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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.

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

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 (2007); 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 (2016); Kroesen (2014)), which allows an easier transition to sustainable transport if the right conditions are provided (Heinen and Ogilvie (2016). 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 (2007)). Briefly, multimodal travellers are more prevalent amongst women, 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 (2007); 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** 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 3**. **Section 4** is dedicated to the findings drawn from the HAPC models, followed by **Section 5** in which these findings are further discussed.

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 2.3**, variations in some of the correlates of multimodality could be strongly embedded in cohort succession.

Figure 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.

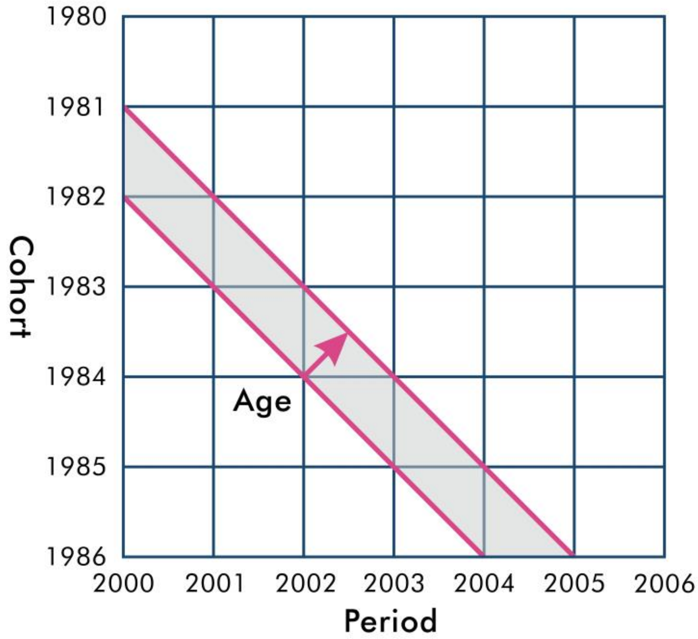

Figure 1 Nexus between age, period, and cohort (based on Yang and Land (2016)).

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 (2007) 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 (2007) 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. 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 slightly 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 (2017)). 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 (2017) 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.

2.3. 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).

2.4. 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.

3. Research Design

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 England[1] (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.

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[2]. 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 3.4**).

3.2. Multimodality measurement

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 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.

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

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

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

In **Eq. (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[3]; (6) railway[4]; (7) taxi; and (8) other[5]. 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, 2018a), 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 declining over time during the week[6]. 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.

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**.

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

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

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

[6] 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.

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 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:

$$Y_{ijk} = \alpha_{jk} + \beta_1 AGE_{ijk} + \beta_2 AGE_{ijk}^2 + \sum_{n=3} \beta_n X_{nijk} + e_{ijk} \tag{2}$$

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_{nj} 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:

$$\alpha_{jk} = \gamma_0 + u_{0j} + v_{0k} \tag{3}$$

$$u_{nj} \sim N\left(0, \tau^2\right),\ v_{nk} \sim N\left(0, \psi^2\right),\ n \geq 1 . \tag{4}$$

In **Eq. (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 jth period averaged over all cohorts. v_{0k} is the slope of the kth cohort that explains the residual random effect of the kth cohort averaged over all periods. u_{nj} and v_{nk} follow a normal distribution with variance τ^2 and ψ^2, respectively (**Eq. (4)**).

According to **Eqs. (2)-(4)**, the combined model is established as follows:

$$Y_{ijk} = \gamma_0 + \beta_{1jk} AGE_{ijk} + \beta_{2jk} AGE_{ijk}^2 + \sum_{n=3} \beta_{njk} X_{nijk} + u_{0j} + v_{0k} + e_{ijk} \tag{5}$$

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.

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 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[7]. 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[8]. We

[7] The predicted OM_PI for specific age *i* averaged over periods and cohorts is calculated based on Eq. (5), when other variables are set to zero: $\hat{y} = \hat{\gamma}_0 + \hat{\beta}_1\left(\left(Age_i\text{-}48.3\right)/10\right) + \hat{\beta}_2\left(\left(Age_i\text{-}48.3\right)/10\right)^2$

[8] 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.

then successively compared the temporal patterns in the predicted OM_PI across ages between Model 1 and Models 2-6 (**Figure 2**). **Figure 2** contains five subfigures (A-E), each of which 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 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.

