 (4.545E-03)	-1.100E-03 (2.993E-03)	-5.420E-03 (3.661E-03)
1980-1984	-3.930E-03 (4.105E-03)	-4.940E-03 (4.569E-03)	-9.490E-03 (4.059E-03) *	7.340E-04 (3.317E-03)	-8.570E-03 (4.884E-03)	-1.340E-03 (3.255E-03)	-5.990E-03 (3.962E-03)
1985-1990	-6.300E-03 (4.523E-03)	-7.990E-03 (4.984E-03)	-9.080E-03 (4.493E-03) *	-9.000E-04 (3.684E-03)	-1.201E-02 (5.333E-03) *	-3.750E-03 (3.628E-03)	-3.390E-03 (4.367E-03)
Post-1990	-1.888E-02 (5.071E-03) ***	-2.211E-02 (5.525E-03) ***	-1.532E-02 (5.063E-03) **	-1.161E-02 (4.155E-03) **	-2.566E-02 (5.935E-03) ***	-1.572E-02 (4.109E-03) ***	-8.600E-03 (4.901E-03)
Model Fit							
AIC	-103524	-101745	-102270	-102441	-100357	-99641	-122427
BIC	-103522	-101742	-102267	-102438	-100354	-99638	-122425

Note: OM_PI-8 was used as the dependent variables.

Model 1: the maximally adjusted model. Model 2-6: the models that respectively excluded physical mobility, work, economic, accessibility, and mobility resources constraints from the maximally adjusted model. Model 7: sensitivity analysis 1 (including the number of trip stages).

ψ, *, **, and *** denotes significant at the significance level of 0.10, 0.05, 0.01, and 0.001, respectively.

Figure 2.4 illustrates the predicted mean value of OM_PI across periods after the effects of age and cohort were accounted for[10]. The solid blue, solid grey, and dash red lines represent the predicted mean value of OM_PI, grand mean of OM_PI, and 95% confidence interval, respectively. From 2001 to 2009, the OM_PI showed a gentle increase of 0.006, followed by a decrease between 2009 and 2010 (from 0.239 to 0.230). This figure remained rather stable since 2010, except for the slight rebound in 2017. It should be noted that, in addition to the decrease between 2009 and 2010, the magnitude of changes in the predicted OM_PI over the entire observed period and over specific consecutive years is rather small. The predicted OM_PI in 2017 (0.231) was fairly similar as in 2001 (0.232), and it fell between 0.238 and 0.228 over the past 18 years (except for 2009 and 2010).

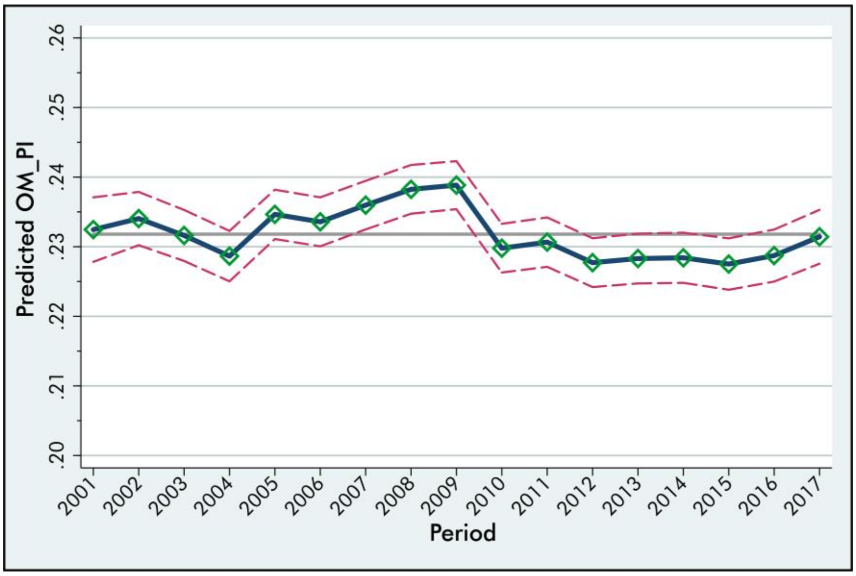

Figure 2.4 Predicted mean values of OM_PI across periods.

Note: the predicted mean value of OM_PI-8 was calculated using coefficients in Model 1. The solid blue, solid grey, and dash red lines represented the predicted mean value of OM_PI, grand mean of OM_PI, and 95% confidence interval, respectively.

Figure 2.5 displays the predicted mean value of OM_PI across cohorts after the effects of age and period have been accounted for[11]. The solid blue, solid grey, and dash red lines represent the predicted mean value of OM_PI, grand mean of OM_PI, and 95%

[10] The predicted OM_PI for a specific period *j* averaged over ages and cohorts is calculated based on Eq. (2.5), when the other variables are set to zero: $\hat{y} = \widehat{\gamma_0} + \widehat{u_{0j}}$

[11] The predicted OM_PI for a specific cohort *k* averaged over ages and periods is calculated based on Eq. (2.5), when the other variables are set to zero: $\hat{y} = \widehat{\gamma_0} + \widehat{v_{0k}}$

confidence interval, respectively. The overall temporal pattern in multimodality could be roughly divided into three stages. At first, along with the replacement of generational membership, earlier cohorts have exhibited a continuous increase in individual multimodality until peaking for the cohort born between 1945 and 1949 (predicted **OM_PI**: 0.251). Subsequently, there was a slump in multimodality before the **OM_PI** reaches its minimum of 0.222 at the cohort born between 1965 and 1969. This figure dropped by 0.029 from 1945-1949 to 1965-1969 cohort. This decline is quite substantial; if we compare it with the age effects, 0.029 is almost equivalent to the level of decline in multimodality during the transition from adolescence to middle adulthood (from 16 to 38 years old; estimated by **Model 1**). In other words, a 16-year-old traveller born in 1965 would be at the same level of multimodality as a 38-year-old traveller born in 1945, if they could exist in an identical year. Finally, multimodality rose slightly for the remaining cohorts, followed by a falling trend for the cohort born in or after 1985. Furthermore, our multistep analyses showed that when one specific type of spatial mobility constraint was removed from the main model, the magnitude of the changes in cohort variance components was quite similar across models (except the model with work constraints excluded), ranging from 0.000046 to 0.000071 (**Model 2-5**). This indicates that the cohort-specific changes in multimodality could be partially explained by the joint influence of multiple spatial mobility constraints, with the exception of work constraints.

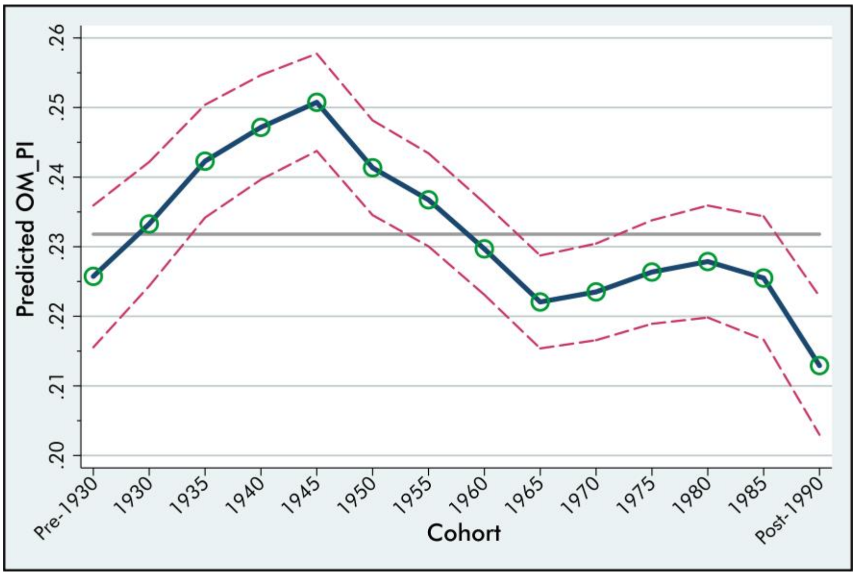

Figure 2.5 Predicted mean values of OM_PI across cohorts.

Note: the predicted mean value of OM_PI-8 was calculated using coefficients in Model 1. The solid blue, solid grey, and dash red lines represented the predicted mean value of OM_PI, grand mean of OM_PI, and 95% confidence interval, respectively.

Finally, our sensitivity test 1 (including the number of trip stages; **Model 7**) resulted in a decrease in the magnitude of the estimated random coefficients for specific periods and cohorts (particularly the cohort born at and after 1985). This implies that the number of trip stages may partially explain the estimated temporal patterns in multimodality across periods and cohorts. The sensitivity analysis performed by adopting the three-mode-based OM_PI as a dependent variable (sensitivity test 2) showed similar findings to our main model (**Table 1** and **Table 2** in **Supplementary Material**). We found that, similar to our findings derived from the estimations using the eight-mode-based choice set, the total variance in multimodality accounted for by cohorts was larger than that explained by periods, although the gap between them was smaller (**Model 1** in **Table 2** in **Supplementary Material**). The patterns in multimodality across periods and cohorts also remained fairly similar using the more aggregated choice set. Sensitivity tests 3-5 (using the alternative sample sets A, B, and C) produced results that were largely consistent with the those derived from the original sample set in terms of the significance of correlates (**Table 3, 5, 7** in **Supplementary Material**) and the temporal patterns in multimodality (**Appendix A.2**).

2.5. Discussion and conclusion

The research reported in this paper investigated the extent to which individual multimodality varies by age, period, and cohort, using 17 consecutive waves of the NTS in England, 2001 to 2017. In light of the mathematical coupling between age, period, and cohort, the HAPC model was used to disentangle the confounding effects between these three variables. Our analyses showed that the effects of age, period, and cohort on multimodality were significant and independent of each other.

Our results showed that travellers tend to be, on average, less multimodal as they age, which is in line with prior studies (e.g., Heinen and Mattioli (2019a); Klinger (2017); Molin et al. (2016)). As indicated by our multistep analyses, the effect of age might be moderated by multiple spatial mobility constraints – work and physical mobility constraints in particular – which largely accelerate the falling of multimodality before and after reaching middle adulthood, respectively. A plausible explanation is that, during the adolescence-to-adulthood transition, changes in employment status are universally catalysed. Moving from student to full-time employee contributes to the tight budget of discretionary time as well as to more commuting/business trips that are characterised by strong temporal and spatial fixity (Elldér, 2014). These changes may result in fewer opportunities to use a variety of modes and higher repeatability of daily mode choices. Subsequently, for the remainder of their lifespan, people are more likely to undergo a deterioration in their physical performance and experience a decline in mobility (Morgan et al., 2014)). Within this context, individuals are, to a large extent, restricted from using active modes, e.g., walking, cycling, and the use of public transit, thereby reducing the richness of their mode choice sets.

We found that the overall temporal pattern in multimodality remained relatively stable from 2001 to 2017 in England, despite the fluctuations. Our findings were, to a certain extent, inconsistent with the previous studies, which reported an increase in multimodality between two time periods after 2000 (see: Buehler and Hamre (2014) for trends between 2001 and 2009; and Streit et al. (2015) for trends between 1998-2002 and 2010-2012). We also compared our results with the research by Heinen and Mattioli (2019a). They used the NTS data and multivariable linear regressions that simultaneously accounted for age and period; a significant downward trend in England between 2002 to 2015 was found. In contrast, for our research, the OM_PI slightly decreased by only 0.006 during the same period. This comparison suggests the necessity of incorporating the cohort effect into the surveillance of temporal patterns in multimodality. Moreover, we saw a decline in multimodality between 2009 and 2010. These changes were not as salient as the fluctuations in ageing and cohort succession. This decline in 2009 happened shortly after the 2008-09 financial crisis. Comparing 2007 with 2009, 1.3% of trip stages shifted from car driver to bus, walk, and bicycle. In 2010, the car driver modal share rebounded by 1.5% on average, at the cost of a fall in walk and bicycle modal shares.

This research yielded new insights into the nexus between multimodality and birth cohort. We revealed that multimodality was unequally distributed across cohorts. The cohort-specific changes in multimodality could be partially explained by the variations in multiple spatial mobility constraints in relation to the cohort succession. It was also observed that compared to period effects, cohort effects, which have been largely overlooked by previous studies, substantially explain the observed changes in multimodality over time. One of the most intriguing findings for cohort effects is that multimodality reached the lowest levels for the cohort born between 1945 and 1969, even when controlling for all covariates. This may largely be attributed to the surge in driving share shaped by *baby boomers'* distinctive early life conditions and formative experience. Baby boomers refer to the demographic cohort born between 1946 and 1964 during the post-war population explosion (Eggebeen and Sturgeon, 2014). According to the 2001-2017 NTS data (**Figure 2.6-A**), the share in car driver trip stages, being at the highest levels (0.56) for baby boomers, followed an inverted U-shaped curve according to cohort succession. By contrast, reversed patterns were noticed for bus and car passenger modal share, which continued to decrease for cohorts born before 1965 and rebounded thereafter. In the early years of baby boomers, the end of World War II enabled industrialised countries, such as the US and Western European countries, to usher the 'golden age of capitalism,' marked by two decades of economic growth, high levels of productivity, and low unemployment (Marglin and Schor, 1991). The lifestyles were, therefore, dramatically changed. In particular, due to the prosperity of automobile industries, termination of petrol rationing, and a more affluent life, people were more able to afford private cars and were more prone to drive (e.g., Gunn (2018); Thompson et al. (2012)). Between the 1950s and the mid-1960s, the number of households with at least one car roughly tripled in Great Britain (Leibling, 2008), and the share in total car use (including travel as driver and passenger) surged by 40% (**Figure 2.6-B**). Studies have suggested that youth is an impressionable period when individuals are highly susceptible to the influence of social context, and on this basis, their worldviews, values, and beliefs can be substantially shaped (e.g., Down and Wilson (2013); Wray-Lake et al. (2010)). Therefore, baby boomers might have developed strong pro-car and pro-driving attitudes in their youth (see, e.g., Chatterjee et al. (2018); Owram (1997)). It is also reasonable to believe that these attitudes could be maintained and lead to a large driving share when baby boomers reach the minimum age for a driver's license (circa 1960-1980 onwards) and onwards. This could be partially reflected on the fact that the modal share in car travel rose by 30% between 1960 and the mid-1990s (**Figure 2.6-B**). This, as well as the lack of effective supportive policies for other modes of transport (see, e.g., Gunn (2018)), potentially contributed to the decline in multimodality for the cohorts born between 1945 and 1969.

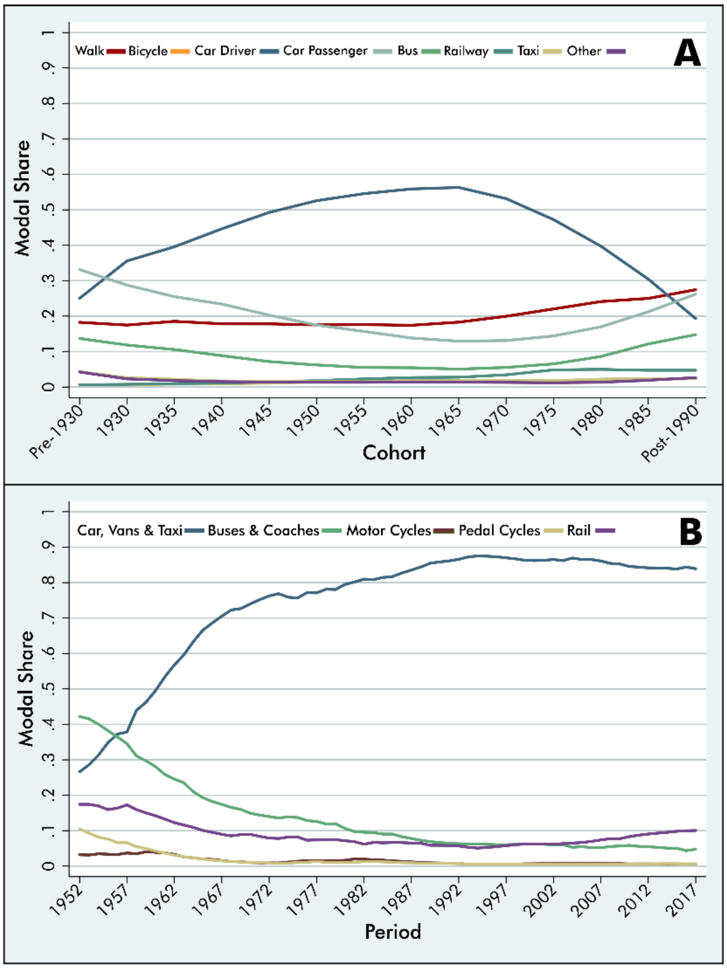

Figure 2.6 Trends in (A) the modal share in England across cohorts (based on the 2001-2017 NTS data) and (B) the modal share in Great Britain from 1952 to 2017 (based on Department for Transport (2018c)).

From a demographic standpoint, our analyses were unable to support the view of a long-term increase in multimodality. It was found that following the cohorts of the mild upward trend, multimodality started to decrease for the cohort born at and after 1985. This finding is potentially related to the distinctive growth process of the post-1985 cohort, during which the use of the internet came to be prevalent. Studies have suggested that increasing 'virtualisation' has largely contributed to the decline in daily mobility in recent generations (e.g., Frändberg and Vilhelmson (2011)). Travelling less, the post-1985 cohort may, therefore, have fewer opportunities to use specific modes, which in turn, results in a less multimodal travel pattern. Our speculation is supported by our sensitivity analysis (S1) that the salient decline for the post-1985 cohort was hardly present after controlling for the number of trip stages. This finding is of importance for policy-making, as it, to a certain extent, indicates a future trend of multimodality.

Going beyond our specific findings, we believe that the HAPC method employed is of a wider application value, in the *ex-post* evaluation of long-range policies on improvements of sustainable transport. For evaluating long-range policies targeted at either specific cohorts or a part of the (sub-)population at one point in time, it is necessary to regularly trace travel patterns of the target groups over a long period, and compare them with the baseline ones. However, ageing of individuals, changes in social contexts, and cohort succession are necessarily intertwined. The observed effects of such policies inevitably contain some time-related confounding effects that are not within the original aim of the policies. As illustrated in our analyses, the HAPC model is able to disentangle the confounding effects between age, period, and cohort, thereby providing an effective and comprehensive tool for *ex post* policy evaluation.

This research also has several limitations. First, the continuous indicator we applied to measure multimodality does not explicitly provide insight into the modes used. As such, we cannot draw strong conclusions on variation in specific modes from our analyses. Our interpretations and the implications of our findings should be, therefore, treated with caution. For example, changes in multimodality do not necessarily correspond with changes in car use (despite the dominant role of car use in our country of study), especially at the disaggregate level. We used descriptive analyses and existing literature on the post-war socioeconomic transformation to speculate on the causes of the observed patterns. This enabled us to suggest that decreased levels of multimodality for baby boomers may be attributed to increased levels of driving. However, resulting from the measurement of multimodality and the interconnection between age, period, and cohort, we cannot be absolutely certain of this interpretation, nor can we automatically draw similar conclusions related to car use for other observed patterns (e.g., for other cohorts). APC analyses on the exclusive use of various modes would be an important supplement to our findings. Second, the time span (17 years) of our data may not be sufficiently long, although, to our best knowledge, the NTS data is the only data currently available with national-wide population representativeness and high-quality multiday travel diaries. Due to the potential 'peak car' phenomenon in recent decades in England (e.g., Headicar (2013)), looking at the data with a longer time span may reveal more salient changes in multimodality across periods. Third, individual multimodality showed a decline for the cohort born in or after 1985, yet our sensitivity analyses were not able to verify the robustness of the temporal pattern for the post-1990 cohort. A revisit to this finding in the future is recommended.

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Chapter 3

The level and determinants of multimodal travel behaviour: Does trip purpose make a difference?

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Abstract

Multimodality refers to the phenomenon of using more than one mode of transport in a given period. Encouraging multimodality potentially provides an effective solution to reduce CO2 emissions and induce modal shifts towards sustainable transport. This research investigates the extent to which the level and correlates of multimodality differ by trip purpose. We used one-week travel diaries of the English National Travel Survey. Our analyses showed that the level of multimodality varied by trip purpose and the associated time-space variability as well as by the number of trip stages. We found that the level of variability in departure time and travel distance was greater for leisure trips than for maintenance trips, which was in turn greater than for work trips. Trips that were more variable in departure time and travel distance showed on average higher levels of individual multimodality, but only if sufficient stages (at least 3) were made. Moreover, we detected cross-purpose disparities in correlates of multimodality in terms of significance and variance explained. This research may provide support to the development of trip purpose-specific policies aiming to increase multimodality.

Keywords: Multimodality; Trip purpose; Heckman selection model; Travel Behaviour; Constraint

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3.1 Introduction

In recent years, the notion of multimodality has attracted increasing attention in transport practices (e.g., European Commission (2014)) and research (e.g., An et al. (2020)). Multimodality is defined as the phenomenon of using more than one mode of transport in a given period (Kuhnimhof et al., 2012a). Existing studies suggest that encouraging multimodality is an effective measure to promote a more sustainable transport system. For example, multimodal travellers, under the same travel distance, emit less CO2 than less multimodal or monomodal travellers (e.g., Heinen and Mattioli (2019b)). Moreover, travellers with more multimodal patterns are more likely to alter their mode use over time (e.g., Kroesen (2014)), to be more susceptible to transport infrastructure interventions (e.g., Heinen and Ogilvie (2016a)), and to be more willing to adopt new transport services (e.g., Diana (2010)). Facilitating multimodality may therefore allow policymakers to induce modal shifts towards sustainable transport.

