The Level and Determinants of Multimodal Travel Behavior: 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 behavior; constraint

1 Introduction

In recent years, the notion of multimodality has attracted increasing attention in transport practices (e.g., EC (2014)) and research (e.g., An, Heinen, and Watling (2020)). Multimodality is defined as the phenomenon of using more than one mode of transport in a given period (Kuhnimhof et al., 2012). Existing studies suggest that encouraging multimodality is an effective measure to promote a more sustainable transport system. For example, multimodal travelers, under the same travel distance, emit less CO2 than less multimodal or monomodal travelers (e.g., Heinen and Mattioli (2019b)). Moreover, travelers 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 (2016)), 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 & 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, Chatterjee, and Heinen (2016); Molin, Mokhtarian, and Kroesen (2016); Buehler and Hamre (2014); Nobis (2007)). Studies have also suggested that multimodality is widely present in developed societies (e.g., Kuhnimhof, et al. (2012); Ralph (2016)) and that there is an upward trend in recent decades (e.g., Kuhnimhof, et al. (2012); Streit, Allier, Weiss, Chlond, and Vortisch (2015)). However, British studies contradicted this and demonstrated that individual multimodality decreased between 1995 and 2015 (Heinen & 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.

2 Background

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

2.1 Travel Behavior-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 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, Kwan, and Chai (2013)). Activities in committed time represent those that are bound to others through promise, such as household responsibilities (Reinseth, Kjeken, Uhlig, & Espnes, 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 behavior in grocery shopping, several attributes of shops, e.g., price and service, are as comparably important as the location of shops (e.g., Schenk, Löffler, and Rauh (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., M. S. 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 1 about here]

2.2 Multimodality and Trip Purpose

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 2**), and the findings suggest trips made for discretionary activities may be more multimodal than those made for oblationary activities. For example, Vij, Carrel, and Walker (2011) analyzed modality styles in 226 Germany travelers and found that multimodal travelers (defined as if 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.

[Table 2 about here]

Despite that these studies offer insights in 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 & 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.

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 analyzing 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 analyzed 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 a 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 labor 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 showed that multimodal travelers more likely 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, Clark, and Bartle (2016) observed that working part-time was more prevalent for travelers who did not or only partially used cars to commute (compared to car-only travelers). The authors also showed that travelers 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 behavioral patterns and trip purposes.

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 inference. 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.

3.1 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 behavior 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 behaviors 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 behavior using the NTS (e.g., Heinen and Chatterjee (2015); Crawford (2020)).

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., travelers have no purpose of their own other than to accompany another person) for the 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 (2007)). 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 travelers into non-overlapping groups, but they do not gauge the level of individual multimodality (Heinen & 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 traveler. 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 & 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 & Pirra, 2016). We used the OM_PI for our main analyses and investigated the others in sensitivity analyses (see **Section 3.4**).

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

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

$$OM\_PI_{im} = \sum_{k=1}^{N_{im}} \left(S_{imk} \ln \frac{1}{S_{imk}} \frac{1}{\ln N_{im}} \right) \tag{2}$$

$$S_{imk} = f_{imk}/f_{im} \tag{3}$$

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, 2018). 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 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. (2)**), 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, Zwart, van Wee, and van den Hoorn (1999).

3.4 Correlates

Drawing on Hägerstrand's (1970) research on constraints of spatial travel behavior, 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 A**):

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.

3.5 Statistical Analyses

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**). We first looked into the OM_PI-7 indicator for all individuals who traveled 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 (S. Lee & 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 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 sub-section.

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 behavior studies (e.g., Holz-Rau, Scheiner, and Sicks (2014); Kaplan, Nielsen, and Prato (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 modeling 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. (4)**):

$$E(\boldsymbol{y}) = \boldsymbol{X\beta} + \boldsymbol{u}; \boldsymbol{u} \sim N(0, \sigma^2) \tag{4}$$

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. (5)**):

$$w_i \begin{cases} 1, & if\ w_i^* = \boldsymbol{z}_i \boldsymbol{\gamma} + v_i \geq \mathbf{0} \\ 0, & if\ w_{im}^* < 0 \end{cases} \tag{5}$$

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 (z_i) related to the occurrence of the trip. $\boldsymbol{\gamma}$ refers to coefficients of z_i. v_i is a residual. Following Hägerstrand's (1970)'s framework for the constraints of travel behavior, we initially set z_i as the variables listed in **Appendix A**. 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:

$$E(\boldsymbol{y}|y_i \geq 0) = \boldsymbol{X\beta} + \boldsymbol{\varphi}\lambda(\boldsymbol{z}_i\boldsymbol{\gamma});\ \boldsymbol{\varphi} = \sigma\boldsymbol{\rho};\ \boldsymbol{\rho} = cov(\boldsymbol{u}, \boldsymbol{v}) \tag{6}$$

where $\lambda(z_i\gamma)$ refers to the IMR evaluated at $z_i\gamma$ 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. (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).

4 Results

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. (2012); Fountas, Sun, Akizu-Gardoki, and Pomponi (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**). The patterns for more detailed classification of trip purposes were similar.

[Table 3 is about here]

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), which suggests 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 4**). This was for individuals with at least one stage.

[Table 4 about here]

We then conducted Tukey-Kramer tests to determine the relative level of multimodality concerning different purposes (**Table 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.

[Table 5 about here]

Our sensitivity tests showed highly consistent results (see, **Tables 1**, **2**, and **3** 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 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 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 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.