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**). 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.

Figure 4 illustrates the predicted mean value of OM_PI across periods after the effects of age and cohort were accounted for[9]. 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 5 displays the predicted mean value of OM_PI across cohorts after the effects of age and period have been 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. 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**).

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[9] The predicted OM_PI for a specific period j averaged over ages and cohorts is calculated based on Eq. (5), when the other variables are set to zero: $\hat{y} = \hat{\gamma}_0 + \hat{u}_{0j}$

[10] The predicted OM_PI for a specific cohort k averaged over ages and periods is calculated based on Eq. (5), when the other variables are set to zero: $\hat{y} = \hat{\gamma}_0 + \hat{v}_{0k}$

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 1980. 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.

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 1980). 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 B**).

Table 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 (reference)							
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 (reference)							
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 (reference)							
Work Constraints							
Economic Status							
Full-time (reference)							
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	-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) ***
No (reference)							
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 (reference)							
Economic Constraints							
Household Income							
£50,000 and over (reference)							
£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 (reference)							
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 (reference)							
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 (reference)							
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 (reference)							
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 (reference)							
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 (reference)							
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.

Table 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).

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

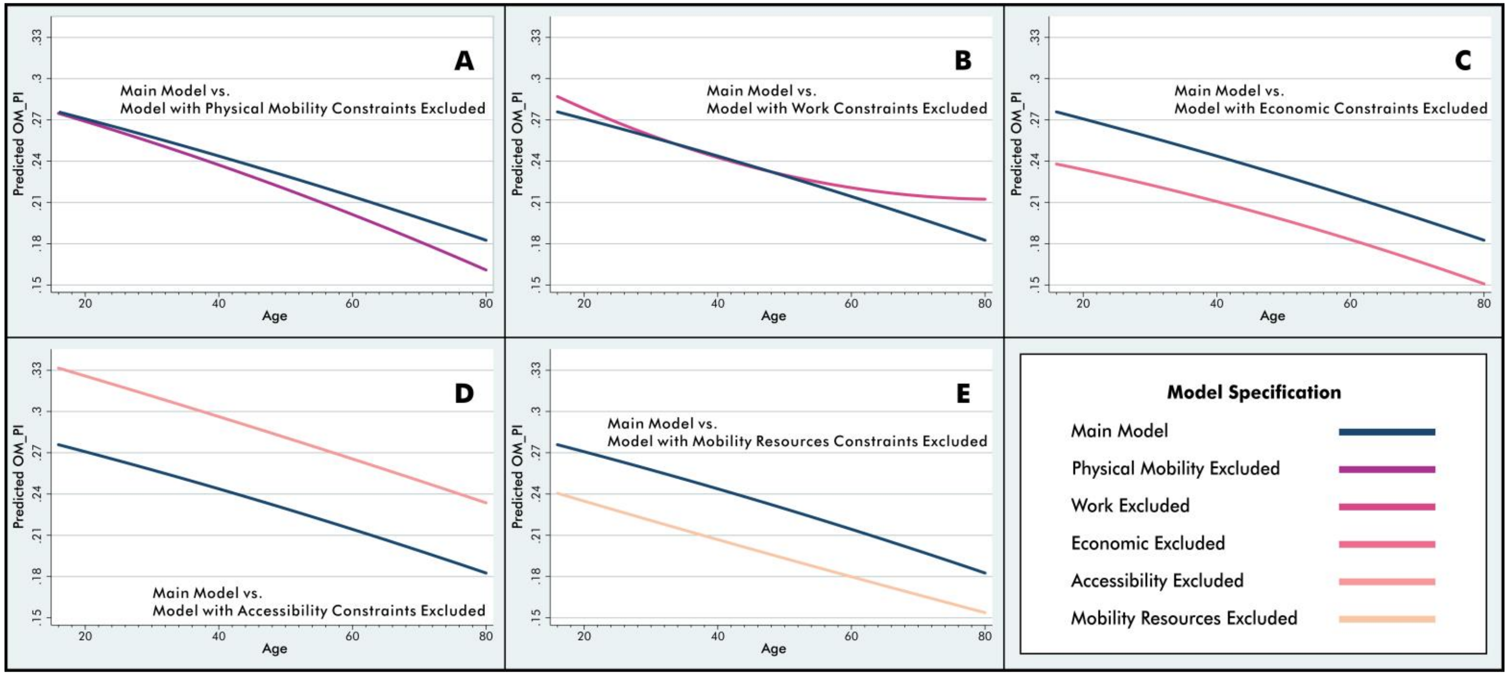


Figure 2 The extent to which a specific type of spatial mobility constraint moderates the age-multimodality relation.