The scientific debate regards individual multimodality as a characteristic of individuals' travel patterns (Heinen and Mattioli, 2019a). Existing studies have revealed various correlates of multimodality, such as sociodemographic characteristics, features of the (residential) built environment, and life events (e.g., An et al. (2020); Scheiner et al. (2016); Molin et al. (2016); Buehler and Hamre (2014); Nobis (2007a)). Studies have also suggested that multimodality is widely present in developed societies (e.g., Kuhnimhof et al. (2012a); Ralph (2016)) and that there is an upward trend in recent decades (e.g., Kuhnimhof et al. (2012a); Streit et al. (2015)). However, British studies contradicted this and demonstrated that individual multimodality decreased between 1995 and 2015 (Heinen and Mattioli, 2019a) and from cohorts born in 1985 onwards (An et al., 2020).

Despite these useful insights, we know relatively little beyond the understanding of individual multimodality based on *undifferentiated* or *exclusive* trip purposes. The vast majority of existing studies share one shortcoming: they investigated multimodality for all trips combined, independent of trip purpose, or for trips with only one specific purpose – in most cases, commuting. As a consequence, there is hardly any information about the extent to which multimodality varies by trip purpose. Moreover, although a plethora of literature has looked into correlates of multimodality, disparities in the effects of such correlates across trip purposes remain unknown.

This paper aims to investigate the differences in levels of individual multimodality across trip purposes and to explore the disparities in correlates of multimodality across trip purposes. We used data from the National Travel Survey (NTS) for England (2016). The large sample size and 7-day travel diaries of NTS allow us to differentiate individual multimodality by trip purpose for a national representative sample.

3.2 Background

This section discusses two topics. We first discuss the potential mechanism by which travel behaviour may vary by trip purpose. We then provide a review on how levels and correlates of multimodality differ by trip purpose.

3.2.1. Travel behaviour-trip purpose nexus

People perform activities and corresponding trips with different levels of time-space variability. Early time-geographic studies found that individuals had greater flexibility both in allocating time and in selecting locations when making discretionary activities than when performing obligatory ones (e.g., Jones (1977)). Ås'(1978) conceptualization elucidated a bigger picture of this issue. Ås(1978) categorized activities into four groups according to the time constraints and freedom of choice in performing activities: activities in (1) necessary time; (2) contracted time; (3) committed time; and (4) free time (**Table 3.1**). Activities in necessary time are made to satisfy physiological needs (e.g., sleeping), which require no (or very limited) travel. The majority of travel demand derives from the need to participate in activities in contracted, committed, and free time.

Contracted time refers to the time allocated to activities for paid work. Activities in contracted time are subject to strong space fixity constraints (Elldér, 2014), whilst they exhibit larger fluctuations in time use, due to the potential for variations in departure times and working hours (e.g., Shen et al. (2013)). Activities in committed time represent those that are bound to others through promise, such as household responsibilities (Reinseth et al., 2012). Committed-time activities potentially have a more flexible time budget than those conducted in contracted time, since they can be undertaken by other household members or be postponed. Travel distance also less likely constrains the engagement in committed-time activities. For example, regarding consumer behaviour in grocery shopping, several attributes of shops, e.g., price and service, are as comparably important as the location of shops (e.g., Schenk et al. (2007)). Finally, free time is the time spent away from the aforementioned activities, and can be planned as well as on the spur of the moment (e.g., Lee and McNally (2003)). Given the multiplicity of free time activities, people have a greater opportunity to visit various locations. Free time activities are therefore considered the least time- and space-bound.

Table 3.1 Characteristics of human activities and corresponding trips.

Classifications of activities	Typical activities	Flexibility in the degree of time allocation	Flexibility in the degree of location selection
Activities in contracted	Work-related (e.g., paid work and education)	Low	Very low
Activities in committed	Maintenance (e.g., shopping and other	Medium	Medium
Activities in free time	Leisure (e.g., social and recreation)	High	High

3.2.2. Multimodality and trip purposes

A few studies have investigated disparities in levels of individual multimodality across trip purposes. Most of these studies were conducted by adopting aggregate, cluster-level analyses (**Table 3.2**), and the findings suggest trips made for discretionary activities may be more multimodal than those made for obligatory activities. For example, Vij et al. (2011) analysed modality styles in 226 Germany travellers and found that multimodal travellers (defined as if the share of trips made by the primary mode was less than 90%) were less common among individuals who frequently made work trips (43%) than among those who frequently made non-work trips (70%). Similarly, Buehler and Hamre (2015) using the US National Household Travel Survey (NHTS) found that the share of multimodal car users (i.e., individuals who used a car and at least one other mode) decreased by 6% if recreational trips were excluded. Ralph (2016) also found by employing a latent class model on the NHTS that roughly 60% of 'Multimodals' made at least one errand/social trip on the survey day, whilst only less than 30% of this group ran a commute trip.

Despite that these studies offer insights into the varying prevalence of multimodality by trip purposes, these studies are limited in several ways. First, it is inconclusive whether the findings can be ascribed to intergroup differences in trip shares or to characteristics of group members. Existing studies mainly used descriptive analyses of the prevalence of trips made for different purposes, comparing monomodal and multimodal groups to draw conclusions. Given the absence of statistical control for multimodality correlates, such descriptive analyses could induce confounding bias. Second, the discussed studies considered relatively few trip purposes, which may not reflect the multiplicity of human activities. Finally, these studies applied methods for evaluating multimodality were only able to capture intrapersonal modal variability in a simplified way. They defined multimodality using aggregate measures, based on pre-defined (Buehler and Hamre, 2015; Vij et al., 2011) or data-driven (Ralph, 2016) groups. Such measures do not allow the investigation of levels of intrapersonal modal variability in a quantitative way, meaning that there is no insight into the extent to which multimodality differs by members within and between groups; this in turn potentially exaggerates intragroup homogeneity and intergroup heterogeneity.

Table 3.2 Literature of the relationship between trip purposes and multimodality.

	Data	Multimodality measurements	Trip purposes considered	Analytical approaches	Main findings
Vij, Carrel, and Walker (2011)	Mobidrive data set	Predefined groups: quasi-unimodal (QU) Bike/Walk; QU Auto; QU Transit; multimodal Green; multimodal All	Work; non-work	Comparing the share of multimodal travelers between individuals who had made >5 work trips (work trip group) during the survey weeks and those who had made >5 non-work trips (non-work trip group)	Multimodal travelers were more prevalent in the work trip group than in the non-work trip group
Buehler and Hamre (2015)	US NHTS	Predefined groups: monomodal car users; multimodal car users; walk, bicycle, public transportation (WBT) only users	Recreational; utilitarian	Comparing the change in share of different travelers after excluding utilitarian and recreational trips	Multimodal car users decreased by 6.1% if recreational trips were excluded, whilst excluding utilitarian trips lead to 1.3% drop in the share of such users
Ralph (2016)	US NHTS	Groups from latent class models: Driver; Long-distance Trekker; Multimodal; Car-less	Commute; shop; errand; social; other	Comparing the share of trip purposes across different travelers	Multimodal travelers made a larger share of errands and social trips than the others
Susilo and Axhausen (2014)	Mobidrive and Thurgau data sets	Continuous index: HHI	Leisure; daily shopping; long-term shopping; private business; pick-up/drop-off; work; work-related business; school; other	Comparing the average value of the HHI across trip purposes	Leisure and private business trips had higher variability in mode choice than trips for obligatory activities (e.g., work, school, and pick-up/drop-off)

For a disaggregate level analysis, Susilo and Axhausen (2014) made a substantial contribution to the topic by studying the individual day-to-day repetition of activity-travel patterns, using the Mobidrive and Thurgau travel diary surveys. They examined the stability/variability of combinations of four travel attributes (i.e., mode use, trip purposes, departure time, and location) over six weeks, considering nine trip purposes, using a continuous indicator (the Herfindahl–Hirschman Index (HHI)), to measure multimodality. Their results nonetheless had a similar outcome as the studies discussed above, and showed that leisure and private business trips, compared to trips made for obligatory activities (e.g., work, school, and pick up/drop off trips), had higher variability in location, departure time, and mode choice.

Yet, similar to the other discussed studies, this research was mostly descriptive, and the sample size of the study was relatively small (317 individuals in Mobidrive; 230 individuals in Thurgau). The small sample size increases the risk of selection bias. Since not each individual in question made all defined types of trips and since the study considered a large number of trip purposes, the selection bias might be aggravated. The reason is that when analysing specific purposes, this research excluded individuals with a missing value of the HHI. The calculation (and statistical comparisons) of average purpose-specific multimodality may not be reliable without considering the fact that some individuals could have made the 'missing' trips, but due to self-selection or the limit of survey duration, they did not do so (see, Heckman (1979)). The overlooking of missing values also contributes to non-random censored sampling, and consequently makes the analysed samples inconsistent between trip purposes. Thus, it is inconclusive whether the trip purpose itself contributed to the observed differences in multimodality, without population-representative data and analytical approaches to tackle the 'missing not at random' (MNAR) problem.

A large number of studies on multimodality have looked into its correlates. These studies have predominantly investigated all trips together, without differentiating by purpose. Existing literature has found that multimodality varies by individual sociodemographic characteristics. Multimodal individuals (and multimodal groups) are more likely female (e.g., Vij et al. (2011)), in part-time employment, have higher educational attainment (e.g., Molin et al. (2016)), earn a higher income (e.g., Buehler and Hamre (2015)). Life trajectories have also been linked to multimodality. An et al. (2020) observed that baby boomers who were born between 1960 and 1964 presented, on average, a lower level of multimodality than other cohorts. Scheiner et al. (2016) found that individuals became more multimodal after their child moved out, whilst entering a labour market reduced multimodality. In addition, several studies have looked into factors that could be directly influenced by transport policies, e.g., mobility resources and spatial accessibility factors. Panel studies showed that acquiring a driving license and increasing car availability may decrease multimodality (e.g., Scheiner et al. (2016)); by contrast, moving to cycling- and public transport-friendly cities may increase multimodal patterns (e.g., Klinger (2017)). Cross-sectional studies have also shown that multimodal travellers are more likely to live in areas with a larger population (e.g., Heinen and Chatterjee (2015)) and a greater population density (e.g., Blumenberg and Pierce (2014)).

Very few studies have focused specifically on one single purpose; if so, they have mainly focused on commuting. While there appear to be similarities with studies using undifferentiated trips, Heinen (2018) found that multimodal commuters were more likely to have less income and to have a car and bicycle available occasionally (rather than always or never). Contrary to most studies looking at all trips independent of trip purpose, Chatterjee et al. (2016) observed that working part-time was more prevalent for travellers who did not or only partially used cars to commute (compared to car-only travellers). The authors also showed that travellers who partially used cars for commuting were more likely to work in multiple locations, which was not revealed in research looking at all trips together (e.g., Heinen and Chatterjee (2015)).

In summary, existing studies suggest that multimodality is not necessarily equally distributed for each purpose. There is evidence that trips for discretionary activities may be linked with higher levels of multimodality than those made for obligatory activities. The few studies available also suggest that correlates of multimodality for all trips differ from those that relate to trips for a specific purpose, such as commuting. However, shortcomings exist in the methodology and data used by the discussed studies limit the robustness of the findings and the ability to investigate the relationship between multimodal behavioural patterns and trip purposes.

3.3 Method

This research investigates the heterogeneity in multimodality across trip purposes. To better understand how and why levels and correlates of multimodality may vary by trip purpose, we identify four major issues yet to be sufficiently tackled and address them in our research. Firstly, we use population-representative data with a large sample size, which ensures more reliable estimates for the entire population. Secondly, we adopt multivariate sample-selection statistical methods to reduce confounding and selection bias, which allows us to draw stronger statistical inferences. Thirdly, we apply disaggregate-level measures to capture intrapersonal modal variability. Fourthly, we establish a set of explanatory models that, while separated by trip purpose, share unified specifications. This allows us to conduct systematic comparisons of the effects of multimodality correlates between purposes.

3.3.1. Data

We used the NTS for England (2016) (Department for Transport, 2019c). The NTS is a repeated cross-sectional survey of households. It is a nationwide survey, which since 2013 has been restricted to only the residents in England. The NTS holds several particular strengths related to our research. First, it has records on the trip purpose of each trip – with a large variety of purposes –, which allows us to differentiate individual multimodality by purpose. Second, the applied seven-day travel diaries cover a relatively long data collection period, which allows us to calculate multimodality indicators for various trip purposes, and makes it more effective in capturing occasional trip purposes. Third, the NTS is representative of the population of England (Department for Transport, 2019b).

The NTS collects personal/household information and week-long travel behaviour by face-to-face interviews and self-administered travel diaries, respectively. The NTS contains multiple data sets. We used four of these data sets: (1) personal characteristics extracted from the *Individuals* file; (2) household characteristics extracted from the *Households* file; and (3&4) seven-day stage-/trip-level travel behaviours extracted from the *Stages* and *Trips* files. We limit our analyses to individuals aged 16 and over, corresponding with existing works on variability in travel behaviour using the NTS (e.g., Heinen and Chatterjee (2015); Crawford (2020)).

3.3.2. Measuring purpose-specific multimodality

In the NTS, a trip refers to a one-way course of travel with one purpose. We classified trips by seven types of trip purpose: Commuting/Education; Business; Shopping; Personal business; Social; Recreation; and Other. There are 12023 individuals who made at least one trip during the survey week in the 2016 NTS. The number of individuals who made at least one trip for the aforementioned seven purposes is 6487, 2583, 9078, 5076, 7256, 5812, and 3837, respectively. The NTS contains escorting trips (i.e., travellers have no purpose of their own other than to accompany another person) for commuting/education, business, and shopping purposes. We allocated those trips to their respective trip purpose, but also conducted a sensitivity analysis in which they were excluded. Following the conceptualization from Ås (1978), we categorized the aforementioned trips into three groups: (1) work trips (commuting/education and business trips); (2) maintenance trips (shopping and personal business trips); and (3) leisure trips (social and recreation trips). There are 7089, 9912, and 9242 individuals who made at least one trip for these purposes, respectively.

Existing works measured individual multimodality in three categories: (1) pre-defined characterizations, (2) data-driven approaches, and (3) continuous indicators. The pre-defined characterization approach focuses on the inherent duality of the concept of 'mixture.' Individuals can, therefore, be defined as either multimodal or unimodal according to their primary travel mode, and to whether they use other/specific modes, without sufficient consideration of the intensity of using these modes (e.g., Vij et al. (2011); Buehler and Hamre (2016); Nobis (2007a)). Data-driven approaches building on unsupervised classification methods are also widely used for measuring multimodality (e.g., Ralph (2016); Heinen (2018)). In contrast to pre-defined characterizations, data-driven approaches incorporate multidimensional travel characteristics (including but not limited to mode uses and modal intensities) into the measurement. Nevertheless, both pre-defined characterizations and data-driven approaches are limited in capturing the intrapersonal variability of mode use. These two measurements aim to categorize travellers into non-overlapping groups, but they do not gauge the level of individual multimodality (Heinen and Mattioli, 2019a).

Continuous indicators jointly consider both the diversity of modes used and their intensity (see, e.g., Diana and Pirra (2016)). On this basis, drawing on classic interdisciplinary studies on measures of diversity, inequality, and heterogeneity, continuous indicators are able to quantify multimodality for *each* individual. Diana and Pirra (2016) systematically examined the existing potential continuous indicators, in terms of their properties and applicability. Following Cowell (2011), a total of nine indicators, either measuring concentration or variation, were assessed in terms of properties that should belong to desirable inequality indexes. They concluded that there is no indicator that mathematically outperforms others in all situations, and that their suitability for application varies by case. In particular, three indicators (a modified Herfindahl–Hirschman index (HHm), and an original and modified objective mobility personal index (OM_PI)) were recommended for applications in which some individuals are unable to use certain modes due to constraints.

We measured purpose-specific individual multimodality through four indicators: (1) number of modes used (NMU); (2) difference between the share of primary and secondary modes used (DSPS), where for a given individual, the primary and secondary modes are those that respectively account for the largest and second largest share; (3) HHI, as applied by Susilo and Axhausen (2014); and (4) OM_PI, as proposed by Diana and Mokhtarian (2009). We computed these indicators based on the stage level information. In the NTS, a trip may have several constituent stages, which are differentiated by a modal transfer. The NMU provides an intuitive representation of the multiplicity of modes used by a traveller. Second, DSPS measures the degree of an individual's dependence on a specific mode of transport. Third, the HHI and OM_PI are well-suited to capture intrapersonal variability by simultaneously taking into account both the diversity of modes used and their intensity. The HHI can serve well as a measure of concentration, as it emphasizes the importance of modes with large shares (Susilo and Axhausen, 2014). Because the OM_PI is 'replication variant' (i.e., the multimodality index will not remain the same when replicating given modes with their corresponding intensities), this indicator can be fitted to circumstances where specific modes are not accessible to some individuals (Diana and Pirra, 2016). We used the OM_PI for our main analyses and investigated the others in sensitivity analyses (see Section 3.3.4).

The purpose-specific HHI and OM_PI were measured as follows:

$$HHI_{im} = \sum_{k=1}^{N_{im}} {S_{imk}}^2 \tag{3.1}$$

$$OM\_PI_{im} = \sum_{k=1}^{N_{im}} (S_{imk} \ln{(1/S_{imk})}\,(1/\ln N_{im})) \tag{3.2}$$

$$S_{imk} = f_{imk}/f_{im} \tag{3.3}$$

where HHI_{im} and OM_PI_{im} respectively represent the values of HHI and OM_PI for individual i whilst travelling for purpose m. N_{im} indicates the total number of modes used by individual i for purpose m. S_{imk} denotes the share of specific mode k within this context; it was quantified based on the number of stages undertaken by mode k (i.e., f_{imk}) and the total number of stages (i.e., f_{im}) individual i made for purpose m within the travel diary week. The HHI and OM_PI indicators take a value between 0 and 1. A smaller value of the HHI and a greater value of the OM_PI reflects a higher level of multimodality, respectively.

The NMU, DSPS, HHI, and OM_PI indicators were generated for both seven- and three-mode based choice sets (hereafter denoted by the abbreviations NMU-7/3, DSPS-7/3, HHI-7/3, OM_PI-7/3). These mode choice sets, which considered both data availability and prevalence of different mode use in England, were defined based on existing studies and DfT reports on multimodality using the NTS (e.g., Heinen and Mattioli (2019b); Heinen and Chatterjee (2015); Department for Transport (2019a)). Specifically, the seven-mode indicator considered: walk, bicycle, private car, bus (local and non-local coach services), rail (surface rail and London underground), taxi, and other (motorcycle and other private/public transport); the three-mode indicator: private car, public transport (bus, rail, taxi, and other), and active travel (walk and bicycle). In the calculation of the indicators, we applied weights for the travel diary data according to NTS guidance (Department for Transport, 2018a). A short walks weight (referred to as SSXSC in the guidance) was applied to account for the fact that those trips are only measured for one day of the travel diary. A trip/stage travel weight (referred to as W5) was used to account for the fact that individuals tend to drop their level of reporting over time, during the survey week.

3.3.3. Measuring purpose-specific time-space variability

We applied the HHI to characterize individual variability in departure time of purpose-specific trips, following Susilo and Axhausen (2014). This measure is similar to that used for multimodality (**Eq. (3.1)**), the only difference being the use of classified departure time (using a one-hour interval) in place of the mode used for each trip. We used the coefficient of variation (ratio of standard deviation to mean) to reflect individual variability in distance travelled for specific purposes, following Rietveld et al. (1999).

3.3.4. Correlates

Drawing on Hägerstrand's (1970) research on constraints of spatial travel behaviour, the study of Heinen and Chatterjee (2015) revealed that constraints in various domains have an impact on intrapersonal modal variability, albeit varying in the strengths of their effects. In the current research, we considered the following six domains of multimodality correlates (**Appendix B.1**):

1. Social role constraints, covering age, gender, and (not) having a child in the household.
2. Physical mobility constraints, covering (not) having walking difficulties.
3. Work constraints, covering economic status and (not) working in multiple locations.
4. Economic constraints, covering household income.
5. Accessibility constraints, covering settlement population density, settlement land-use mix, housing tenure.
6. Mobility resource constraints, covering access to household vehicles, acquisition of a full car license, bicycle ownership, driver status; and (not) holding a public transport season ticket.