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 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 1**). Most noticeable was that the level of multimodality in work trips was the lowest, with a relatively low threshold (i.e., 3).

[Figure 1 about here]

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 modeling 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 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 6 about here]

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); settlement population density (for work and maintenance trips, but not for leisure 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. (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 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 failed to account for only 23.55% (i.e., 100%-76.45%) of all explained variance (see figures in parentheses in

Table 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 7 about here]

Our sensitivity analysis showed generally similar findings. Nevertheless, there were some differences. The analysis performed by changing indicators (**Tables 4**, **5**, and **6** 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.

5 Discussion and Conclusions

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 analyzed 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; travelers 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, Habibian, & Khodaii, 2020).

We also found that travelers 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 travelers 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 travelers 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 & 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 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, Dijst, and Burghouwt (2002); Krizek (2003); see, Gim (2011) and Tran, Chikaraishi, Zhang, and Fujiwara (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.

5.2 *Discussions on Policy Implications*

This research could help to develop policies to encourage multimodal travel behavior. 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.

5.3 Limitations

We used high-quality, national-representative, one-week travel diaries well suited for analyzing 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.

Declaration of Interest

The authors declare that they have no competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

Table 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 time	Work-related (e.g., paid work and education)	Low	Very low
Activities in committed time	Maintenance (e.g., shopping and other family/personal affairs)	Medium	Medium
Activities in free time	Leisure (e.g., social and recreation)	High	High

Table 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)

Table 3. Time-space variability of trips across purposes.

	Work	Maintenance	Leisure	ANCOVA
Departure time	3.089 (1.503)	3.388 (1.633)	3.814 (1.994)	p<0.001
Travel distance	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	ANCOVA
Departure time	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	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: we reported mean values and standard deviations (in parentheses). We reported the reciprocal of the HHI (departure time variability) so that a greater value of the HHI reflects a higher level of variability.

Table 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 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.

Table 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.

Table 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.

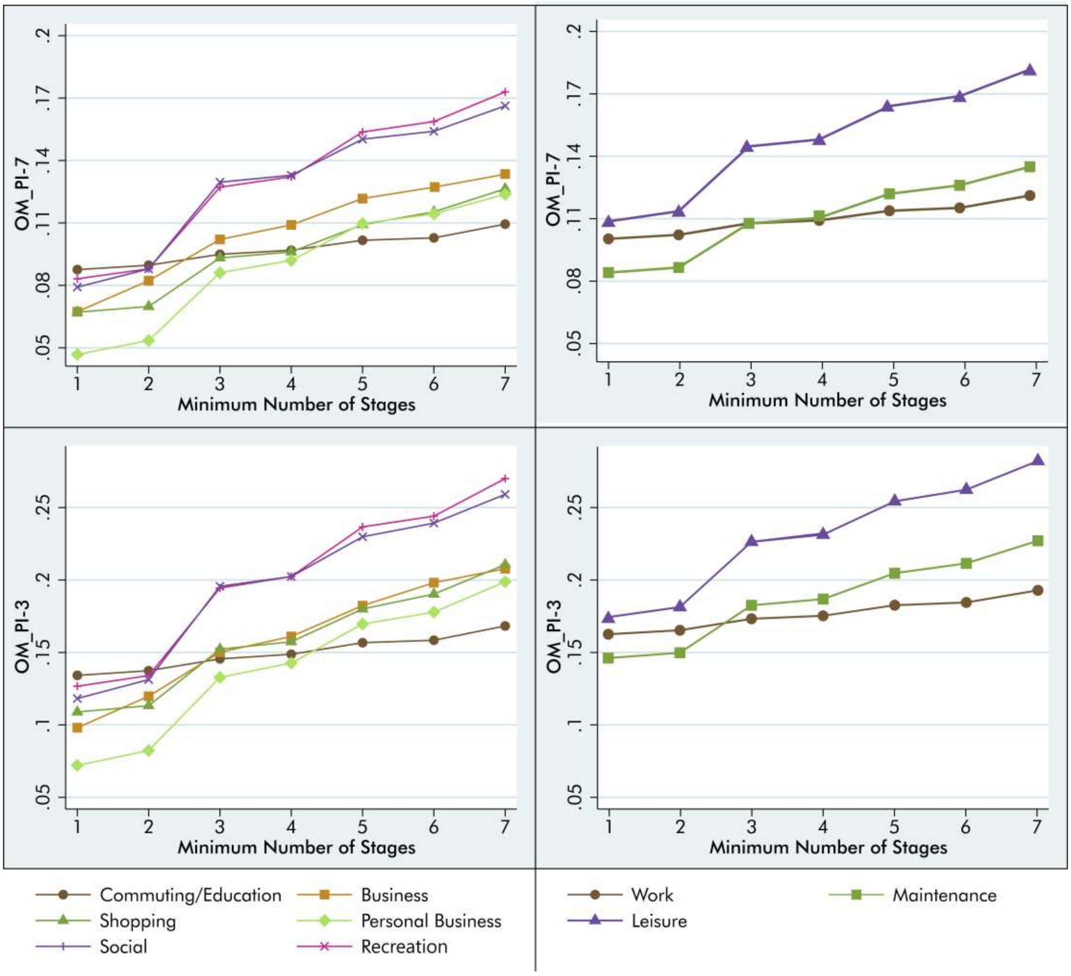

Figure 1. Patterns in relative levels of purpose-specific multimodality as a function of the minimum number of stages. *Note:* multimodality is measured by OM_PI-3/7.

Appendix A. 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

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