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).

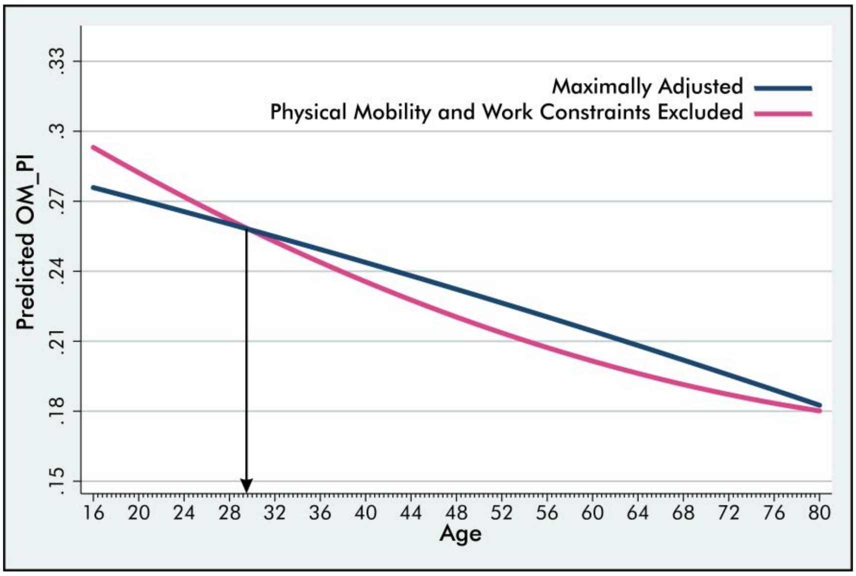


Figure 3 The extent to which physical mobility and work constraints moderate the age-multimodality relation.

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).

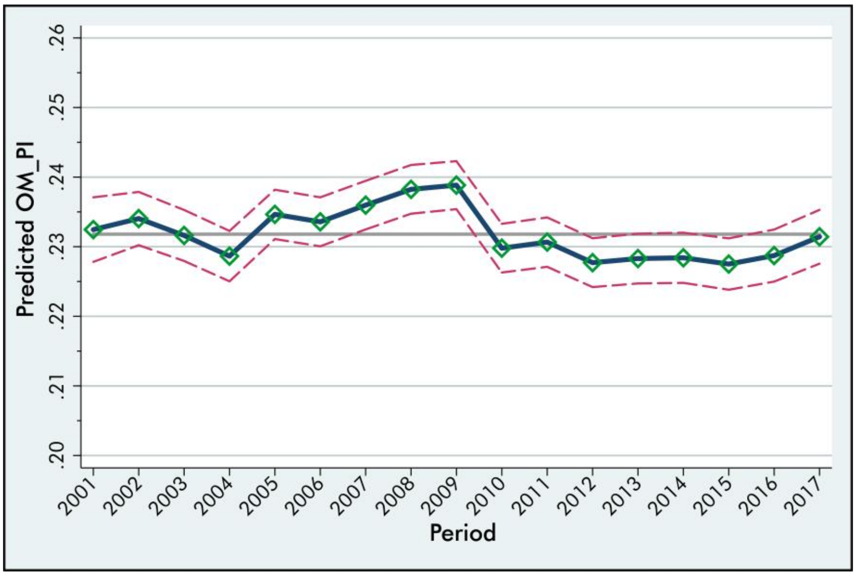


Figure 4 Predicted mean values of OM_PI across periods.

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.