3.3.5. Statistical analyses

3.3.5.1. Multiple comparisons

We applied an analysis of covariance (ANCOVA) to examine whether there were significant differences in the level of multimodality across trip purposes, accounting for multimodality correlates (see Section 3.3.4). We first looked into the OM_PI-7 indicator for all individuals who travelled at least one stage during the survey week. We conducted multiple comparisons of each pairwise group to determine relative levels of purpose-specific multimodality. However, this procedure is associated with a higher probability of accumulating false positives, as the overall type I error depends on the number of comparisons made (Armstrong, 2014). To reduce potential type I errors, we conducted Tukey-Kramer tests. The Tukey-Kramer test uses the q statistic adjusted by the harmonic mean of the cell sizes to control type I errors and simultaneously takes into account the circumstances where group sample sizes are unequal (Lee and Lee, 2018). According to the comparison results, we categorized all the groups in question into several possible overlapping subsets. For the interpretation, groups within the same subset do not significantly differ from each other regarding multimodality, whereas groups within different non-overlapping subsets show significant differences.

We conducted sensitivity analyses by repeating our analyses (1) using different indicators; (2) adopting a three-mode-based choice set; (3) excluding escort trips; and (4) considering individuals who lived outside Greater London. Existing evidence revealed that the number of stages is closely connected with multimodality (An et al., 2020). The larger the number of stages, the greater the potential opportunity of using different modes. For NTS data, the number of stages significantly differs by trip purpose, ranging from 11.3 for commuting trips to 4.1 for personal business trips. We thus implemented sensitivity analyses by increasing the minimum threshold of the number of stages. Despite the representativeness of the NTS data as a whole, the omission of individuals who have not travelled for specific purposes during the travel diary week and the exclusion of individuals with insufficient number of stages for the sensitivity analyses may result in non-randomly selected samples. As such, we applied corrections to the ANCOVA to reduce the potential impact of selection bias, by adopting the Heckman selection model, as explained in the following section.

3.3.5.2. Heckman selection models

We estimated multivariate regressions to explore the disparities in multimodality correlates across trip purposes. Because individuals may not travel for some purposes during the survey week, multimodality is not necessarily observed for all purposes for each individual. However, the censored estimation models that exclude individuals with a missing value of multimodality may contribute to selection bias, which in turn, results in both biased and inconsistent estimations. The reason is that in such models, the actual sample used may not be a random population sample and thus the residuals may be correlated with the independent variables, which violates the exogeneity assumption of least squares estimators (Heckman, 1979). We therefore applied the two-step Heckman selection model (Heckman, 1976), which has been widely adopted in travel behaviour studies (e.g., Holz-Rau et al. (2014); Kaplan et al. (2016)), to reduce selection bias.

The Heckman selection model uses a control function idea. This model computes a selection parameter, namely, the inverse Mills ratio (IMR), based on the likelihood of whether a dependent variable can be observed and then incorporates the IMR into an explanatory regression model. By doing so, this model allows us to make full use of the random-sampled population-representative NTS data when modelling each considered trip purpose and avoid an arbitrary (re)selection of individuals. On this basis, we could also compare the variance explained by specific variables across trip purposes, as the models for these purposes were estimated based on a consistent sample. This provides quantitative insights into the magnitude of effects of multimodality correlates in different trips. The first step of the Heckman selection model estimates the so-called *equations of interest* (**Eq. (3.4)**):

$$E(\boldsymbol{y}) = \boldsymbol{X\beta} + \boldsymbol{u}; \boldsymbol{u} \sim N(0, \sigma^2) \tag{3.4}$$

where in this case $\boldsymbol{y}$ denotes the OM_PI-7 for travelling for the purpose of interest. y_i can only be observed if $y_i \geq 0$. Otherwise, y_i is said to be *censored*. $\boldsymbol{X}$ and $\boldsymbol{\beta}$ respectively denote the correlates and coefficients. Residuals $\boldsymbol{u}$ follow a normal distribution with a mean of 0 and a standard deviation of σ. Whether y_{im} is censored is related to the latent process, i.e., the second step of the Heckman model – given by the *selection equations* (**Eq. (3.5)**):

$$w_i \begin{cases} 1, \ if\ w_i^* = \boldsymbol{z}_i\boldsymbol{\gamma} + v_i \geq \boldsymbol{0} \\ 0, \ if\ w_{im}^* < 0 \end{cases} \tag{3.5}$$

where w_i indicates whether individual i made at least one trip (w_i=1) for the purpose of interest or not (w_i=0). w_i is determined by a latent variable w_i^*, which is a function of correlates ($\boldsymbol{z}_i$) related to the occurrence of the trip. $\boldsymbol{\gamma}$ refers to coefficients of $\boldsymbol{z}_i$. v_i is a residual. Following Hägerstrand's (1970)'s framework for the constraints of travel behaviour, we initially set $\boldsymbol{z}_i$ as the variables listed in **Appendix B.1**. To avoid potential multicollinearity issues, the Heckman selection model commonly requires an exclusion restriction: at least one variable that appears in the selection equation is excluded in the equation of interest (Ogundimu, 2021). We excluded housing tenure, as it may be closely correlated with the occurrence of various trips (e.g., Dias et al. (2020); Sturgis and Jackson (2003)) but may not significantly affect multimodality (e.g., Heinen and Chatterjee (2015)). We established the combined Heckman selection model as follows:

$$E(\boldsymbol{y}|y_i \geq 0) = \boldsymbol{X\beta} + \boldsymbol{\varphi}\lambda(\boldsymbol{z}_i\boldsymbol{\gamma});\ \boldsymbol{\varphi} = \sigma\boldsymbol{\rho};\ \boldsymbol{\rho} = cov(\boldsymbol{u}, \boldsymbol{v}) \tag{3.6}$$

where $\lambda(\boldsymbol{z}_i\boldsymbol{\gamma})$ refers to the IMR evaluated at $\boldsymbol{z}_i\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ is the corresponding coefficient. The IMR is defined as the ratio of the standard normal density to the standard normal cumulative distribution function. A significantly non-zero value for the IMR coefficient (i.e., $\boldsymbol{\varphi}$) indicates the presence of selection bias and that the Heckman selection model statistically outperforms the censored least squares model (Scott, 2019).

We applied the Heckman correction to the ANCOVA. Unlike **Eq. (3.4)**, we simultaneously took into account all considered types of purposes in the equation of interest of the Heckman correction-based ANCOVA. We adopted two treatments in the selection equation. For each purpose, we defined an individual to be censored when travelling with zero stages (in the main analysis) or an insufficient number of stages (in the sensitivity analysis). We added trip purposes, correlates related to the occurrence/frequency of trips, and their interaction terms in the equation. This adjustment is applied to control for the purpose-specific missingness of multimodality in multiple comparisons.

We estimated three independent regressions focusing on work, maintenance, and leisure trips. We removed highly correlated variables from the selection equations; there was no high-level multicollinearity (the variance inflation factor<5) amongst the input variables in the equations of interest after we recategorized age dummy variables. We adopted the HC1 robust standard error, as proposed by MacKinnon and White (1985), to tackle potential heteroskedasticity. The large sample size largely ensures that our models are relatively robust against non-normal residuals (Goldberger, 1983). We conducted six sensitivity analyses: (1) adopting different indicators as dependent variables; (2) using the OM_PI-3 as dependent variables; (3) including the number of stages as an additional explanatory variable; (4) considering only individuals who had made at least three purpose-specific stages; (5) not considering escort trips; and (6) considering only individuals living outside Greater London (i.e., excluding those living in Greater London).

3.4 Results

3.4.1. Descriptive analyses

Individuals made on average 26 trips (45 trip stages) during the survey week. Work, maintenance, and leisure trips respectively accounted for 39%, 24%, and 23% of these trips. Individuals used the private car most frequently on average 63%, followed by walking (20%), bus (8%), and rail (3%). These figures are, to a certain extent, comparable with the distribution of mode share in several other European countries, such as Germany, Norway, and Belgium (see, Kuhnimhof et al. (2012a); Fountas et al. (2020))

59% of the individuals were multimodal, as they had used more than one mode of transport. However, individuals used on average only 1.89 modes. The difference in share between the primary and secondary modes was large (67%). Overall, individuals had a relatively low level of mode choice variability (OM_PI: 0.198; HHI: 0.763).

The trips exhibited a large variation in travel distance. The standard deviation of trip distance (19.2 miles) was more than twice as large as the mean value of trip distance (9.5 miles). The distribution of departure times of trips was relatively even; 5.8% to 8.2% of trips happened per hour from 9am to 5pm. Leisure trips were associated with the highest level of variability in travel distance and departure time, followed by maintenance trips and work trips (**Table 3.3**). The patterns for more detailed classification of trip purposes were similar.

Table 3.3 Time-space variability of trips across purposes.

	Work	Maintenance	Leisure	ANCOV
Departure time variability	3.089 (1.503)	3.388 (1.633)	3.814 (1.994)	p<0.001
Travel distance variability	0.268 (0.429)	0.516 (0.463)	0.574 (0.565)	p<0.001
Number of stages	12.549 (9.548)	7.708 (6.828)	7.016 (6.359)	p<0.001

	C/E	Business	Shopping	PB	Social	Recreation	ANCOV
Departure time variability	2.768 (1.212)	2.941 (1.782)	2.922 (1.375)	2.299 (1.270)	3.085 (1.581)	2.931 (1.639)	p<0.001
Travel distance variability	0.158 (0.328)	0.359 (0.444)	0.428 (0.439)	0.290 (0.411)	0.418 (0.485)	0.400 (0.527)	p<0.001
Number of stages	11.293 (8.890)	6.079 (6.795)	6.147 (5.578)	4.059 (4.160)	5.028 (4.806)	4.879 (4.787)	p<0.001

Note: figures reported are mean values and standard deviations (in parentheses). We report the reciprocal of the HHI to reflect the departure time variability, so that a greater value of the indicator reflects a higher level of variability.

Categorisation of trip purposes: work (commuting/education and business); (2) maintenance (shopping and personal business); and (3) leisure (social and recreation).

Abbreviations: Commuting/Education (C/E); Personal business (PB).

3.4.2. Multimodality levels across trip purposes

We examined whether there were significant differences in levels of individual multimodality across trip purposes using ANCOVA with the Heckman correction. The IMR coefficient was significantly different from zero (-0.052; p<0.001), suggesting the necessity of correcting selection bias. Individual levels of multimodality (OM_PI-7) significantly varied by trip purpose (p<0.001), and descended in order of the level of multimodality from commuting/education, social, recreation, business, shopping, to personal business trips (**Table 3.4**). This was for individuals with at least one stage.

We then conducted Tukey-Kramer tests to determine the relative level of multimodality concerning different purposes (**Table 3.5**). Multimodality descended from commuting/education and social trips (Subset 1), social and recreation trips (Subset 2), shopping and business trips (Subset 3), to personal business trips (Subset 4). This indicated that leisure trips presented a higher level of multimodality than most other purposes, except commuting/education trips. In contrast, maintenance trips were associated with a lower level of multimodality than the others, except for business trips.

Our sensitivity tests showed highly consistent results (see, **Tables 9**, **10**, and **11** in **Supplementary Material**). When using another indicator, the main difference was that business, shopping, and personal business trips no longer significantly differed from each other using the DSPS-7 and HHI-7 indicators. The results for the seven- and three-mode-based OM_PI were largely similar, except shopping and business trips no longer remained in the same subset after using the OM_PI-3 (**Table 3.5**). These examinations indicated a relatively high robustness of our findings to the definition of multimodality. The division of subsets also remained similar after we excluded escort trips or individuals who lived in Greater London.

To investigate how multimodality could be impacted by the number of stages, we looked at the extent to which the levels of multimodality by trip purpose changed when increasing the minimum threshold of the number of stages that needed to be made by an individual to be included in the calculations (**Figure 3.1).** As the threshold increased, the level of multimodality also increased for most trip purposes. Only for commuting/education did the level not substantially change. The order of relative levels of purpose-specific multimodality was seen to depend on the number of trip stages. If only considering a few (<3) stages, commuting/education, social, and recreation trips were more multimodal than business, shopping, and personal business trips. When there is a higher threshold of the number of stages, social and recreation trips remained the highest level of multimodality. However, as the threshold increased, commuting/education trips gradually became less multimodal than the remaining types of trips.

Table 3.4 Variations in levels of individual multimodality across purposes.

Minimum Number of Stages: 1							
	Work		Maintenance		Leisure		ANCOVA
OM_PI-7	0.103 (0.173)		0.087 (0.154)		0.111 (0.180)		$p<0.001$
OM_PI-3	0.157 (0.271)		0.140 (0.253)		0.170 (0.278)		$p<0.001$
Number of stages	12.5 (9.5)		7.7 (6.8)		7.0 (6.4)		$p<0.001$
Number of observations	7089		9912		9242		
	C/E	Business	Shopping	PB	Social	Recreation	ANCOVA
OM_PI-7	0.088 (0.162)	0.067 (0.148)	0.067 (0.138)	0.047 (0.121)	0.083 (0.159)	0.079 (0.159)	$p<0.001$
OM_PI-3	0.134 (0.256)	0.098 (0.225)	0.109 (0.228)	0.072 (0.193)	0.127 (0.249)	0.118 (0.243)	$p<0.001$
Number of stages	11.3 (8.9)	6.1 (6.8)	6.1 (5.6)	4.1 (4.2)	5.0 (4.8)	4.9 (4.8)	$p<0.001$
Number of observations	6487	2583	9078	5076	7256	5812	
Minimum Number of Stages: 3							
	Work		Maintenance		Leisure		ANCOVA
OM_PI-7	0.110 (0.177)		0.110 (0.166)		0.147 (0.194)		$p<0.001$
OM_PI-3	0.169 (0.277)		0.178 (0.273)		0.225 (0.299)		$p<0.001$
Number of stages	13.59 (9.49)		9.5 (6.9)		8.9 (6.5)		$p<0.001$
Number of observations	6537		7558		6733		
	C/E	Business	Shopping	PB	Social	Recreation	ANCOVA
OM_PI-7	0.095 (0.166)	0.102 (0.173)	0.093 (0.154)	0.086 (0.153)	0.127 (0.183)	0.130 (0.188)	$p<0.001$
OM_PI-3	0.146 (0.264)	0.150 (0.263)	0.152 (0.257)	0.133 (0.244)	0.194 (0.285)	0.196 (0.287)	$p<0.001$
Number of stages	12.2 (8.8)	9.0 (7.3)	8.1 (5.8)	6.7 (4.9)	7.2 (5.2)	7.315 (5.220)	$p<0.001$
Number of observations	5902	1582	6241	2364	4338	3257	
Minimum Number of Stages: 7							
	Work		Maintenance		Leisure		ANCOVA
OM_PI-7	0.123 (0.183)		0.137 (0.173)		0.183 (0.203)		$p<0.001$
OM_PI-3	0.189 (0.288)		0.225 (0.284)		0.283 (0.308)		$p<0.001$
Number of stages	15.41 (9.3)		13.6 (7.0)		12.9 (6.8)		$p<0.001$
Number of observations	5328		4155		3547		
	C/E	Business	Shopping	PB	Social	Recreation	ANCOVA
OM_PI-7	0.109 (0.174)	0.133 (0.182)	0.126 (0.164)	0.124 (0.163)	0.173 (0.194)	0.166 (0.196)	$p<0.001$
OM_PI-3	0.168 (0.277)	0.208 (0.289)	0.211 (0.273)	0.199 (0.259)	0.270 (0.296)	0.259 (0.298)	$p<0.001$
Number of stages	14.4 (8.8)	13.2 (8.1)	12.7 (6.1)	12.5 (5.5)	12.1 (6.0)	12.1 (5.8)	$p<0.001$
Number of observations	4557	822	2716	704	1557	1225	

Note: we reported mean values and standard deviations (in parentheses).

Abbreviations: Commuting/Education (C/E); Personal business (PB).

Table 3.5 Relative level of individual multimodality pertaining to different purposes.

Indicators	Seven modes	Three modes
Minimum number of stages: 1		
OM_PI	S1: {Commuting/Education}; {Social} S2: {Social}; {Recreation} S3: {Business}; {Shopping} S4: {Personal Business}	S1: {Commuting/Education}; {Social} S2: {Social}; {Recreation} S3: {Shopping} S3: {Business} S5: {Personal Business}
Minimum number of stages: 3		
OM_PI	S1: {Recreation}; {Social} S2: {Business}; {Commuting/Education}; {Shopping} S3: {Commuting/Education}; {Shopping}; {Personal Business}	S1: {Recreation}; {Social} S2: {Shopping}; {Business}; {Commuting/Education} S3: {Commuting/Education}; {Personal Business
Minimum number of stages: 7		
OM_PI	S1: {Social}; {Recreation} S2: {Shopping}; {Business}; {Personal Business} S3: {Commuting/Education}	S1: {Social}; {Recreation} S2: {Shopping}; {Business}; {Personal Business} S3: {Commuting/Education}

Note: S1-S4 denotes the subsets derived by the multiple comparisons; there is no significant difference between trips in the same subset regarding multimodality. A smaller sequence number of a subset indicates a higher level of multimodality for trips within this subset (e.g., S1> S2); within each subset, trips are sorted in descending order regarding multimodality.

We repeated the Tukey-Kramer tests with a threshold of three and seven stages. Theoretically, using three- or seven-mode-based indicators, only individuals who travelled at least three or seven stages could be fully multimodal. For the threshold of three stages, unlike in our examinations of all individuals, multimodality for commuting/education was no longer different from that for business, shopping, and personal business trips (**Table 3.5**). For the threshold of seven stages, commuting/education trips were found to be significantly less multimodal than shopping, personal business, and business trips. The Tukey-Kramer tests on trip purposes classified by time-space variability (i.e., work, maintenance, and leisure trips) yielded largely similar results to those with the more detailed classification of purposes (**Figure 3.1**). Most noticeable was that the level of multimodality in work trips was the lowest, with a relatively low threshold (i.e., 3).

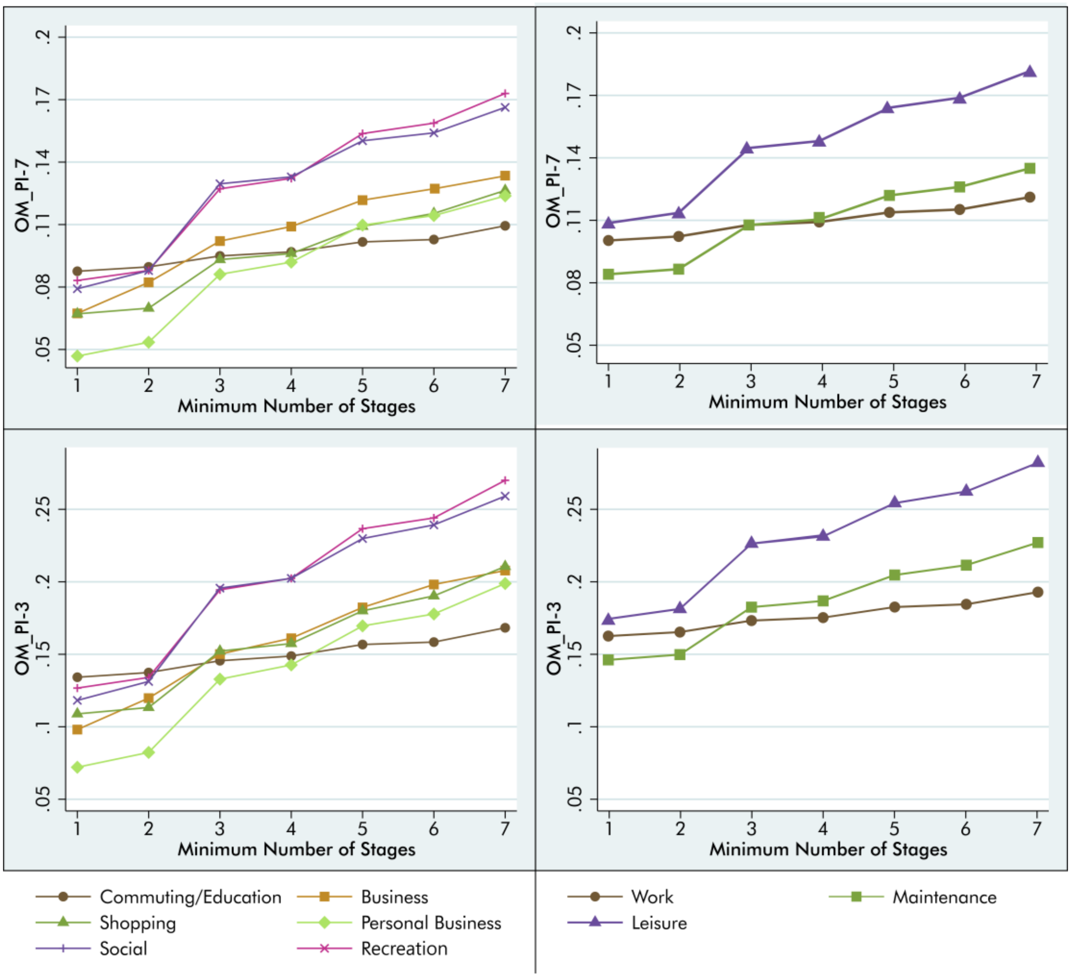

Figure 3.1 Patterns in relative levels of purpose-specific multimodality as a function of the minimum number of stages. Note: multimodality is measured by OM_PI-3/7.

3.4.3. Correlates of multimodality across trip purposes

We applied Heckman selection models to explore the disparities in correlates of multimodality across trip purposes. The IMR coefficient for all the established models differed from zero (-0.05, -0.05, and -0.13 when modelling work, maintenance, and leisure trips, respectively) at the significance level of 0.01. This suggests that, for our data, the Heckman selection model is more desirable than the censored least squares model in terms of producing unbiased estimates of multimodality correlates. Eight correlates were significantly associated with multimodality for all three considered trip purposes (**Table 3.6**). Higher levels of multimodality for work, maintenance, and leisure trips were all associated with working part-time, higher household income, greater residential land use-mix, more limited availability to household vehicles, holding a full car license, owning a bicycle, being the main driver of the household vehicle, and holding a public transport season ticket.

Table 3.6 Correlates of multimodality by trip purposes.

	Work Trips	Maintenance Trips	Leisure Trips
	Coef. (robust SE)	Coef. (robust SE)	Coef. (robust SE)
Social Role Constraints			
Age			
>65	-0.050 (0.011) ***	-0.008 (0.006)	-0.036 (0.006) ***
16-64 (Ref)			
Gender			
Female	0.009 (0.004) *	0.003 (0.004)	-0.005 (0.005)
Male (Ref)			
Having a Child in Household			
Yes	0.010 (0.005) *	-0.001 (0.004)	-0.033 (0.005) ***
No (Ref)			
Physical Mobility Constraints			
Having Walking Difficulties			
Yes (Ref)			
No	0.014 (0.011)	0.041 (0.006) ***	0.035 (0.010) ***
Work Constraints			
Economic Status			
Full time (Ref)			
Part time	0.011 (0.005) *	0.015 (0.005) **	0.012 (0.007) ψ
Unemployed	0.000 (0.020)	0.029 (0.014) *	0.003 (0.016)
Retired and other (including students)	-0.013 (0.012)	0.022 (0.005) ***	-0.010 (0.008)
Multiple Work Locations			
Yes	0.013 (0.006) *	-0.005 (0.005)	-0.004 (0.006)
No (Ref)			
Economic Constraints			
Household Income			
£50,000 and over	0.041 (0.005) ***	0.008 (0.004) ψ	0.022 (0.006) ***
£25,000 to £49,999	0.019 (0.005) ***	0.005 (0.004)	0.005 (0.005)
Less than £25,000 (Ref)			
Accessibility Constraints			
Settlement Population Density			
Population density	1.733E-4 (8.779E-5) *	1.487E-4 (6.581E-5) *	2.461E-6 (7.993E-5)
Settlement Land-use Mix			

Entropy index	0.053 (0.010) ***	0.056 (0.008) ***	0.081 (0.010) ***
Mobility Resource Constraints			
Access to Vehicles			
No household vehicle	0.033 (0.009) ***	0.061 (0.007) ***	0.098 (0.011) ***
1 household vehicle	0.022 (0.005) ***	0.021 (0.004) ***	0.022 (0.005) ***
>2 household vehicle (Ref)			
Holding Full Car License			
Yes	-0.084 (0.007) ***	-0.038 (0.006) ***	-0.050 (0.010) ***
No (Ref)			
Owning a Bicycle			
Yes	0.019 (0.004) ***	0.012 (0.003) ***	0.012 (0.007) ***
No (Ref)			
Driver Status			
Main household car driver	-0.077 (0.008) ***	-0.025 (0.006) ***	-0.027 (0.007) ***
Not a main household car driver (Ref)			
Holding PT Pass			
Yes	0.092 (0.006) ***	0.043 (0.004) ***	0.039 (0.007) ***
No (Ref)			
Intercept	0.135 (0.019) ***	0.024 (0.016)	0.109 (0.040) ***
IMR Coefficient	-0.049 (0.013) ***	-0.050 (0.018) **	-0.131 (0.044) **
Number of Observations	7089	9912	9242
R^2	0.154	0.090	0.077

Note: ψ, *, **, and *** denotes p<0.10, p<0.05, p<0.01, and p<0.001, respectively. The OM_PI-7 was used as the dependent variables.

Nevertheless, there were also differences between the models. First, several correlates were only significantly associated with multimodality for specific trip purposes: being female and working in multiple locations (only for work trips); having walking difficulties (for maintenance and leisure trips, but not for work trips); having a child in the household and being 65 and over (for leisure and work trips, but not for maintenance trips).

A second difference was that there were variations in the R-Squared across the regression equations (see, **Eq. (3.6)**). This indicates that the total explained variance varied by trip purpose. Estimations for work trips were associated with the highest R-Squared, regardless of the multimodality indicators we adopted. In contrast, the R-Squared values for modelling maintenance and leisure trips were lower, which were approximately half of those obtained when estimating work trips. These issues revealed that, compared with maintenance and leisure trips, the correlates we considered have more explanatory power in accounting for the level of multimodality regarding work trips.

A third difference was presented in the variance explained by each domain of mobility constraints (**Table 3.7**). Of all constraints, mobility resource constraints accounted for the largest share of explained variance when modelling all three considered types of trips. However, the share of total variance explained by mobility resource constraints meanwhile exhibited the largest difference across purposes. The corresponding share was the largest for modelling work trips (11.28%), followed by the model using maintenance trips (5.34%), and the smallest for modelling leisure trips (4.22%). It was also shown that mobility resource constraints did not account for only 23.55% (i.e., 100%-76.45%) of all explained variance (see figures in parentheses in **Table 3.7**) in multimodality of work trips, whilst this figure was 38.09% and 42.21% for multimodality in maintenance and leisure trips, respectively. The other constraints were less explanatory for multimodality, accounting for 0.08%-1.14% of the total variance. The across-purpose disparities in the share of total variance explained by such constraints were also smaller, ranging from ±0.03% to ±0.95%. Nevertheless, constraints presenting relatively high explanatory power were found to be different across purposes. Most notable was that work and accessibility constraints predicted, compared to the others, a larger share of variance (1.25% and 1.11%) in the estimations for maintenance and leisure trips, respectively. These figures may seem small, yet in the corresponding estimations, work and accessibility constraints respectively consisted of 14.30% and 14.75% of all explained variance, which were 1.3-8.8 times as large as those accounted for by constraints in other domains.

Table 3.7 Percentage of variance explained by different mobility constraints.

Constraints	Work Trips	Maintenance Trips	Leisure Trips
Social Role	1.14% (7.69%)	0.61% (7.05%)	0.72% (9.92%)
Physical Mobility	0.08% (0.58%)	0.14% (1.65%)	0.60% (8.21%)
Work	0.51% (3.44%)	1.25% (14.54%)	0.30% (4.10%)
Economic	0.63% (4.25%)	0.32% (3.68%)	0.35% (4.78%)
Accessibility	1.12% (7.60%)	0.96% (11.17%)	1.11% (15.20%)
Mobility Resource	11.28% (76.45%)	5.34% (61.91%)	4.22% (57.79%)
Total variance explained	14.76%	8.63%	7.30%

Note: figures reported are the percentage of (1) total variance accounted for by specific mobility constraints; and (b) explained variance accounted for by specific mobility constraints (in parentheses). The sum of the percentages of variance explained approaches, but does not equal, the R-squared of the corresponding model, since the variance explained by the IMR is not reported.

Our sensitivity analysis showed generally similar findings. Nevertheless, there were some differences. The analysis performed by changing indicators (**Tables 12**, **13**, and **14** in **Supplementary Material**) and choice sets to measure multimodality showed similar results, and no substantial change in the variance explained by various mobility constraints. The main differences were found when modelling leisure trips; owning a bicycle and working part-time came to be insignificant for the leisure trip models using the NOM-7 and DSPS-7. When we additionally adjusted for the number of stages, several variables changed their significance: working part-time, having a child, and working in multiple locations (for work trips); working part-time and household income (for maintenance trips); and being retired/students as well as owning a bicycle (for leisure trips). This suggests that the association between multimodality and these variables may be mediated by the difference in the number of stages travelled for specific purposes. When we looked at only individuals who had made at least 3 stages, the R-squared in the models for work, maintenance, and leisure trips increased to 0.156, 0.127, and 0.122, respectively. When we excluded escort trips, the relationship between having a child and multimodality for work trips became insignificant, suggesting that escort trips may mediate such a relationship. When we only considered individuals who lived outside Greater London, our results remained fairly similar in terms of the direction and significance of multimodality correlates.

3.5 Discussion and conclusion

3.5.1. Discussions on principal findings

Going beyond an extensive focus on multimodality for undifferentiated and exclusive trips, this study explored how multimodality differs by trip purpose. We analysed the level of purpose-specific multimodality from the standpoint of time-space variability of corresponding trips. Our results indicated that in general, the level of individual multimodality is positively linked with the time-space variability of trips (i.e., variability in travel distance and departure time), but only if sufficient travel stages (at least three) are made for specific purposes. This means that multimodality is the highest for leisure trips, followed by maintenance trips, and the lowest for work trips. However, if individuals with limited stages are also included, higher time-space variability of trips do not necessarily result in a higher level of multimodality.

This research offers new insights into the disparities in correlates of multimodality across trip purposes. Firstly, we identified several correlates that correspond to multimodality for only specific trip purposes. For example, working in multiple locations and being female tended to increase multimodality for work trips, but not in the case of other trips. One explanation may be that multiple locations contribute to higher space-variability in work trips; travellers may diversify their mode use to cope with different spatial constraints. Studies have found that women are less dependent on private cars compared to men and instead use public and active transport more for work-related activities, as women, on average, travel a shorter distance and make more trip stages (e.g., Hjorthol (2000); Root and Schintler (1999)). This is also supported by our data. For each work trip on average, women travel 7.2 km and make 1.8 stages, whilst men travel 12.3 km and make 1.6 stages. The share in the use of private cars, public transport, and active transport for women are respectively 63%, 22%, and 15%, whilst these figures are respectively 68%, 18%, and 14% for men. Some studies indicate the gender difference in mode use may be ascribed to the uneven distribution of domestic responsibilities, although the reasons remain uncertain (Hatamzadeh et al., 2020).

We also found that travellers with no walking difficulties were more multimodal for all but work trips. This could be explained by the fact that, compared with other trips, people make work trips with a higher frequency and a lower level of time-space variability.

Travelers may thus be more familiar with transport settings and environmental contexts during work trips. This helps to ease the burden of using public and active transport for travellers who have walking difficulties when they travel to work. Correspondingly, walking difficulties may have less of an effect on multimodality for work trips.

Travelers who have a child in their household were associated with a lower level of multimodality only for leisure trips but a higher level of multimodality only for work trips. A plausible reason for our findings is that, different from work and maintenance trips, the selection of destinations for leisure trips may be restricted because of child care responsibilities. By contrast, as indicated by our sensitivity analysis, having a child leads to more escort (education) trips on average, which provides travellers with more opportunities to use different modes.

Travelers aged 65 and over, compared to their younger counterparts, were less multimodal for work and leisure trip activities, but not for maintenance trips. On the one hand, older adults are more likely to have physical difficulties using certain modes, e.g., walking and cycling, which in turn may reduce their mode choice sets and the possibility to be fully multimodal. On the other hand, they are generally under less time pressure than younger respondents. This allows older adults a more flexible time budget to make daily household responsibilities and provides more location alternatives to conduct maintenance activities (e.g., O'Hern and Oxley (2015)), which potentially increases the multiplicity of modes.

Secondly, we found that the total variance explained for maintenance and leisure trips was low, and roughly half of that for work trips. A possible reason is that although we adopted a rich set of explanatory variables in this research, the selection of variables was based on the literature focusing on undifferentiated and commuting trips. We might thus have omitted variables correlated with multimodality for maintenance and leisure trips. The low explained variance for maintenance and leisure trips may also be attributable to the fact that individuals' self-selection plays a more important role in determining to (not) make trips for discretionary activities. This is because demand for discretionary activities is generally lower than that for obligatory activities; discretionary activities are also scheduled with less priority than obligatory ones are (Buliung and Kanaroglou, 2007). As a consequence, there is a large gap in the number of trips made for work (10.1), maintenance (6.2), and leisure (6.0) purposes. This reduces the interpersonal differences in observed multimodality for maintenance and leisure trips and the ability of correlates to capture such differences. Our speculation can be partially corroborated by our sensitivity analyses, with the R-squared values becoming similar for modelling all three types of trips after the exclusion of individuals with a limited number of stages travelled.

Thirdly, we observed that the variance explained by mobility resource constraints substantially decreased from modelling work, to maintenance, then to leisure trips. This indicates that mobility resource constraints may have less explanatory power for multimodality in trips with a higher level of time-space variability. We speculate that although mobility resource constraints may reduce the choice set, performing trips with high time-space variability may be less likely to be restricted by using specific modes as a result of high flexibility of these trips. Apart from mobility resource constraints, we found that work and accessibility constraints explained a larger share of variance than the other (social role, physical mobility, and economic) constraints for respectively modelling maintenance and leisure trips. Moreover, existing literature has suggested that trips with higher time-space variability are less susceptible to the effect of residential contexts on travel intensities, such as travel distance and frequency (e.g., Elldér (2014); Dieleman et al. (2002); Krizek (2003); see, Gim (2011) and Tran et al. (2012) for exceptions). This is partially contradicted by our results on multimodality, which showed that the variance explained by accessibility constraints was similar, regardless of trip purposes.

3.5.2. Discussions on policy implications

This research could help to develop policies to encourage multimodal travel behaviour. Firstly, the between-purpose differences in correlates we found could inform trip purpose-based policy prioritization to reduce inequalities in multimodality. For example, Heinen and Chatterjee (2015) tried to explain their finding that women are more multimodal overall, and speculated that women make more maintenance trips. However, we showed that work trips potentially contribute more to this difference. Improving spatial accessibility to employment rather than shopping may thus be more effective to reduce the gender gap in multimodality. This strategy helps to balance commuting distance between men and women, and in turn, the gender difference in car-dependence during commuting. Similarly, developing age-friendly public transport in recreational areas and around workplaces may help to reduce existing age-differences in multimodality, as this is largely present in leisure and work trips.

Secondly, our findings may help to inform policies that increase multimodality for as large a population as possible. We suggest that policies targeted at mobility resource constraints should be given a higher priority in the policy agenda, as such constraints influence multimodality most, regardless of trip purposes. For example, policymakers could expand subsidies for public transport passes, raise vehicle tax rates to restrict the purchase of cars, and increase public investments in bicycle networks/shelters to encourage bicycle ownership. However, unlike studies that have made similar recommendations (e.g., Klinger (2017)), we argue that policies targeted at altering mobility resources constraints alone may not be sufficient to promote multimodality over a wide population. Our argument may particularly be true for people who have a great demand for carrying out discretionary activities, as mobility resource constraints are less influential on multimodality for trips with higher time-space variability. Our work suggests therefore that these policies need to be accompanied by measures specifically aimed at encouraging multimodality in maintenance and leisure trips. Against this backdrop, implementing measures to change work and accessibility constraints, such as encouraging flexible work hours and promoting settlement land use diversity, could potentially be fruitful. This is because, as our analyses revealed, work and accessibility constraints may have a greater impact on multimodality in maintenance and leisure trips than for other trip purposes.

3.5.3. Limitations

We used high-quality, national-representative, one-week travel diaries well suited for analysing multimodality, but our research has nevertheless several limitations. Firstly, we considered seven types of typical trip purposes to capture human activities in a systematic way. Despite this large number, it is still limited in reflecting the comprehensiveness of activities due to their miscellaneous nature and thus, in turn, in characterizing the subtle differences in the time-space variability between specific activities (see e.g., Buliung and Kanaroglou (2007) for reviews). Future studies could use data sets that simultaneously cover sufficient trip stages and a more diversified classification of trip purposes. Secondly, we conducted this research based on English data, and thus our findings are England specific and generalization should be made with care. Similarities in findings are likely to be greater with similar high-income countries. Thirdly, our analyses can only reveal correlations as we used cross-sectional data and Heckman selection models. Longitudinal designs in combination with more sophisticated statistical methods (e.g., propensity score matching) could be applied to better understand the causal relationship between multimodality and its determinants.

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Chapter 4

Multimodals present high-level cognitive dissonance: Investigating the nexus between attitudes and multimodal travel behaviour

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Abstract

Multimodality refers to using more than one mode of transport in a given period. Encouraging multimodality potentially provides a solution to induce modal shifts towards sustainable transport. This research investigates how mode-specific attitudes are distributed across clusters and levels of multimodal travel behaviour using the Netherlands Mobility Panel. We found that the difference in attitudes between modes was smaller for travellers in multimodal clusters and smaller among travellers with a higher level of multimodality. However, the mode with the highest level of use was not necessarily connected with the most positive attitude. Moreover, inconsistent with existing studies, our results showed that multimodal public transport users, compared with car-dominant users, presented a higher level of dissonance between mode use and corresponding attitudes. Travellers with a higher level of multimodality tended to be attitudinally dissonant with their primary mode use, but consonant with their set of mode choices. The majority of dissonant multimodal travellers had the most positive attitudes towards car use. Our research corroborates the hypothesis of there being a high potential for multimodal travellers to change their mode use towards more sustainable transport, but this may not be effectively achieved without supporting policies. Our findings may also provide insights into the psychological mechanism underlying a recent important finding, namely, that multimodal travellers tend to change their mode use over time.

Keywords: Multimodal travel behaviour; Attitude; Cognitive dissonance; Travel behaviour change

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4.1. 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 and Ajzen, 2011). Extensive evidence from diverse multidisciplinary backgrounds has suggested that attitudes play an important role in the enactment of behaviour (Armitage and Conner, 2001). Since 1970s, the notion of attitudes has been increasingly invoked in studies on travel behaviour (Kroesen et al., 2017). Attitudes have been applied as, for instance, latent variables in hybrid choice models (e.g., Chorus and Kroesen (2014)), indicators to segment a population of travellers (e.g., Anable (2005)), and controlled variables in modelling the built environment-travel behaviour relation to reduce residential self-selection confounding (e.g., 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 (e.g., Heinen et al. (2011); Moody et al. (2019)). A few studies considered more than one mode but separately analysed their relations with attitudes (e.g., Kroesen and Chorus (2018); De Vos (2018)). For example, De Vos (2018) studied how mode-specific attitudes were distributed across various travellers who ever used one given mode of transport (e.g., bus users and car users). Recently, several studies have looked into how multimodal travel behaviour (also termed multimodality), which is defined as using more than one mode of transport in a given period – is associated with attitudes (e.g., Ramos et al. (2020); Hunecke et al. (2020); Ton et al. (2019); Große et al. (2018); Mehdizadeh and Ermagun (2018); Molin et al. (2016)).

Deciphering the nexus between attitudes and multimodality is important for supporting policies to promoting sustainable transport. It has been suggested that encouraging multimodality potentially provides a solution to induce modal shifts towards more sustainable transport. Evidence has shown that multimodal travellers tend to switch their mode use over time (e.g., Kroesen (2014); Heinen and Ogilvie (2016a)). Individuals who are more multimodal are more inclined to change (e.g., Heinen (2018)), more open to adopting new transport services (e.g., Diana (2010)), and more susceptible to transport interventions (e.g., Heinen and Ogilvie (2016a)).

Most existing studies on the relation between attitudes and multimodality considered general attitudes, such as environmental awareness (e.g., Große et al. (2018); Mehdizadeh and Ermagun (2018)), political orientation (e.g., Ramos et al. (2020)), and social milieus (e.g., Hunecke et al. (2020)). Two studies explicitly analysed mode-specific attitudes (Molin et al., 2016; Ton et al., 2019). Applying mode-specific attitudes allowed the researchers to draw on Festinger's (1957) cognitive dissonance theory, and on this basis, to explore traveller's potential to change their mode use. Festinger's (1957) cognitive dissonance theory defined a state of consonance as a state when a behaviour and an attitude are aligned with each other, and dissonance if they are not aligned. According to the cognitive dissonance theory, a state of dissonance results in psychological discomfort, which in turn, drives people to do their best to alter either their behaviour or their attitudes, until they are no longer in conflict with each other. Along this line, Ton et al. (2019) and Molin et al. (2016) found that multimodal travellers were generally associated with a high level of consonance between attitudes and mode use. They also showed that multimodal groups, compared to monomodal groups, hold more positive/less negative attitudes towards more than one mode.

However, these two studies share three shortcomings. First, they focus on how mode-specific attitudes are distributed across clusters of multimodality, whilst overlooking the relationship between mode-specific attitudes and levels of multimodality. Second, we argue that the methods applied do not allow the comparison of attitudes towards different modes; thus, whether a traveller is dissonant or consonant is inconclusive. Third, these studies apply incomplete frameworks drawn from the theory of planned behaviour to characterise mode-specific attitudes, which may lead to biased measurements of attitudes. We will elaborate on these issues in the following section (Section 4.2).

This paper aims to investigate the relationship between attitudes and multimodality using the 2016 Netherlands Mobility Panel (in Dutch: MobiliteitsPanel Nederland; MPN). This research has two objectives. First, it investigates how mode-specific attitudes are distributed across different distinctive clusters and levels of multimodality. Second, it explores the extent to which mode-specific attitudes are consonant/dissonant with the actual mode use across travellers with various mode use patterns.