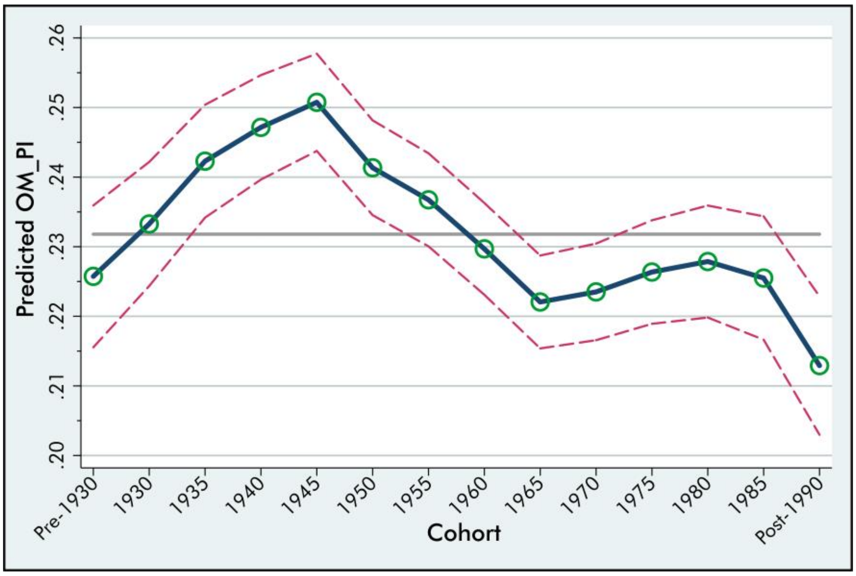


Figure 5 Predicted mean values of OM_PI across cohorts.

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.

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 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 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 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.

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.

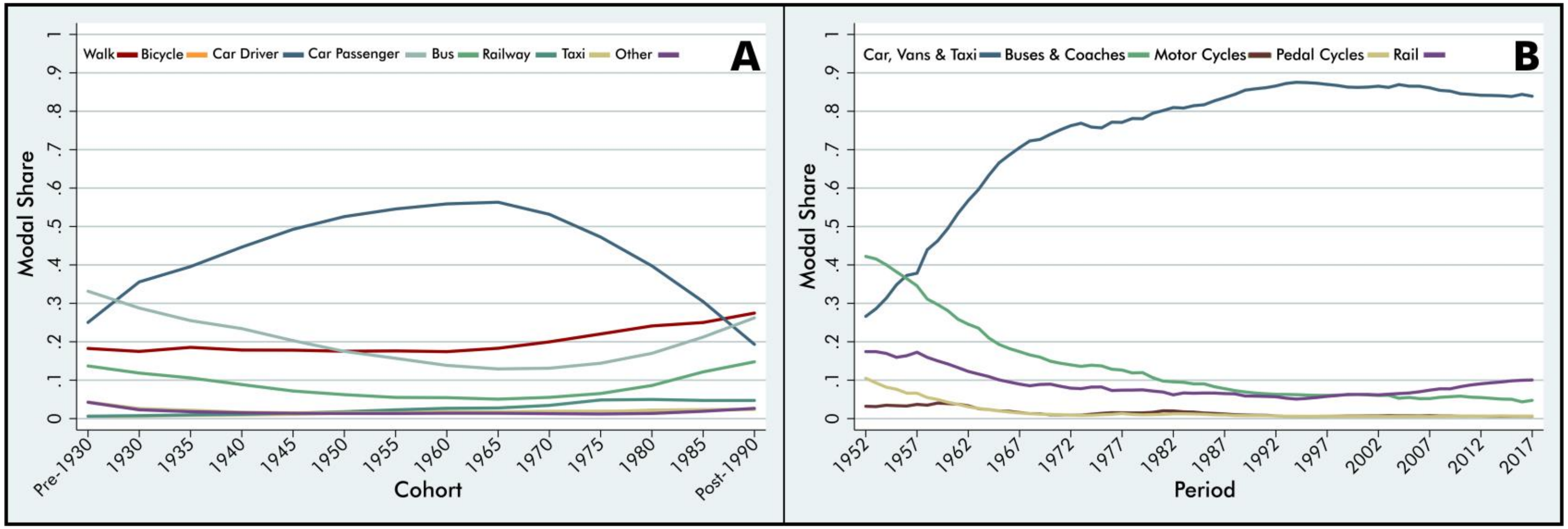


Figure 6 Trends in (A) the modal share in England across cohorts (based on the 2001-2017 NTS data) and (B) the modal share in Great Britain from 1952 to 2017 (based on Department for Transport (2018b)).