4.2. Literature review and research gaps

Recent research by Ton et al. (2019) and Molin et al. (2016) explicitly studied the relationship between mode-specific attitudes and multimodality. These two studies used a similar approach to characterise multimodality and mode-specific attitudes. They applied latent cluster analysis to identify clusters in relation to mode use patterns, and used exploratory factor analysis (EFA) to measure multidimensional aspects of mode-specific attitudes. Their results showed that multimodal clusters, in comparison with monomodal or less multimodal clusters, hold more positive or less negative attitudes towards more than one mode. The major difference between these two studies is that they adopt different approaches to measure the level of dissonance between mode use and corresponding attitudes. Molin et al. (2016) investigated whether the rank of the most positive aspect of mode-specific attitudes (e.g., the convenience of driving) and modal share is consistent across multimodal clusters. They found that four out of five identified multimodal clusters were associated with a high level of mode use-attitude consonance, whilst multimodal public transport users showed a mild level of dissonance. Ton et al. (2019) provided a more detailed picture of the mode use-attitude dissonance of multimodal clusters. The authors defined dissonant travellers as travellers who did not use their most-preferred mode, namely, the mode with the most positive attitudinal aspects on average, within survey days at all and compared the percentage of the dissonant travellers across clusters. The results showed that *no* members in the multimodal public transport clusters were dissonant travellers, whilst 38% of exclusive car users were dissonant travellers.

However, these studies have several limitations. First, these studies defined multimodality often in a simplified way. While existing studies shed light on how attitudes are distributed across clusters with different mode-use patterns, they largely overlook the relationship between attitudes and the level of multimodality. The identified clusters were generated based on a data-driven clustering approach, i.e., latent cluster analysis, which centres on group-level information on which modes and how frequently these modes are used (Heinen and Mattioli, 2019a). Such approaches do not gauge the level of multimodality at the individual level; accordingly, regarding multimodality, the extent to which individuals differ from each other within and between clusters remains largely unknown.

The second limitation is that the measured attitudes in the existing studies cannot be compared between modes. It is therefore inconclusive as to how attitudes towards different modes are distributed within certain groups, and more importantly, whether the attitude-mode use relation for these groups is consonant or not. Although EFA explores the multidimensional aspects of an attitude, such a method is limited in aggregating these aspects, and in turn, in characterising the construct of an attitude towards a mode as a whole. Thus, little information can be drawn about the comparison of individuals' *overall* preferences between modes. This issue could be severely problematic when the generated aspects of attitudes are not consistently measured between modes (e.g., the flexibility of driving vs. the safety of cycling) or different aspects underpinning an attitude exhibit a large difference regarding intensity (e.g., having a positive perception towards the flexibility of cycling but a negative perception towards the safety of cycling). Another problem related to the comparableness issue is that the potential difference in the degree of an individual's preference towards different modes is not captured by existing studies. This is because the computed attitudinal variables were standardised to a mean of zero. Put differently, the average level of attitudes towards different modes were implicitly assumed the same, which is counterfactual to the evidence indicated by several studies (e.g., Van Wee et al. (2002); Steg (2003); De Vos (2018)). While standardised measures of attitudes are commonly applied in studies on a single behaviour, absolute levels of attitudes fit better with the interest of analysing compound behaviour.

The third limitation is that the existing studies applied incomplete belief-based frameworks to characterise mode-specific attitudes. According to the theory of planned behaviour (TPB) (Ajzen, 1985), an attitude is the sum of several beliefs in relation to a behaviour; each belief is determined by the multiplication of the expectancy of an outcome (e.g., driving is safe) and the perceived importance attached to this outcome (e.g., safety is important in daily travelling). The existing studies used only outcome expectancies in measuring attitudes. Omitting outcome evaluations may contribute to biased measurements of attitudes (Fishbein and Ajzen, 2011). For example, one's negative attitude towards driving could be overstated for those who believe that walking is eco-friendly, yet do not believe travelling in an eco-friendly way to be important. A number of recent studies demonstrated that, after data was controlled for belief strengths, the perceived importance related to expected outcomes of general travelling – the so-called 'transport priority' – was significantly associated with binary mode choices (e.g., Egset and Nordfjærn (2019); Mehdizadeh et al. (2017); Şimşekoğlu et al. (2015)) and choices to be multimodal (e.g., Mehdizadeh and Ermagun (2018)).

To address the identified research gaps, our research jointly takes into account both data-driven approaches and continuous indicators to distinguish clusters and measure levels of multimodality. We use the principal component analysis (PCA) and sum scoring to characterise an individual's overall attitudes towards different modes, whilst simultaneously considering the outcome expectancy, outcome evaluation, and between-mode difference in the intensity of attitudes. On these bases, we examine how the distribution of mode-specific attitudes and the level of mode use-attitude dissonance are connected with clusters and levels of multimodality.

4.3. Research design

4.3.1. Data

We used the 2016 MPN data. 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. The MPN data is suitable for investigating the relationship between attitudes and multimodality for two reasons. First, the MPN includes a relatively comprehensive set of attitudinal variables that are directly connected with mode use. This allows us to incorporate not only the belief-strength but also the outcome evaluation, which has been largely overlooked in the existing literature. Second, the MPN has a three-day trip-based travel dairy which enables us to characterise individual multimodality. The detailed information about the survey design, data collection, and variable specification of the MPN is elaborated on by Hoogendoorn-Lanser et al. (2015).

4.3.2. Measuring comparable mode-specific attitudes

We measured mode-specific attitudes based on the TPB (Ajzen, 1985). For a given mode, seven composites of beliefs were determined by the product of outcome expectancies and their attached outcome evaluations. We measured the outcome expectancy based on participants' statements, which indicate the extent to which the participants agree with statements on seven outcomes, such as 'I find travelling by car comfortable', using a 5-point Likert scale that ranges from 'strongly disagree' to 'strongly agree'. The outcomes examined were comfort, relaxation, pleasure, flexibility, time-saving, safety, and prestige, and were measured for four modes, i.e., car, bicycle, bus/tram/metro (BTM), and train. It should be noted that we considered only four modes of transport, namely, car, bicycle, BTM, and train, which is a limitation of this research. We measured the outcome evaluation by a 5-point Likert scale to statements such as 'Travelling must be comfortable'. We scored outcome expectancy and outcome evaluation by unipolar (from +1 to +5) and bipolar (from -2 to +2) fashions, respectively, to avoid the often-criticised 'double negative' problem (see, e.g., French and Hankins (2003)). The Cronbach's alphas for the seven computed beliefs related to each mode were greater than 0.84, which indicates that there are high levels of internal consistency amongst the mode-specific beliefs. Therefore, for a given mode, the computed beliefs are suitable for underpinning the same construct, namely, the attitude towards the mode in question (Wadkar et al., 2016).

We then used two approaches to measure comparable mode-specific attitudes based on the composites of beliefs: sum scoring and PCA. Both sum scoring and PCA fall under the larger umbrella of latent factor analysis (McNeish and Wolf, 2020). 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 (e.g., McCartan and Elliott (2018); Kroesen et al. (2017); Hrubes et al. (2001)), owing to its conciseness and high validity (e.g., Fishbein and Ajzen (2011)). However, this approach implicitly assumes all beliefs carry an equal weight in underpinning an attitude, which is inconsistent with studies on salient beliefs (e.g., Fishbein and Ajzen (2011)).

PCA has been extensively used for producing composite indices in various contexts (see, Nardo et al. (2005) for reviews). This method maximally preserves the information contained by beliefs in the dimensionality reduction, and it uses factor loadings and eigenvalues to differentiate the contribution of these beliefs in underpinning an attitude. PCA largely ensures the comparability of measured attitudes between modes for two reasons. First, the covariance matrix-based PCA can be applied to the absolute value of beliefs, which captures the between-mode differences in the intensity of individuals' attitudes. Second, several aggregation methods of PCA have been developed, which provide solutions to aggregate multiple PCs into one composite indicator (e.g., Nicoletti et al. (2000); Gómez-Limón and Riesgo (2009); Fernando et al. (2012)), although it is inconclusive which method is mathematically outperformed. This allows us to measure an individual's overall attitude towards specific modes.

For each considered mode, we applied PCA to the seven computed belief compounds. That is, we separately implemented the PCAs according to the mode use. Because the MPN recorded outcome expectancy and outcome evaluation the same scaling system (i.e., Likert scale), we applied the PCA based on the covariance matrix of the absolute value of the beliefs. Following Nardo et al. (2005), we retained only the components with an eigenvalue greater than one, and performed varimax rotation, to capture information of the beliefs by a small number of PCs. We extracted one PC for car-, bicycle-, and BTM-related beliefs. When applied to train-related beliefs, the method yielded two PCs, which largely reflect affective and instrumental attitudes of using trains. **Appendix C.1** provides the information on the component loadings. We used a variance-based weighted aggregation method, developed by Nicoletti et al. (2000), to compute mode-specific attitudes as follows:

$$A_{im} = \sum_{k=1}^{k=n}\left(PC_{imk}\left(e_{mk}/\sum_{k=1}^{k=n} e_{mk}\right)\right) \tag{4.1}$$

$$PC_{imk} = \sum_{j=1}^{j=7}\left(w_{mkj}b_{imkj}\right) \tag{4.2}$$

$$w_{mkj} = \left(l_{mkj}\right)^2/\sum_{j=1}^{j=7}\left(l_{mkj}\right)^2 \tag{4.3}$$

where A_i 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_i takes into account the extent to which different PCs explain information contained by beliefs 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 beliefs j (b_{imkj}) (**Eqs. (4.2)-(4.3)**). The weight of b_{imkj} (w_{mkj}) is derived by squaring the factor loading (l_{mkj}) of b_{imkj}; a square loading value represents the variance explained by a given belief in a given PC. w_{mkj} is scaled to unity sum in the calculation.

4.3.3. Characterising clusters and levels of multimodality

The existing literature has developed a diverse array of measurements of individual multimodality. These measurements can be divided into two broad categories, namely, clustering approaches and continuous indices. These two types of measurements characterise related but distinct aspects of the notion of multimodality (Heinen, 2018). Using predefined criteria or unsupervised data-driven methods, clustering approaches classify individuals into various clusters regarding their modality patterns. Such approaches primarily focus on which and how many modes are frequently used by individuals in each identified cluster on average, yet they are limited in quantifying the level of variations in mode use by specific individuals. In contrast, continuous indices measure the level of individual multimodality (e.g., An et al. (2020); Susilo and Axhausen (2014); Diana and Pirra (2016)), but are not indicative of which modes are being used

Previous studies on the attitude-multimodality relationship have been predominately conducted based on clustering approaches (e.g., Hunecke et al. (2020); Molin et al. (2016); Ton et al. (2019)). In order to understand such a relationship comprehensively, we apply both data-driven approaches and continuous indices to characterise multimodality. First, we applied a k-means clustering approach to identify modality patterns. The core issue for the implementation of the k-means clustering is that it requires prior information on the number of clusters, and it can be highly sensitive to such information (Patil and Baidari, 2019). A Silhouette method, as proposed by Rousseeuw (1987), is therefore applied to determine the optimal number of clusters. The Silhouette coefficient measures the extent to which a specific individual in our context is similar to other individuals in the same cluster relative to those in the 'neighbour' clusters. 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 used for identifying modality styles are the share in stages made by car, foot, bicycle, BTM, and train as well as the total number of stages travelled during the survey days. Six clusters were ultimately determined for our analysis, as the greatest average value of Silhouette coefficients was detected under such a scenario.

Second, we used 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 (e.g., An et al. (2020); Scheiner et al. (2016)). The OM_PI is developed based on Shannon's Entropy index, which is a well-tested index to reflect inequality (Diana and Mokhtarian, 2007). Diana and Pirra (2016) suggest that the OM_PI is a desirable index for measuring multimodality when given modes are not accessible for specific travellers, as this index will not remain the same when replicating given modes with their corresponding intensities. The HHI is an extensively accepted measure of market concentration (Matsumoto et al., 2012). Because the HHI focuses more on the concentration of mode use, it allows us to highlight habitual travel behaviour and capture the existence of a regular pattern of an individual's multimodality. The OM_PI measures the variation, whilst the HHI reflects the concentration (Heinen and Mattioli, 2019a). A higher level of multimodality can thus be indicated by a greater value of the OM_PI and a smaller value of the HHI. These two indices were measured as follows:

$$OM\_PI_i = \sum_{k=1}^{N_i} (S_{ik} \ln(1/S_{ik})(1/\ln N_i)) \tag{4.4}$$

$$HHI_i = \sum_{j=1}^{N_i} S_{ij}{}^2 \quad (4.5)$$

where OM_PI_i and HHI_i refer to the value of OM_PI and HHI for individual i, respectively. N_i indicates the actual number of modes used by individual i during the survey days. S_{ij} is the share of stages made by specific mode j.

4.3.4. Analytical approaches

We used a one-way analysis of variance (ANOVA) to examine whether there were statistical differences in mode-specific attitudes across clusters and levels of multimodality. Following the ANOVA, we applied the Tukey-Kramer test for posthoc comparisons. We then looked into how clusters and levels of multimodality were associated with the dissonance between mode use and corresponding attitudes. De Vos (2018) and Ton et al. (2019) defined dissonant travellers as those who did not use their most preferred mode ever during survey days. We extended this conceptualisation by considering three types of dissonant travellers: dissonant travellers regarding (1) use of primary mode; (2) use of primary or secondary modes; and (3) mode choice set. 'Dissonant travellers regarding the use of primary mode' refers to travellers who did not use their preferred modes (i.e., modes with the most positive attitudes) most frequently. 'Dissonant travellers regarding the use of primary or secondary mode' denotes travellers whose share in their preferred modes does not rank in the top two amongst the four modes considered. 'Dissonant travellers regarding the mode choice set' refers to travellers who did not use their preferred mode at all during the survey days. The reason for such a labelling method is that whether travellers used their preferred modes or not, independent of the share of such modes, determines the diversity of the travellers' mode choice set. We used the Chi-squared test to examine whether there were statistical differences in the percentage of dissonant travellers across clusters and levels of multimodality and applied the Bonferroni procedure for performing posthoc multiple comparisons. We finally applied binary logit models to explore the extent to which clusters and levels of multimodality may affect the likelihood of being mode use-attitude dissonant (coding: dissonance=1; consonance=0), accounting for individual socioeconomic characteristics. The individual socioeconomic characteristics considered were age, gender, household income, employment status, residential population density, and ownership of cars, bicycles, and public transport subscriptions.

4.4. Results

4.4.1. Clusters and levels of multimodality

We generated six clusters of multimodality based on k-means clustering. We labelled these clusters according to the average shares of mode use: (1) CAR MOSTLY; (2) WALK

MOSTLY; (3) BICYCLE MOSTLY; (4) CAR+WALK+BIKE; (5) MM BTM; and (6) MM TRAIN (**Table 4.1**). The prefix 'MM' refers to 'multimodal'.

CAR MOSTLY cluster

The largest cluster is the CAR MOSTLY cluster (share: 38.2%). Travellers in this cluster almost exclusively use the car, using the car on average for 86% of stages. The CAR MOSTLY travellers rarely travelled on foot (3.8%) and by bicycle (4.8%), and only 0.6% of them ever used public transport during the survey days. The CAR MOSTLY travellers thus have the lowest level of multimodality (OM_PI: 0.13; HHI:0.86). The CAR MOSTLY cluster has, compared with other clusters, a higher percentage of middle-aged adults (40-59), people who are employed, people with medium-to-high household income, car owners, and individuals who live in low-density areas.

WALK MOSTLY cluster

9.2% of respondents fit the WALK MOSTLY cluster. The WALK MOSTLY members travel on foot in the majority (66%) of stages, whilst occasionally using a car and/or bicycle and hardly using public transport. This cluster is associated with a lower level of multimodality (OM_PI: 0.34; HHI: 0.61) than the average level. Compared with other clusters, the WALK MOSTLY cluster has a higher percentage of older (aged 60 and over) adults and retired/unemployed individuals.

BICYCLE MOSTLY cluster

The BICYCLE MOSTLY cluster is the second largest cluster (22.9%). The BICYCLE MOSTLY travellers primarily rely on bicycle transport (modal share: 76%). Member 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: 0.25; HHI: 0.70). Young individuals and bike owners are more prevalent in this cluster than those in other clusters.

CAR+WALK+BICYCLE (CWB) cluster

The CWB cluster contains 16.5% of the respondents. The CWB cluster largely differs from the three clusters mentioned above in that it has a higher level of mixture of walking (23%), cycling (21%), and car use (48%) shares, and in turn, a higher level of multimodality (OM_PI: 0.47; HHI: 0.49). Travellers in this cluster make most trip stages (number of stages: 17.22). The CWB cluster contains a high share in females, the employed, and car owners.

MM BTM cluster

The MM BTM cluster is relatively small (5.0%). This cluster uses BTM the most (modal share: 33%) of all clusters, but nevertheless, more than 60% of stages 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 relatively many females, students, people living in the high-density area, people with high household income, individuals who own a bike but no cars, and individuals who have a public transport subscription.

MM TRAIN cluster

The MM TRAIN cluster has a share of 8.2%. More than one fifth (23%) of stages are made by train. Members in this cluster also frequently use other modes, with stages made by walking, cycling, and using of the car accounting for 30%, 27%, 12%, respectively. This cluster is associated with the highest level of multimodality (OM_PI: 0.64; HHI: 0.36). The MM TRAIN cluster has a high percentage of young (aged 18-39) adults, students, people who have a public transport subscription, residents living in a high-density area, and bike owners. Travellers in this cluster also have the longest daily travel distance (79.8) on average.

Table 4.1 Characteristics of the identified multimodal groups.

	CAR MOSTLY	WALK MOSTLY	BICYCLE MOSTLY	CWB	MM BTM	MM TRAIN	Overall
N	1591	381	954	687	208	340	4162
Multimodality (mean)							
OM_PI	0.13	0.34	0.25	0.47	0.54	0.64	0.29
HHI	0.86	0.61	0.70	0.49	0.43	0.36	0.68
Mode share (mean)							
Car	0.86	0.21	0.17	0.48	0.12	0.12	0.48
Walk	0.04	0.66	0.05	0.23	0.39	0.30	0.16
Bicycle	0.05	0.10	0.76	0.21	0.11	0.27	0.27
BTM	0.00	0.01	0.00	0.02	0.33	0.07	0.03
Train	0.00	0.00	0.00	0.01	0.03	0.23	0.02
Other	0.05	0.02	0.01	0.06	0.02	0.02	0.04
No. stages (mean)	7.61	8.50	8.52	17.22	14.32	15.75	10.49
Distance travelled	19.95	7.81	7.49	23.61	46.47	79.76	22.80
Age (%)							
12-17	1.6%	2.4%	17.6%	1.9%	12.0%	6.2%	6.3%
18-39	35.9%	33.9%	31.0%	40.9%	58.2%	64.7%	38.9%
40-59	43.8%	31.0%	30.8%	34.1%	14.9%	22.9%	34.9%
60 and over	18.7%	32.8%	20.5%	23.1%	14.9%	6.2%	19.9%
Gender (%)							
Female	48.2%	58.3%	56.4%	60.3%	58.7%	53.2%	53.9%
Male	51.8%	41.7%	43.6%	39.7%	41.3%	46.8%	46.1%
Employment Status							
Employed	71.0%	43.6%	46.2%	59.8%	38.5%	55.6%	58.1%
Student	3.5%	6.0%	25.2%	7.9%	40.9%	36.8%	14.0%
Retired	12.7%	22.0%	13.5%	15.3%	11.1%	3.8%	13.4%
Unemployed	12.8%	28.3%	15.1%	17.0%	9.6%	3.8%	15.6%
Household Income							
<National benchmark income (<27000 €)	32.5%	43.8%	37.8%	36.1%	38.0%	34.1%	35.8%

1-2X national benchmark income (27000-65000 €)	41.4%	33.9%	37.5%	38.9%	30.8%	39.4%	38.7%
>2X national benchmark income (>65000 €)	10.8%	6.8%	10.3%	12.2%	15.9%	15.0%	11.2%
Unknown	15.3%	15.5%	14.4%	12.8%	15.4%	11.5%	14.4%
Ownership (%)							
Car	95.6%	77.7%	70.3%	92.1%	57.2%	77.1%	84.2%
Bicycle	67.1%	68.5%	83.6%	76.0%	79.8%	86.8%	74.7%
PT subscription	17.3%	34.1%	31.3%	31.1%	80.3%	88.8%	33.3%
Residential Density							
>1500 persons/km²	45.1%	55.9%	52.2%	52.4%	63.0%	60.0%	51.0%
1000-1500 persons /km²	22.1%	20.2%	22.1%	19.8%	13.9%	20.9%	21.1%
<1000 persons/km²	32.8%	23.9%	25.7%	27.8%	23.1%	19.1%	27.9%

Note: the figures in bold refer to the largest mean value or share across clusters.

4.4.2. Attitude-multimodality relationship

4.4.2.1. Clusters of multimodality

We first looked into the distribution of mode-specific (PCA-based) attitudes across clusters of multimodality (**Table 2.2**). Our results showed that, for most clusters, individuals' attitudes towards car use were most positive on average. The exception being members in the BICYCLE MOSTLY cluster, who preferred bicycle use most. In contrast, the attitude towards the use of BTM was the lowest in all identified clusters and was positive only in the MM BTM cluster. Posthoc comparisons showed that, of all clusters, mode-specific attitudes were the most positive in the cluster with the highest level of use. For example, the MM BTM had more positive attitudes towards BTM than the other clusters. Nevertheless, for the MM BTM and MM TRAIN clusters, modes with higher levels of use did not correspond to more positive attitudes. For MM BTM travellers, attitudes towards the use of BTM were the least positive amongst all modes. For the MM TRAIN travellers, attitudes towards the use of bicycle and train ranked only second and third, respectively, whilst the share of using these two modes was greater than the share of car use. Moreover, we found that the difference in attitudes between modes was significantly smaller for the MM BTM, MM TRAIN, and BICYCLE MOSTLY clusters than that for the other clusters. This was in contrast to the CAR MOSTLY cluster, which showed the largest differences in attitudes between modes.

We then focused on the percentage of dissonant or consonant travellers across clusters of multimodality (**Figure 2.1-A**). At the significance level of 0.05, the MM BTM cluster had a larger proportion of dissonant travellers than the other clusters. This was the case for all the definitions of dissonant travellers: 74.0%, 52.9%, 45.2% were dissonant regarding the use of primary mode, use of primary or secondary mode, and mode choice set, respectively. The **MM TRAIN** cluster had the second largest share of dissonant travellers for the use of primary mode (55.6%) and the use of primary/secondary mode (40.6%). The **BICYCLE MOSTLY** cluster had the second largest share of dissonant travellers for the mode choice set. In contrast, the **CAR MOSTLY** cluster had the smallest share of dissonant travellers for the use of primary use (30.5%). The **CWB** cluster had the smallest shares of dissonant travellers for the use of primary/secondary mode (17.9%) and the mode choice set (16.5%), but these figures did not significantly differ from those for the **CAR MOSTLY** cluster (22.3% and 22.3%, respectively). For dissonant travellers, the majority of them in the **MM BTM** (58.2% to 57.8%) and **MM Train** (74.5% to 80.2%) clusters preferred car use most, independent of the definitions of dissonant travellers. Most dissonant travellers in the **CAR MOSTLY** (58.8% to 63.4%) and **MM CWB** (36.1% to 54.1%) clusters preferred cycling most. When we used sum scoring-based attitudes, our findings remained similar for the cross-cluster comparisons of the mode-specific attitudes (**Table 2.2**) and the percentage of dissonance travellers (**Figure 4.1-B**). A major difference was that the overall prevalence of dissonant travellers decreased by 9.7% to 15.6%. The **MM TRAIN** cluster also changed to having the second largest share of dissonant travellers regarding the mode choice set.

Table 4.2 The distribution of mode-specific attitudes across multimodal clusters.

	CAR MOSTLY	WALK MOSTLY	BICYCLE MOSTLY	CWB	MM BTM	MM TRAIN	Overall	One-way ANOVA
			PCA-based attitudes					
Car	**4.88**	3.74	3.67	4.34	3.44	3.49	4.22	p<0.001
Bike	2.49	2.95	**3.87**	3.37	2.32	3.43	3.06	p<0.001
BTM	-1.56	-0.49	-0.48	-1.14	**0.45**	-0.65	-0.97	p<0.001
Train	-0.40	0.69	0.84	0.21	1.25	**1.59**	0.33	*p*<0.001
Variance of attitudes across modes	11.79	8.40	8.15	10.12	7.13	8.08	9.83	*p*<0.001
			Sum scoring-based attitudes					
Car	**30.99**	24.15	23.42	27.62	*22.20*	23.01	26.98	*p*<0.001
Bike	14.85	18.06	**23.57**	20.33	14.34	21.31	18.55	*p*<0.001
BTM	-8.61	-2.27	-2.23	-5.85	**3.22**	-2.84	-5.05	*p*<0.001
Train	-1.85	4.82	5.56	2.14	7.83	**10.42**	2.61	*p*<0.001
Variance of attitudes across modes	**441.97**	313.92	300.47	364.45	274.58	295.27	364.65	*p*<0.001

Note: in bold denote the largest value of a given variable across all clusters.

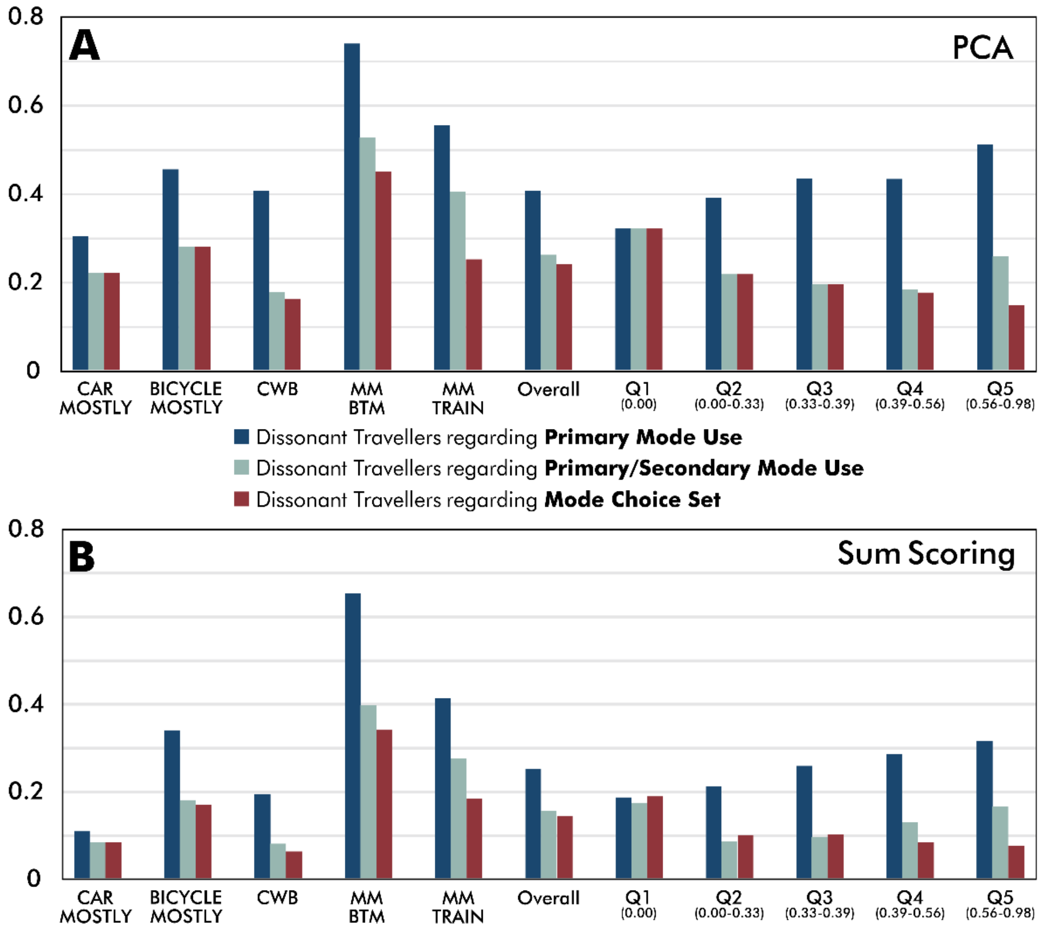

Figure 4.1 Percentages of dissonant travellers across clusters and levels of multimodality. *Note:* in parentheses denote ranges of the OM_PI of each quintile.

4.4.2.2. Levels of multimodality

Table 4.3 shows the distribution of mode-specific attitudes between levels of multimodality. Q1 to Q5 denotes quintiles of the level of individual multimodality, with Q5 being the highest level of multimodality (i.e., largest of the OM_PI). There was a significant difference (p<0.001) in mode-specific attitudes across levels of multimodality. Posthoc comparisons showed that travellers in the two highest multimodality quintiles (Q5 and Q4) held the most positive attitudes towards the use of BTM and train. Similarly, the two highest multimodality quintiles (Q5 and Q4) had more positive attitudes towards bicycle use than the lowest quintile (Q1). In contrast, these patterns were largely the opposite of the pattern for the car-use attitude. The least multimodal quintile (Q1) held the most positive attitudes towards car use, followed by Q2-Q4, and Q4-Q5. Our results also showed that the two highest multimodality quintiles (Q5 and Q4) had, compared to the two lowest quintiles (Q1 and Q2), significantly smaller differences in their attitudes towards different modes.

Figure 4.1-A presents the distribution of dissonant travellers by cluster and multimodality quintiles. Depending on the definition of dissonance, different patterns emerge. Looking at whether their primary mode use matches attitudes, there was a pattern that quintiles with higher levels of multimodality had a higher share of dissonant travellers (post-hoc comparisons: Q5 > Q2 or Q1; Q4>Q1). When following the definition on the matching of attitudes and primary/secondary mode use, there was a U-shaped relationship between the multimodality level and the share of dissonant travellers. Dissonant travellers were most common in Q1 (32.2%) and Q5 (26.0%), and it was smallest in Q3 (18.5%). Lower levels of multimodality tended to have larger shares of dissonant travellers regarding the mode choice set (post-hoc comparisons: Q1>Q2, Q3, Q4, or Q5; Q2>Q5). These dissonant travellers accounted for 32.2% in Q1, which was more than twice that in Q5 (15.0%). Independent of multimodality levels, most dissonant travellers (48.6% to 77.5%) had the most positive attitude towards car use, followed by those who preferred bicycle use most (16.1% to 45.8%), except that more dissonant travellers in Q2 preferred bicycle use most. The difference in the percentage between those who preferred the use of cars and bicycles is the largest (range of gap: 29.3% to 60.9%) in the most multimodal dissonant travellers (Q5). The cross-cluster comparison of mode-specific attitudes and the percentage of dissonant travellers were robust against different measurements of attitudes (**Figure 4.1-B**) and the level of multimodality (**Appendix C.2** and **C.3**). A notable difference was that we found a more salient pattern for the relationship between higher quintiles of multimodality levels and larger shares of dissonant travellers regarding primary mode use when we used sum scoring-based attitudes

Table 4.3 The distribution of mode-specific attitudes across levels of multimodal travel behaviour.

	Q1 (0.00)	Q2 (0.00-0.33)	Q3 (0.33-0.39)	Q4 (0.39-0.56)	Q5 (0.56-0.98)	Overall	One-way ANOVA
			PCA-based attitudes				
Car	**4.63**	4.24	4.23	4.08	3.78	4.27	p<0.001
Bike	2.37	3.33	3.36	3.56	**3.57**	3.07	p<0.001
BTM	-1.34	-1.30	-1.05	-0.57	**-0.49**	-1.02	p<0.001
Train	-0.24	0.31	0.13	0.77	**1.08**	0.29	p<0.001
Variance of attitudes across modes	**10.83**	10.67	10.56	8.71	8.23	9.98	p<0.001
			Sum scoring-based attitudes				
Car	**29.47**	27.34	26.56	25.39	24.73	26.98	p<0.001
Bike	14.18	20.07	20.80	21.35	**21.97**	18.55	p<0.001
BTM	-7.40	-6.76	-4.80	-2.87	**-1.87**	-5.05	p<0.001
Train	-0.99	2.53	1.83	5.62	**7.41**	2.61	p<0.001
Variance of attitudes across modes	**543.29**	519.09	504.51	428.23	397.73	364.65	p<0.001

Note: in bold denote the largest value of a give variable across levels of multimodality.

Figures in parentheses denote the ranges of the OM_PI of each quintile.

Members in WALK MOSTLY cluster were excluded.

4.4.2.3. Multivariate analyses

We applied binary logit models to examine the extent to which multimodal travel behaviour may be associated with the likelihood of mode use-attitude dissonance, accounting for socioeconomic characteristics. Our results showed that the cluster membership and level of multimodality were significantly associated with the likelihood of mode use-attitude dissonance. This corroborates our findings reported in Sections 4.4.2.1 and 4.4.2.2. For the multimodality clusters (**Table 4.4**), compared with the CAR MOSTLY cluster, all the other clusters (the BICYCLE MOSTLY, CWB, MM BTM, and MM TRAIN clusters) showed a higher likelihood of dissonance regarding primary mode use. This pattern remained similar for the MM BTM cluster when looking at the dissonance for primary/secondary mode use and mode choice set, whilst the CWB cluster showed lower likelihoods of dissonance than the CAR MOSTLY cluster. Compared with the CAR MOSTLY cluster, the MM TRAIN cluster was also more likely to be dissonant for primary/secondary mode use. Independent of the definition of dissonance, the MM BTM cluster had the largest odds ratio (OR) (range: 1.830 to 4.666), indicating that this cluster was 0.830 to 3.666 times more likely to be psychologically dissonant with mode use than the CAR MOSTLY cluster. The MM TRAIN cluster had the second largest ORs when modelling the likelihood of dissonance for the use of primary mode (OR: 1.839) and the use of primary/secondary mode (OR: 1.481).

Table 4.4 Multivariate analyses on the likelihood of dissonance for multimodality clusters.

	Dissonance for primary mode use			Dissonance for primary/secondary mode use			Dissonance for mode choice set		
	Coef	S.E.	OR	Coef	S.E.	OR	Coef	S.E.	OR
Multimodality clusters									
CAR MOSTLY (ref)									
BICYCLE MOSTLY	0.454 ***	0.100	1.575	-0.033	0.115	0.967	-0.009	0.115	0.991
CWB	0.392 ***	0.105	1.479	-0.451 **	0.132	0.637	-0.558 ***	0.136	0.572
MM BTM	1.540 ***	0.199	4.666	0.847 ***	0.187	2.333	0.604 **	0.189	1.830
MM TRAIN	0.609 ***	0.150	1.839	0.393 *	0.161	1.481	0.256	0.175	1.279
Age									
12-18	0.204	0.285	1.226	-0.040	0.298	0.960	0.206	0.304	1.228
19-40	-0.189	0.168	0.828	-0.242	0.188	0.785	-0.198	0.190	0.820
41-60	-0.275 ψ	0.163	0.760	-0.393 *	0.183	0.675	-0.365 *	0.186	0.694
>60 (ref)									
Gender									
Male (ref)									
Female	0.003	0.078	1.003	-0.078	0.088	0.925	-0.053	0.090	0.949
Employment status									
Employed (ref)									
Student	0.377 *	0.154	1.458	0.280 ψ	0.162	1.323	0.012	0.172	1.012

Retired	-0.025	0.187	0.976	-0.132	0.210	0.877	-0.117	0.213	0.889
Unemployed	0.197	0.125	1.218	0.200	0.143	1.222	0.201	0.144	1.222
Income									
<1x national benchmark (ref)									
1-2x national benchmark	0.029	0.083	1.029	-0.027	0.094	0.973	-0.053	0.095	0.948
>2x national benchmark	0.186	0.121	1.204	0.025	0.137	1.025	-0.018	0.140	0.982
Car owner									
Yes	-0.303 *	0.136	0.739	-0.647 ***	0.139	0.524	-0.606 ***	0.142	0.545
No (ref)									
Bicycle owner									
Yes	0.041	0.092	1.042	-0.044	0.105	0.957	-0.008	0.107	0.992
No (ref)									
PT subscription									
Yes	0.253 **	0.094	1.288	0.332 **	0.105	1.394	0.331 **	0.107	1.392
No (ref)									
Population density									
High (ref)									
Medium	-0.013	0.098	0.987	-0.268 *	0.114	0.765	-0.310 **	0.117	0.734
Low	0.025	0.090	1.026	-0.056	0.101	0.946	-0.088	0.102	0.916
Intercept	-0.528 *	0.234	0.590	-0.361	0.254	0.697	-0.424	0.258	0.654
Nagelkerke R-squared		0.099			0.100			0.089	

Note: we excluded individuals in the WALK MOSTLY cluster and those who did not reported their household income from the models.

$^{\psi}$, *, **, *** denote significant at the significance level of 0.10, 0.05, 0.01, 0.001, respectively.

For the level of multimodality (**Table 4.5**), a higher level of multimodality presented a higher likelihood of dissonance regarding the use of the primary mode. The OR for the OM_PI indicator was 3.347. This means that fully multimodal travellers were 2.347 times more likely to be dissonant with their primary mode use than those who relied on only one mode of transport. We found a U-shaped relationship between the level of multimodality and the likelihood of dissonance for primary or secondary mode use (coefficient of the OM_PI: -3.536; coefficient of the OM_PI squared: 3.078). Finally, an increased level of multimodality was linked with a decreased likelihood of being dissonant for mode choice set. Fully multimodal travellers were only 0.144 as likely as monomodal travellers to not use their preferred modes.

Table 4.5 Multivariate analyses on the likelihood of dissonance for the level of multimodality.

	Dissonance for primary mode use			Dissonance for primary/secondary mode use			Dissonance for mode choice set		
	Coef	S.E.	OR	Coef	S.E.	OR	Coef	S.E.	OR
Multimodality level									
OM_PI	1.218 **	0.443	3.347	-3.536 ***	0.504	0.029	-1.939 ***	0.539	0.144
OM_PI squared	-0.804	0.658	0.272	3.078 ***	0.754	21.714	-0.862	0.870	0.422
Age									
12-18	0.139	0.282	1.149	-0.256	0.300	0.774	-0.095	0.311	0.909
19-40	-0.159	0.167	0.853	-0.209	0.190	0.811	-0.162	0.195	0.851
41-60	-0.279 $^{\psi}$	0.162	0.757	-0.404 *	0.186	0.668	-0.374 *	0.190	0.688
>60 (ref)									
Gender									
Male (ref)									
Female	0.012	0.077	1.012	-0.074	0.089	0.929	-0.026	0.092	0.974
Employment status									
Employed (ref)									
Student	0.376 *	0.153	1.456	0.455 **	0.164	1.576	0.329	0.178	1.389
Retired	-0.027	0.186	0.973	-0.195	0.213	0.823	-0.154	0.218	0.858
Unemployed	0.207 $^{\psi}$	0.124	1.229	0.164	0.144	1.178	0.186	0.147	1.205
Income									
<1x national benchmark (ref)									
1-2x national benchmark	0.015	0.083	1.015	-0.009	0.095	0.991	-0.055	0.097	0.946
>2x national benchmark	0.200 $^{\psi}$	0.120	1.222	0.103	0.137	1.108	0.058	0.142	1.059
Car owner									
Yes	-0.509 ***	0.132	0.601	-0.818 ***	0.137	0.441	-0.761 ***	0.142	0.467
No (ref)									
Bicycle owner									
Yes	0.041	0.091	1.042	0.010	0.105	1.010	0.073	0.108	1.076
No (ref)									
PT subscription									
Yes	0.395 ***	0.089	1.484	0.735 ***	0.102	2.086	0.725 ***	0.105	2.065
No (ref)									
Population density									
High (ref)									
Medium	-0.033	0.097	0.968	-0.280 *	0.115	0.756	-0.314 **	0.120	0.731
Low	0.006	0.089	1.006	-0.099	0.102	0.905	-0.127	0.104	0.881
Intercept	-0.345	0.231	0.708	0.139	0.254	1.149	0.013	0.261	1.013
Nagelkerke R-squared		0.089			0.123			0.129	

Note: we excluded individuals in the WALK MOSTLY cluster and those who did not reported their household income from the models.

$^{\psi}$, *, **, *** denote significant at the significance level of 0.10, 0.05, 0.01, 0.001, respectively.

4.5. Discussions

This research explored the relationship between multimodal travel behaviour and mode-specific attitudes. We provided insights into the distribution of mode-specific attitudes across multimodal travel behaviour. Of all clusters, mode-specific attitudes were the most positive in the cluster with the highest level of use. For a given cluster, nevertheless, the mode with the highest level of use is *not* necessarily connected with the most positive attitude. This is inconsistent with several studies on the use of a single mode (e.g., Heinen et al. (2011); Moody et al. (2019)). One plausible reason is that, according to the TPB, attitudes, perceived behavioural control, and social norms jointly influence mode use decisions (Ajzen, 1985). Compared with attitudes, the other two elements may be more explanatory in determining such decisions for multimodal travel behaviour. For example, 38% of individuals in multimodal transport clusters are students. They have pro-driving attitudes (PCA-based attitudes towards the use of cars, BTM, and train: 20.2, 1.46, and -0.79) yet are less likely to afford private cars. We also found that the difference in attitudes between modes was smaller for travellers in multimodal clusters and those with a higher level of multimodality. This means that multimodal travellers tend to have more balanced attitudes towards different modes than monomodal and less multimodal travellers. This is partially in line with Diana and Mokhtarian (2009) and Pedersen et al. (2011) that that monomodal travellers, especially monomodal car users, may have fairly different and possibly biased expectations towards various unused modes.

Moreover, we looked into the relationship between multimodal travel behaviour and mode use-attitude dissonance. Inconsistent with existing findings (Molin et al., 2016; Ton et al., 2019), we found that multimodal public transport users, compared with individuals who heavily rely on cars, presented a significantly higher level of dissonance between the mode use (particularly the use of primary modes and use of secondary modes) and corresponding attitudes. We also provided new insights into the relationship between the level of multimodal travel behaviour and the degree of mode use-attitude dissonance. Travellers with a higher level of multimodality tended to be attitudinally dissonant with their primary mode use, but consonant with their mode choice set. This means that travellers who are more multimodal are less likely to use their preferred modes most frequently, but more likely to use their preferred modes occasionally.