Appendix A. Descriptive statistic of the considered correlates

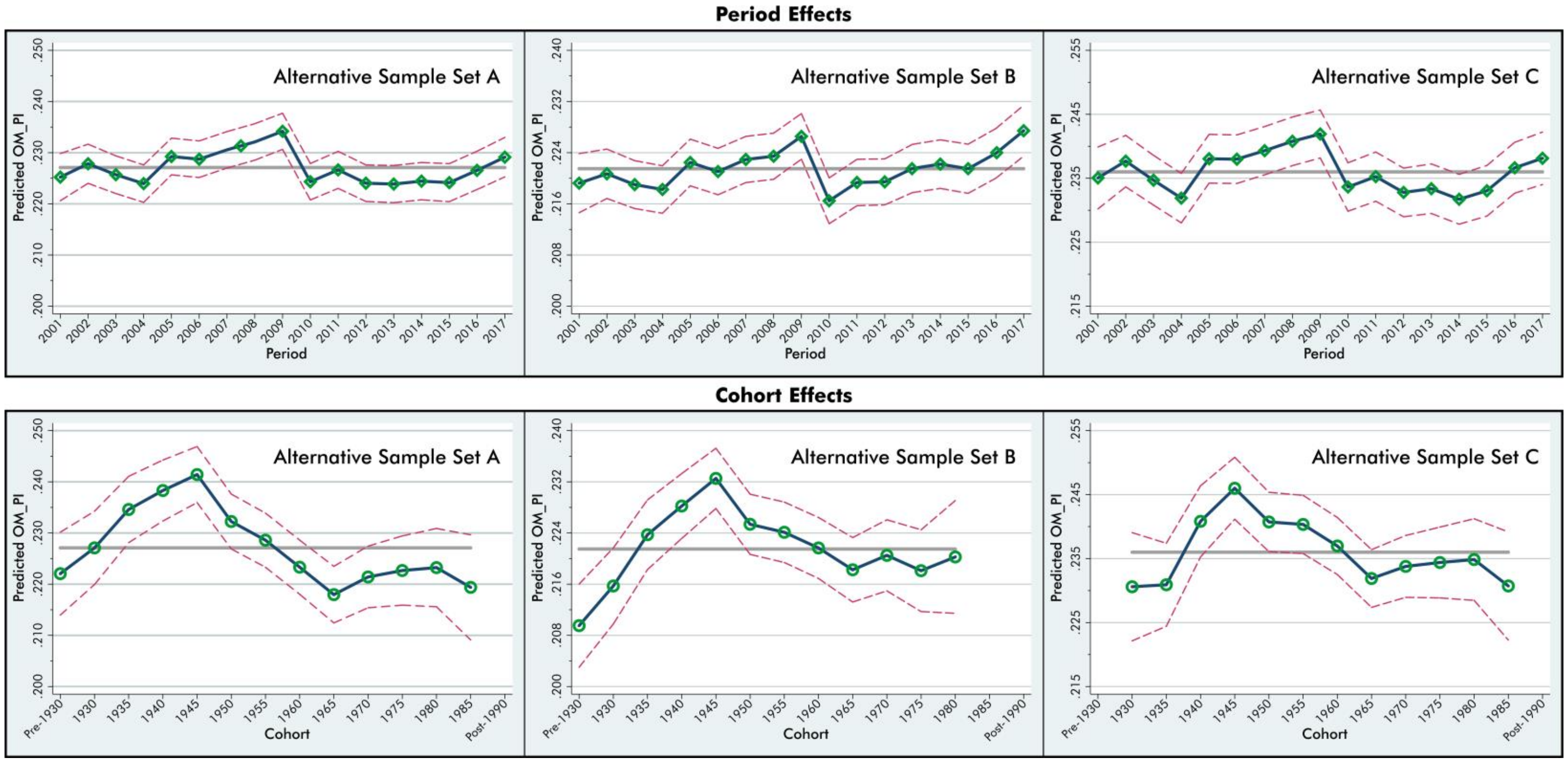
Correlates	Age			Period			Cohort		
	16-40	41-60	61 and over	2001-2006	2007-2012	2013-2017	Pre-1945	1945-1970	Post-1970
Social Role Constraints									
Age	28.8	50.2	72.1	47.1	48.2	49.2	73.5	51.2	28.2
Gender									
Female	52.6%	51.9%	53.1%	52.6%	52.5%	52.4%	53.6%	51.8%	52.7%
Male	47.4%	48.1%	46.9%	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 (reference)	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[a]									
£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%

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

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

Appendix B. Predicted OM_PI across periods and cohorts using alternative sample sets



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