Our research findings on mode use-attitude dissonance may contribute to an advanced understanding of the relation between multimodal travel behaviour and travel behaviour change. Existing evidence has shown that baseline mode use patterns are closely related to modal shift over time (e.g., Heinen (2018); Heinen and Ogilvie (2016a); Kroesen (2014); Diana (2010)); several hypotheses have been proposed to explain the potential mechanism underlying such evidence. For example. Heinen and Ogilvie (2016a) drew on

Jones and Sloman (2003)'s conceptualisation of behavioural change and hypothesised that being multimodal may constitute an experimental phase that lays the groundwork of enacting more established travel behaviour. Kroesen (2014) proposed three potential mechanisms. First, multimodal travellers may have less biased perceptions of the available options compared with monomodal travellers, and therefore they may update their mode use profile more readily. Second, multimodality may be seen as a characteristic reflecting the extent to which travellers deliberately make their mode use decision. Travellers who are more multimodal may thus be more likely to respond to changes in environmental conditions. Third, multimodal travellers may be more familiar with modes (e.g., cycling) that complement others, and on this basis, these travellers may switch their main mode use more feasibly.

Our research findings support an uncovered mechanism: the high-level cognitive dissonance between mode use and attitudes may be one important reason that drives multimodal travellers to change their mode use over time. Cognitive dissonance theory suggests that people hold an inner drive to keep a behaviour and the corresponding attitude consistent, thereby avoiding psychological discomfort (Festinger 1957). When dissonance is present, people do their best to restore the inconsistency between behaviour-attitude pairs (Festinger 1957); in our case, dissonant travellers change either mode use or corresponding attitudes. Since multimodal travellers have a high level of dissonance between main (i.e., primary and secondary) mode use and corresponding attitudes, they may, once conditions are suitable, tend to update their modal patterns by increasing the share of preferred modes over time if their mode-specific attitudes are maintained at the current level.

To promote more sustainable transport, our research supports the following policy recommendations. First, our research corroborates a high potential for multimodal travellers to change their mode use. However, the modal change may not necessarily occur towards a more sustainable transport mode, as our results showed that a large proportion of dissonant multimodal travellers prefer car travel. Without policies to support the use of public transport and active modes, daily travel patterns of multimodal travellers may become car-oriented once environmental conditions favour car use. Second, as travellers with dominant car use are highly consonant concerning their mode use-attitude relation, it could be expected that there is little potential to make them less car dependent in the immediate future, if there are no countermeasures to break the state of consonance. More efforts, such as targeted publicity campaigns, would need to be made to induce these people to have more positive attitudes towards other modes and be aware of the negative consequences of using cars.

This research used a high-quality three-day travel diary to characterise both clusters and levels of multimodal travel behaviour. The MPN data allowed us to measure comparable attitudes towards the use of various modes based on a complete belief-based framework of the TPB. Our research has nevertheless several limitations. Firstly, since we did not consider attitudes towards walking, as the MPN did not contain this information, our findings on the prevalence and distribution of mode use-attitude dissonance should be interpreted with caution and any conclusions limited to the four modes we considered, i.e., cars, bicycles, BTM, and train. To explore a bigger picture of how mode use-attitude dissonance is associated with mode use patterns, future studies could incorporate attitudes in relation to more modes of transport. Secondly, since we did not take into account perceived behavioural control and social norms, we cannot draw a strong conclusion that these two elements may be more explanatory than attitudes in determining mode use for multimodal travel behaviour. Future analyses incorporating these unmeasured constructs would be potentially valuable. Thirdly, we used Dutch data; our findings may therefore not be generalisable to countries with different transport conditions or sociodemographic characteristics. The transferability of our research needs to be examined in other contexts.

4.6. Conclusion

This research investigates how mode-specific attitudes and mode use-attitude dissonance are distributed across clusters and levels of multimodal travel behaviour. Travellers in multimodal clusters and those who were more multimodal had more balanced attitudes towards different modes. However, for a given multimodal cluster, attitudes may not necessarily be correlated with corresponding mode use decisions. Moreover, multimodal public transport users, compared with car-dominant users, had a higher level of mode use-attitude dissonance; travellers with a higher level of multimodality tended to be dissonant with their primary mode use. Most of dissonant multimodal travellers showed most positive attitudes towards car use. Our research corroborates a high potential of multimodal travellers to change their mode use towards more sustainable transport, but this may not be effectively achieved without supporting policies. Our findings may also support the psychological mechanism underlying a recent important finding that multimodal travellers tend to change their mode use over time.

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Chapter 5

Discussions and conclusions

Existing studies suggest that encouraging multimodality may offer a potential solution to establishing shifts towards more sustainable transport. The three papers included in this thesis all revolve around the theme of understanding correlates of multimodality, aiming to extend the conceptual framework used to analyse correlates of multimodality. This thesis provides empirical evidence on how factors in temporal, situational, and attitudinal dimensions may play a role in determining multimodality by respectively looking into age-period-cohort, trip purposes, and attitudes. Based on the findings, several implications could be made to support policies aimed at promoting multimodality and to better understand the potential conditions when promoting multimodality is expected to act as a solution to inducing sustainable modal shifts. This chapter discusses how the original research questions have been answered, methodological contributions, research limitations, outlooks for future research directions, and policy implications.

5.1. Overview of principal findings

This section provides an overview of the results by answering the three research questions. This thesis reveals the multifaceted nature of correlates of multimodality. The results show that age-period-cohort and trip purposes are significantly associated with multimodality. By contrast, mode-specific attitudes may not necessarily be influential for corresponding mode use decisions when multimodality is involved, which contributes to high-level cognitive dissonance amongst multimodal travellers.

> ***RQ1**: To what extent does multimodal travel behaviour change across age, period, and (birth) cohort?*

Chapter 2 showed that the level of individual multimodality significantly varied across age, periods, and cohorts. Age was negatively associated with the level of multimodality. The results were inconsistent with those derived from most existing studies (e.g., Kuhnimhof et al. (2012a); Kuhnimhof et al. (2012b); Buehler and Hamre (2014); Streit et al. (2015)), namely, that multimodality has increased in recent decades. Instead, multimodality presented a downward trend for recent cohorts. The existence of significant cohort-specific variations in multimodality also indicates the important role of early life conditions and formative experience in shaping multimodality.

Specifically, for the age-multimodality relation, individuals became less multimodal as they got older. This relation was moderated by the changes in work and physical mobility constraints along with an increase in age. Changes in work constraints (e.g., a change from a student to a full-time employee) and physical mobility constraints (e.g., developing walking difficulties) accelerated the decline in the level of multimodality before and after an individual reached their 30s, respectively.

For the period-multimodality relation, the level of individual multimodality remained relatively consistent in England, from 2001 to 2017, although there were fluctuations. The most salient change was that multimodality declined between 2009 and 2010.

For the cohort-multimodality relation, multimodality presented significant variations across cohorts. The succession of cohorts, compared with the change in period, better explained the observed variations in multimodality over time. Changes in multiple spatial mobility constraints, i.e., physical mobility, economic, accessibility, and mobility resource constraints, partially moderated the cohort-specific changes in multimodality. Multimodality decreased and hit the bottom for the cohort born between 1945 and 1969. Following several cohorts showing a slight rise, multimodality began to decrease from the cohort born in 1985 onwards.

RQ2*: To what extent does the level and correlates of multimodality differ between trip purposes?*

Chapter 3 showed that individuals presented higher levels of multimodality when they made trips that were more variable in departure time and travel distance, but only when sufficient trip stages were made. Moreover, there were cross-purpose disparities in correlates of multimodality in terms of significance and variance explained.

Specifically, the level of multimodality significantly differed between trip purposes. The level of multimodality jointly depended on trip purposes and the associated time-space variability as well as on the number of trip stages. Variability in departure time and travel distance was the highest for leisure trips, followed by maintenance trips, then for work trips. Individuals showed on average higher levels of multimodality when they made trips that were more variable in departure time and travel distance. However, this was only for the case when sufficient trip stages (at least 3 stages) were made.

Most identified correlates were associated with multimodality, independent of trip purposes. Nevertheless, between-purpose disparities in correlates of multimodality were found. Four correlates corresponded to only specific trip purposes. Working in multiple locations and females were associated with higher levels of multimodality for work trips, but not in the case of the other trips. Having no walking difficulties was associated with higher levels of multimodality for all but work trips. Having a child in the household was associated with lower levels of multimodality only for leisure trips but with higher levels of multimodality only for work trips. Older (aged 65 and over) adults were less multimodal for work and leisure trip activities, but not for maintenance trips.

Moreover, disparities in correlates of multimodality in terms of variance explained were detected across trip purposes. Variance explained by mobility resource constraints substantially decreased from modelling work, to maintenance, then to leisure trips. Mobility resource constraints may thus be less determinant for multimodality in trips with a higher level of time-space variability. Work and accessibility constraints explained a larger share of variance than the other (social role, physical mobility, and economic) constraints for respectively modelling maintenance and leisure trips.

RQ3 *To what extent are mode-specific attitudes associated with multimodality, and how are multimodal travellers attitudinally dissonant/consonant with their actual mode use?*

Chapter 4 showed that for multimodal travel behaviour, attitudes were not necessarily associated with mode use decisions. Multimodal travellers tended to present a high-level of attitude-mode use dissonance. The results support the view that multimodal travellers may have a high potential for modal shifts. The results may also provide explanations of the psychological mechanism by which multimodal travellers tend to change their mode use over time.

Specifically, for the distribution of attitudes, the results showed that travellers in multimodal clusters and those with a higher level of multimodality presented smaller differences in their attitudes across modes. Nevertheless, independent of levels and (most) cluster memberships of multimodality, attitudes towards car use were most positive, compared with other modes. Of all clusters, mode-specific attitudes were the most positive in the cluster with the highest level of use. For a given cluster, nevertheless, the mode with the highest level of use was not necessarily connected with the most positive attitude.

For the degree of mode use-attitude dissonance, the results showed that multimodal public transport users, compared with car-dominant individuals, had a significantly higher level of dissonance between the mode use (particularly the use of primary modes and use of secondary modes) and corresponding attitudes. This is inconsistent with existing studies on the same topic. It was also found that travellers with a higher level of multimodality tended to be attitudinally dissonant with their primary mode use, but consonant with their set of mode choices. This indicates that travellers who are more multimodal are less likely to use their preferred modes most frequently, but more likely to use their preferred modes occasionally.

5.2. Methodological contributions

This section highlights the methodological contributions made in this thesis.

This thesis explains that a prerequisite to understand the effect of either age, period, or cohort on multimodality is to take into account these three variables together in the analysis. The same argument could apply to general travel behaviour, unless one of these variables is proved to have no influence on the travel behaviour in question. Clarifying this is important for not only longitudinal analyses as this thesis showed in Chapter 2 but also cross-sectional analyses. For example, age is one of the key elements in shaping travel behaviour, but it would be infeasible to differentiate the effects of age and cohort in cross-sectional analyses. However, classic linear models fail to simultaneously incorporate age, period, and cohort in an analysis due to the identification problem. The HAPC applied in this thesis makes the joint analysis of these three variables feasible by using random effects. Moreover, the HAPC model could be used for long-term evaluations of transport interventions. For such evaluations, it is important to record baseline travel patterns of sampled people before the implementation of an intervention, and then compare post-intervention travel patterns with baseline ones regularly. Individuals' ageing, changes in social contexts, and cohort succession are necessarily coupled. Evaluations on such an intervention need to disentangle the confounding effects between these issues, and on this basis, to examine whether the intervention really works and whether it works in the way it was initially planned. For example, evaluations of a long-term intervention to increase the use of public transport amongst middle-aged adults should distinguish whether it is the intervention itself or the replacement of cohorts that contributes to the observed changes over time.

This thesis shows that the Heckman selection model is useful for studying the relation between multimodality and trip purposes. Administrated surveys with a multi-week travel diary may be preferable to study such a topic and have been widely applied in broader relevant tropics focusing on the intrapersonal variability/stability of travel patterns (e.g., Susilo and Axhausen (2014); Järv et al. (2014); Schlich and Axhausen (2003)). The reason is that these surveys are deemed to capture both habitual and occasional travel patterns effectively (Susilo and Axhausen, 2014). Such surveys are nonetheless limited in three ways. First, the sample size of these surveys is generally small due to cost issues and drop-outs during the long survey weeks. Second, diary fatigue, which leads to increasing underreporting of trips over time, is more likely to happen as surveys progress (Hoogendoorn-Lanser et al., 2015). Third, as shown in Section 3.2.2, a long data collection period (e.g., six weeks) does not necessarily guarantee that information for all considered trip purposes of each individual in question can be collected. These three issues limit the robustness and transferability of findings derived from multiweek surveys. Against this backdrop, this thesis suggested that future studies on this topic could apply the Heckman selection model to high-quality single-week surveys. By doing so, researchers could take advantage of the large sample size and high representativeness of data such as the NTS, whilst simultaneously avoiding problematic selection bias in modelling.

5.3. Limitations

This thesis contributes to the current knowledge of correlates of multimodality from multidimensional standpoints. It used high-quality travel dairy data of two countries, applied novel approaches, and conducted a rich set of sensitivity analyses. This thesis nevertheless has several limitations; this section discusses two major ones.

Firstly, this thesis uses travel survey data collected in England and the Netherlands. Therefore, the derived findings may not be generalisable to other countries, and the transferability of such findings needs to be investigated. Transferring the findings to other countries could be problematic due to the difference in socioeconomic, cultural, and transport backgrounds between countries. For example, Chapter 2 showed that the level of multimodality decreased in England after baby boomers were born. This thesis speculates that this may be ascribed to distinctive early life conditions and formative experience of baby boomers in terms of driving. However, in low-income countries, most people who were born in the same period did not grow up in a car-dominant society due to low productivity, unaffluent life, and the destruction of society by the war. Therefore, they may hold fairly different attitudes towards various modes from their counterparts in England. This may potentially contribute to different cohort-specific patterns of the level of multimodality. Moreover, the definition of mode choice sets, which are inherently connected with measurements of multimodality, may need to be updated when the study area is changed. The mode choice set needs to be set in accordance with the common mode use in the study. For example, informal modes of transport, e.g., pedicabs, may need to be considered in low-income countries where their use is prevalent.

Secondly, the findings in this thesis can only reflect correlations. More solid causal relationships between variables of interest and multimodality could be examined using more sophisticated research designs (e.g., panel and natural experimental designs) and statistical approaches (e.g., difference-in-difference with propensity score matching). For example, this thesis found that mode-specific attitudes may not necessarily be connected with mode use decisions for multimodal travel behaviour (Chapter 4). However, in the absence of (multiwave) comparisons between baseline and follow-ups as well as of controlled psychological variables, such as perceived behavioural control, social norms, and intentions, this thesis cannot be entirely certain about the causal relationship between attitudes and multimodality. Moreover, Chapter 2 suggests that birth cohort may play an important role in shaping multimodality. However, similar to most APC analyses on other topics, this thesis was unable to establish the causal linkage between birth cohorts and multimodality. While it is difficult (or nearly infeasible) to conduct/mimic a randomised controlled trial to examine the causal effects of cohorts, long-span panel data could be used to trace how children change their attitudes and mode use when they grow up. This may provide useful insights into the causal pathways between cohorts and multimodality.

5.4. Recommendations for future research

This section outlines potential future research directions.

Firstly, the pandemic of COVID-19 has compromised public health, the economy, and people's mobilities. Evidence showed that people have travelled less and reduced the use of public transport after the outbreak of the pandemic (e.g., Almlöf et al. (2021); Zhang et al. (2021)). However, it remains unclear the extent to which this pandemic contributes to long-term travel behaviour changes, let alone changes in multimodality, either in the short or long term. Of particular interest would be to find out whether there are inequalities in these changes. Future studies that use panel or repeated cross-sectional designs could provide useful insights into these issues.

Secondly, transport technologies and services have developed rapidly in recent years. It is recommended to explore how the introduction of new transport services, such as the shared micromobility, automated vehicles, mobility as a service, and the intelligent transport system, align with multimodality. It would be crucial to know how these new services substitute existing modes because this largely determines whether introducing these services could contribute to more sustainable travel patterns.

Thirdly, this thesis is limited in considering the role of the built environment in explaining multimodality. Understanding the multimodality-built environment relation may require the development of new conceptual frameworks and methodologies. For example, the observed effect of the built environment on travel behaviour may vary when the modifiable area unit problem (MAUP) is present (Clark and Scott, 2014). The selection of suitable scales (e.g., a buffer or a zone) at which to measure the built environment is essential to reduce the MAUP. While existing studies on the use of single mode have suggested several scales based on mode-specific travel distances and considerations of planning practices (see, e.g., Yang et al. (2019)), the applicability of these scales to the case of multimodality is unclear. The reason is that multimodality exhibits, compared with the use of single mode, a larger variation in (trip-level) travel distances. A future direction is to examine how MAUP may affect the built environment-multimodality relation and identify suitable analytical scales by using a variety of spatial units. Moreover, existing studies have suggested that the existence of residential self-selection may bias the estimated effect of the built environment and limit the casual inference for the built environment-travel behaviour relation (Cao et al., 2009). It would be interesting to explore multimodal travellers' preference of residential contexts using revealed preference and/or stated preference data.

Fourthly, as shown in the literature review (Section 1.4.3), the identified correlates of multimodality in existing studies were predominately derived based on undifferentiated trips and commuting trips. Little attention has been specifically paid to variables that may have an influence on multimodality for trips with high-level time-space variability. While Chapter 3 showed that some variables (e.g., land use mix) also significantly corresponded to the level of multimodality for trips with high time-space variability (e.g., leisure trips), the effect magnitude of such variables was relatively small. This suggests that policies solely targeting these variables may not increase multimodality by a large margin. It is therefore recommended to devote more research efforts to study multimodality for trips that frequently take place in daily lives yet are less fixed, such as shopping, social, and recreation trips.

Fifthly, this thesis suggests that the high-level dissonance between mode use and corresponding attitudes may be a reason that drives multimodal travellers' long-term modal changes. However, Festinger's (1957) cognitive dissonance theory suggests that a high level of dissonance may result in a change of behaviour *or* attitudes over time. This point was corroborated by Kroesen et al. (2017), who showed that both mode use and corresponding attitudes would change if dissonance was present, although multimodal travellers (compared with monomodal or less multimodal travellers) were more prone to change their current mode use patterns. To better understand the nexus between multimodality and long-term modal changes, it would be valuable to examine to what extent cognitive dissonance may mediate such a nexus using long-span multiwave panel data.

Sixthly, this thesis showed that multimodality is closely connected with individuals' travel intensities; more multimodal travel patterns might be associated with a larger number of trips (and trip stages) and distance travelled. Going beyond these findings, it would be useful to examine the causal relationship between multimodality and travel intensity using longitudinal analyses: are people more multimodal because they have longer distances, or vice versa? Since greater travel intensities correspond with higher levels of transport-related emissions, insights into this question are important for understanding the desirability and conditions required of multimodality in promoting sustainability in the transport sector. For example, if being more multimodal simultaneously results in larger travel distances, measures to mitigate the increased travel distance will be highly required to ensure that the promotion of multimodality could deliver an expected amount of emission reduction.

5.5. Policy implications

This section summaries the policy implications drawn from the findings. This thesis suggests that policymakers need to take into account the complexity of correlates of multimodality to craft policies aimed at encouraging multimodality and to develop effective interventions of sustainable modal shifts. This thesis provides new focuses in the temporal and situational dimensions that such policies could target. It also reflects on the practical value of multimodality when it is expected to act as a solution to induce sustainable modal change.

5.5.1. New focuses to encourage multimodality

This thesis highlights the role of birth cohorts in shaping multimodality. This could provide three cohort-specific implications for forecasting and encouraging multimodality. Chapter 2 showed that there was a downward trend from the cohort born in 1985 onwards. Ryder (1965) posited that each cohort shares similar characteristics but also carries distinct ones with their predecessors. When older cohorts are replaced by younger ones, the continual renewal of populations provides the impetus for structural changes in societies (Ryder, 1965). Cohort-specific patterns therefore indicate a future trend for not only the next generations but also the whole society. As such, it is reasonable to anticipate that the overall level of multimodality in England may continue to decrease in the near future. To curb this trend, policymakers should pay more attention to how young and next generations feel about and use different modes of transport to make future societies more multimodal. Cohort effects represent an integrated impact of early life conditions and formative experiences (Mullen et al., 2020). Therefore, it would be potentially beneficial to create a friendly environment to allow adolescents and young adults to be familiar with active modes and public transport, understand their benefits, develop positive attitudes towards these modes, and use them conveniently. It is also important to let parents know that their mode use patterns could profoundly influence their children's patterns. Policies need to encourage parents to take up responsibilities to use other options when conditions are desirable, rather than to solely depend on cars. Thus, benefits of encouraging parents' multimodality may be passed on to their children. Finally, for the current society, policies on the promotion of multimodality could target late baby boomers and their successors. It was found that people who were born between 1960 to 1969 had a low level of multimodality and reached the bottom. These people accounted for a large proportion (14%) of the total population in England (Office for National Statistics, 2020), owing to the high fertility rate. Accordingly, altering their modality styles would contribute to a relatively large change in multimodality for the whole society.

This thesis also highlighted that the level and correlates of multimodality differed by trip purposes (Chapter 3). This could support policies to target specific trips rather than specific subpopulations, which has been widely studied, to promote multimodality. First, the findings could help to inform trip-specific policies to reduce the inequality in multimodality. It was found that females (for work trips), older adults (for work and leisure trips), people with walking difficulties (for maintenance and leisure trips), and those who had a child in the household (for social trips) presented lower levels of multimodality than their counterparts when they made specific trips. Therefore, measures could be placed on such trips where multimodality inequality was largely present. For example, setting up age-friendly facilities to ease the use of public transport and active modes around recreational areas and workplaces may help to reduce the age gap in multimodality. Similarly, developing a barrier-free transport environment around recreational areas and shopping centres may help to reduce the multimodality inequality between people with and without walking difficulties.

Second, the existing literature has shown that individuals' travel demand for participating in different types of activities varies across individual attributes (e.g., Gim (2011)). To ensure that the scope of policies covers as large a population as possible, it is important to take into account trip purposes. This thesis suggests that policies targeted at mobility resource constraints should be highlighted in the policy agenda because these constraints have the largest influence on the level of multimodality, independent of trip purposes. However, such policies may not be sufficient to promote multimodality over a wide population by themselves. The reason is that mobility resource constraints are less influential on multimodality for trips with higher time-space variability. Policies on changing mobility resource constraints may thus be less efficient to increase multimodality for people who have a greater demand for carrying out discretionary activities. This thesis suggests therefore that these policies need to be accompanied by measures specifically targeting trips with relatively high time-space variability, i.e., maintenance and leisure trips. For example, work and accessibility constraints (compared with the social role, physical mobility, and economic constraints) are found to be more explanatory to the level of multimodality for maintenance and leisure trips, respectively. Implementing measures to change variables in the domain of these two constraints, such as encouraging flexible work hours and promoting mixed land use patterns of settlements, could potentially be useful.

5.5.2. Critical reflections on the practical value of multimodality

This thesis ends by critically reflecting on the practical value of multimodality when it is expected as a solution to achieve higher transport sustainability. This thesis argues that the promotion of multimodality offers not only an opportunity but also a challenge for inducing long-term sustainable modal shifts. Findings in Chapter 4 suggest that multimodal public transport users (compared with car-dominant users) and travellers who have a higher level of multimodality may have a higher potential for changing mode use over time. Nevertheless, multimodal dissonant travellers, were found to have strong pro-car attitudes. Thus, voluntary modal changes for multimodal travellers may not occur towards a more sustainable direction. This inference is in line with existing evidence. For example, Kroesen (2014) showed that when no explicit intervention was implemented, there was no clear pattern as to which direction multimodal transport users and joint car/bicycle users would shift towards. These two types of travellers were found to have similar likelihood to become strict car or strict bicycle users over time. Moreover, Lehtonen et al. (2021) showed that travellers who were more multimodal had a higher intention to use Level 3 automated vehicles. Travellers with medium-to-high levels of multimodality were more prone to reduce the use of public transport. Thus, Level 3 automated vehicles may (partially) replace part of trips currently travelled by sustainable modes in the future. Therefore, policymakers should be aware that an increase in multimodality is only the *first step* towards the development of more established sustainable travel behaviour. Supporting policies, such as those that focus on promoting the use of active modes and public transport, are highly required after the increase in multimodality and should be planned in advance to steer the direction of modal shifts for multimodal travellers. It is also encouraged to conduct regular monitoring during the process of planned modal shifts. Otherwise, the transport system may change in an undesirable direction.

While the multistep strategies potentially provide a solution for developing more established sustainable travel behaviour through the increase in multimodality, given the urgency of tackling climate change, questions remain as to whether these strategies are adequate to achieve their goal at the rapid speed required (see, European Commission (2020)). The reason is that such strategies do not necessarily contribute to modal shifts away from car use and a substantial reduction in transport-related emissions from a short-term standpoint. Therefore, the multimodality-based multistep strategies to promote sustainable transport should better be implemented with other emission mitigation policies jointly or be placed as a part of larger policies in the transport sector.

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Appendix A

Appendix to Chapter 2

A.1 Descriptive statistic of the considered correlates

	Age			Period			Cohort		
Correlates	16-40	41-60	61 and over	2001-2006	2007-2012	2013-2017	Pre-1945	1945-1970	Post-1970
Social Role Constraints									
Age	28.8	50.2	72.1	47.1	48.2	49.2	73.5	51.2	28.2
Gender									
Female	52.6%	51.9%	53.1%	52.6%	52.5%	52.4%	53.6%	51.8%	52.7%
Male	47.4%	48.1%	46.9%	47.4%	47.5%	47.6%	46.4%	48.2%	47.3%
Ethnicity									
White	85.2%	91.6%	96.4%	92.4%	90.3%	88.9%	96.8%	92.1%	84.5%
Mixed Multiple Ethnic Groups	1.6%	0.7%	0.2%	0.8%	1.0%	0.9%	0.2%	0.7%	1.7%
Asian/Asian British	8.2%	4.4%	1.9%	3.9%	5.2%	6.4%	1.6%	4.1%	8.8%
Black/African/Caribbean/Black British	3.3%	2.3%	1.0%	2.0%	2.4%	2.6%	1.0%	2.2%	3.3%
Other Ethnic Group	1.6%	0.9%	0.4%	0.9%	1.1%	1.1%	0.4%	0.9%	1.7%
Physical Mobility Constraints									
Having Walking Difficulties									
Yes	2.7%	8.0%	25.4%	13.8%	10.9%	8.1%	29.5%	8.4%	2.4%
No	97.3%	92.0%	74.6%	86.2%	89.1%	91.9%	70.5%	91.6%	97.6%
Work Constraints									
Economic Status									
Full-time	55.4%	60.6%	8.0%	44.3%	42.9%	43.5%	5.2%	53.9%	54.8%
Part-time	17.3%	18.4%	7.6%	15.0%	15.1%	14.6%	5.8%	17.7%	17.1%
Unemployed	4.4%	2.1%	0.2%	1.9%	3.0%	2.3%	0.1%	1.9%	4.6%
Retired	0.0%	4.7%	79.2%	23.2%	24.2%	25.8%	84.1%	13.4%	0.0%
Student	10.6%	0.3%	0.0%	3.5%	4.3%	4.3%	0.0%	0.3%	11.6%
Other inactive employment	12.3%	13.9%	5.0%	12.1%	10.6%	9.5%	4.8%	12.8%	11.8%
Multiple Work Locations									

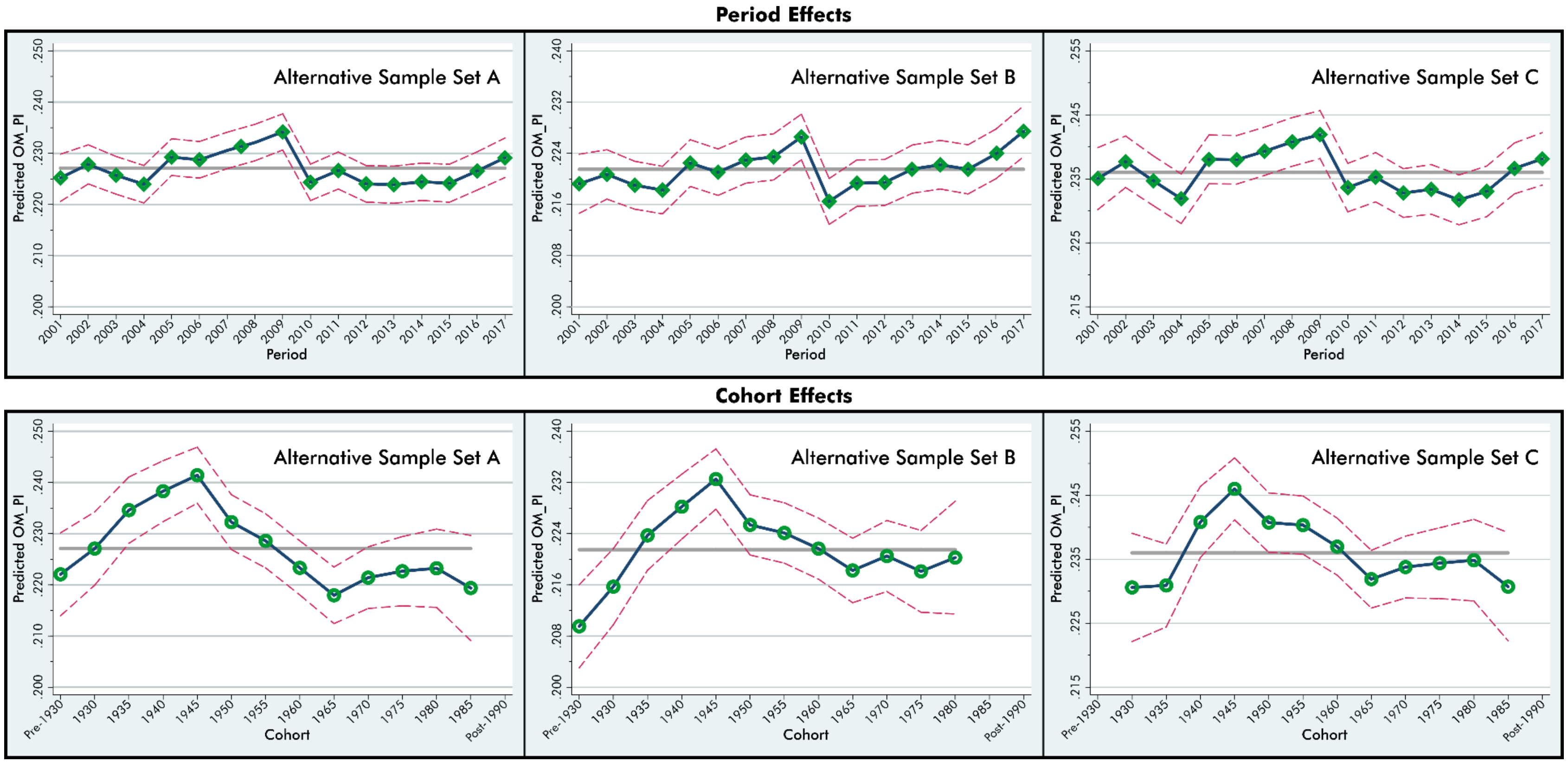
Yes	9.0%	12.4%	3.1%	7.4%	8.4%	9.5%	1.9%	11.2%	9.0%
No	91.0%	87.6%	96.9%	92.6%	91.6%	90.5%	98.1%	88.8%	91.0%
Work from Home									
Yes	1.9%	3.9%	1.8%	2.0%	2.7%	2.9%	1.3%	3.7%	1.9%
No	98.1%	96.1%	98.2%	98.0%	97.3%	97.1%	98.7%	96.3%	98.1%
Economic Constraints									
Household Income									
£50,000 and over	30.0%	32.4%	9.4%	17.6%	26.0%	31.7%	6.3%	28.8%	31.7%
£25,000 to £49,999	33.0%	31.8%	67.5%	48.9%	42.0%	36.0%	73.7%	34.9%	32.4%
£24,999 and less	37.0%	35.8%	23.1%	33.5%	32.0%	32.3%	20.0%	36.3%	35.9%
Accessibility Constraints									
Settlement Type									
London Boroughs	17.5%	12.9%	10.1%	13.0%	13.8%	14.8%	10.2%	12.6%	17.8%
Metropolitan Built-up Areas	16.2%	14.2%	13.8%	15.2%	14.9%	14.3%	14.0%	14.2%	16.3%
Urban over 250 population	16.1%	15.6%	15.1%	16.5%	15.1%	15.4%	15.2%	15.6%	16.0%
Urban with 25k to 250k population	27.0%	26.3%	26.6%	26.5%	26.9%	26.6%	26.3%	26.6%	26.9%
Urban with 3k to 25k population	13.6%	17.0%	18.8%	17.8%	15.8%	14.9%	19.5%	16.9%	13.2%
Rural	9.6%	14.0%	15.6%	11.0%	13.5%	14.0%	14.8%	14.1%	9.8%
Population Density (Persons/ha)									
40 and over	28.2%	20.8%	17.3%	21.3%	21.8%	25.1%	17.1%	20.4%	29.0%
20 to 39.99	26.6%	25.4%	25.3%	24.4%	26.6%	26.5%	25.1%	25.4%	26.9%
5 to 19.99	24.4%	26.0%	27.2%	25.8%	26.5%	24.6%	27.3%	26.1%	24.2%
4.99 and less	20.8%	27.7%	30.2%	28.5%	25.1%	23.8%	30.5%	28.1%	19.9%
Housing Tenure									
Owns/Buying	61.7%	78.8%	80.9%	75.8%	72.6%	70.3%	80.4%	79.3%	59.8%
Rents and other	38.4%	21.2%	19.2%	24.2%	27.4%	29.7%	19.6%	20.7%	40.2%
Mobility Resources Constraints									
Number of Household Vehicles									
2 and over	45.7%	53.5%	24.6%	40.5%	42.8%	43.7%	19.6%	51.0%	45.5%
1	36.4%	35.3%	51.4%	41.5%	39.9%	39.5%	52.7%	37.6%	35.9%
0	17.9%	11.2%	24.0%	18.0%	17.3%	16.8%	27.7%	11.4%	18.6%
Owning a Bicycle									
Yes	41.9%	44.1%	19.9%	35.3%	37.1%	36.5%	16.5%	42.3%	41.3%
No	58.1%	55.9%	80.1%	64.7%	62.9%	63.5%	83.5%	57.7%	58.7%

Holding Full Car License									
Yes	65.9%	84.2%	68.7%	71.3%	73.1%	74.5%	64.4%	83.9%	63.9%
No	34.1%	15.8%	31.3%	28.7%	26.9%	25.5%	35.6%	16.1%	36.1%

Note: the statistics of variables were grouped based on the rough tertile for individuals' age, periods, and cohorts.

Household income was deflated to 1990 values using the Retail Price Index (RPI).

A.2 Predicted OM_PI across periods and cohorts using alternative sample sets



Appendix to Chapter 3

B.1 Overview of the variables in analyses.

	Undifferentiated	Commuting /Education	Business	Shopping	Personal Business	Social	Recreation	Other
Age								
>65	24.9%	5.6%	5.1%	28.9%	35.4%	25.9%	25.7%	21.4%
31-64	57.2%	70.3%	80.4%	57.6%	54.1%	56.1%	57.9%	66.1%
<30	17.9%	24.1%	14.5%	13.5%	10.5%	18.0%	16.4%	12.5%
Gender								
Female	52.7%	50.7%	49.3%	56.3%	55.5%	54.9%	52.4%	55.5%
Male	47.3%	49.3%	50.7%	43.7%	44.5%	45.1%	47.6%	44.5%
Having a Child in Household								
Yes	16.5%	22.7%	23.1%	16.0%	14.1%	15.1%	17.7%	22.7%
No	83.5%	77.3%	76.9%	84.0%	85.9%	84.9%	82.3%	77.3%
Having Walking Difficulties								
Yes	8.1%	2.2%	1.7%	8.3%	11.2%	6.9%	5.6%	4.0%
No	91.9%	97.8%	98.3%	91.7%	88.8%	93.1%	94.4%	96.0%
Economic Status								
Full time	65.00%	70.90%	39.50%	33.00%	42.00%	43.30%	44.10%	46.20%
Part time	19.50%	22.90%	15.20%	14.60%	15.90%	16.10%	19.50%	17.00%
Unemployed	1.00%	0.90%	1.70%	2.10%	1.90%	1.60%	1.70%	1.60%
Retired and other (including student)	14.50%	5.30%	43.60%	50.30%	40.20%	39.00%	34.70%	35.20%
Multiple Work Locations								
Yes	10.1%	9.6%	21.9%	9.1%	8.6%	9.5%	10.4%	11.3%
No	89.9%	90.4%	78.1%	90.9%	91.4%	90.5%	89.6%	88.7%
Household Income								
£50,000 and over	33.6%	44.1%	50.4%	31.5%	30.0%	34.2%	38.2%	38.2%
£25,000 to £49,999	32.5%	34.8%	33.5%	32.7%	32.1%	32.6%	33.3%	34.2%
Less than £25,000	33.9%	21.1%	16.1%	35.8%	37.9%	33.2%	28.5%	27.6%
Settlement Population Density								

Population density (persons/ha; mean)	22.437	22.678	21.621	21.880	21.551	21.619	21.808	20.888
Settlement Land-use Mix								
Entropy index (mean)	0.668	0.678	0.656	0.657	0.647	0.662	0.650	0.639
Housing Tenure								
Owns/buying	70.7%	69.9%	78.4%	72.2%	75.6%	74.3%	78.3%	78.8%
Rents/other	29.3%	30.1%	21.6%	27.8%	24.4%	25.7%	21.7%	21.2%
Access to Vehicles								
No household vehicle	16.2%	11.1%	5.8%	14.9%	14.2%	13.5%	9.9%	6.9%
1 household vehicle	38.9%	34.9%	31.8%	41.3%	41.4%	39.0%	38.7%	40.5%
>2 household vehicle	44.9%	54.0%	62.4%	43.8%	44.4%	47.5%	51.4%	52.6%
Holding Full Car License								
Yes	74.4%	79.1%	91.5%	76.9%	78.5%	78.0%	82.4%	86.6%
No (Ref)	25.6%	20.9%	8.5%	23.1%	21.5%	22.0%	17.6%	13.4%
Owning a Bicycle								
Yes	35.9%	43.0%	51.6%	35.4%	34.8%	37.8%	44.7%	46.0%
No (Ref)	64.1%	57.0%	48.4%	64.6%	65.2%	62.2%	55.3%	54.0%
Driver Status								
Main household car driver	89.2%	89.8%	91.5%	89.6%	89.8%	89.6%	89.1%	89.1%
Not a main household car driver	10.8%	10.2%	8.5%	10.4%	10.2%	10.4%	10.9%	10.9%
Holding a PT Season Ticket								
Yes	33.4%	20.9%	18.3%	35.4%	41.0%	35.3%	35.3%	30.3%
No	66.6%	79.1%	81.7%	64.6%	59.0%	64.7%	64.7%	69.7%
Number of Observations	12023	6487	2583	9078	5076	7256	5812	3837

Appendix to Chapter 4

C.1 Results of the PCAs related to different modes.

Beliefs	Loadings		Cronbach's alpha
	PC1	PC2	
Car			
Comfort	2.505		0.855
Relaxation	3.142		
Pleasure	3.001		
Time-saving	2.310		
Safety	2.541		
Flexibility	2.175		
Prestige	0.774		
Bicycle			
Comfort	3.377		0.845
Relaxation	3.071		
Pleasure	3.165		
Time-saving	2.736		
Safety	2.468		
Flexibility	2.456		
Prestige	0.710		
BTM			
Comfort	3.327		0.872
Relaxation	3.002		
Pleasure	3.184		
Time-saving	3.052		
Safety	1.792		
Flexibility	3.289		
Prestige	0.860		
Train			
Comfort	3.162	1.732	0.843
Relaxation	3.083	1.409	
Pleasure	2.916	1.831	
Time-saving	0.495	3.542	
Safety	2.794	-0.281	
Flexibility	0.748	3.657	
Prestige	0.321	0.744	

C.2 The distribution of mode-specific attitudes across levels of multimodal travel behaviour.

	Q1 (0.18-0.39)	Q2 (0.39-0.50)	Q3 (0.50-0.59)	Q4 (0.59-1.00)	Q5 (1.00)	Overall	One-way ANOVA
PCA-based attitudes							
Car	3.76	4.06	4.23	4.24	**4.63**	4.27	$p<0.001$
Bike	**3.54**	3.50	3.50	3.31	2.37	3.07	$p<0.001$
BTM	**-0.55**	-0.44	-1.05	-1.28	-1.34	-1.02	$p<0.001$
Train	**1.05**	0.86	0.12	0.30	-0.24	0.29	$p<0.001$
Variance of attitudes across modes	8.12	8.58	10.79	10.55	**10.83**	9.98	$p<0.001$
Sum scoring-based attitudes							
Car	24.33	25.98	26.89	27.04	**29.47**	27.27	$p<0.001$
Bike	**21.70**	21.27	21.13	20.11	14.18	18.60	$p<0.001$
BTM	**-2.39**	-1.88	-5.52	-6.73	-7.40	-5.33	$p<0.001$
Train	**6.98**	5.84	1.36	2.59	-0.99	2.38	$p<0.001$
Variance of attitudes across modes	395.14	420.64	532.84	514.62	**543.29**	493.02	$p<0.001$

Note: in bold denote the largest value of a give variable across levels of multimodality.
Figures in parentheses denote the ranges of the OM_PI of each quintile.
Q1 to Q5 denotes quintiles of the level of individual multimodality, with Q1 being the highest level of multimodality (i.e., smallest of the HHI).
Members in WALK MOSTLY cluster were excluded.

C.3 Percentages of dissonant travellers across clusters and levels of multimodality (HHI indicator).