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Identifying the recurring travel patterns among older people: A mobility motif analysis with smartphone track and trace data

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ABSTRACT

Introduction: Understanding older people's mobility patterns and out-of-home activities is crucial for promoting their independence, active ageing and well-being. This study leverages mobility motif analysis to identify recurring travel patterns among older people and investigate how they are associated with out-of-home activity profiles.
Method: We collected continuous 12 weeks of mobility data using a smartphone Track and Trace app on 9147 journeys made by 43 participants (3612 person-days) aged 55 and above in the West Midlands Combined Authority, UK. To address self-selection and low participation rates, we matched participants with national survey data based on out-of-home activity profiles. Using network analysis, we identified distinct mobility motifs within daily travel networks.
Results: A total of 106 distinct mobility motifs were identified, with 19 key motifs representing the most recurring travel patterns, collectively accounting for 92.2 % of all daily travel networks. The distribution revealed high consistency with group profiles. Further analysis revealed inter-group variations in travel frequency, mode use, motif types, and journey purposes among the three groups.
Conclusion: These findings provide evidence-based insights for developing age-friendly urban systems and targeted interventions to enhance mobility inclusivity among older populations. The identified motifs reveal diversity in older people's travel behaviours and highlight the need for addressing mobility barriers to promote active and socially connected lifestyles, enhancing their well-being and quality of life.

1. Introduction

In the UK, projections suggested that by 2041, approximately 26 % of the population will be aged 65 and over, with those aged 50 and above comprising nearly half of all adults (ONS, 2018). Today's older population differs markedly from previous generations in their social, economic, and environmental needs. They are generally more active (Musselwhite et al., 2015), often maintaining aspirations to remain in the workforce and sustain social and recreational networks locally and beyond (Li, 2023a; Lin and Cui, 2021;

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Yang et al., 2023; RTPI, 2004).

Participating in out-of-home (OOH) activities is vital for promoting independence, physical activity, and reducing social isolation among older people (Mackett, 2015). For this population, mobility transcends mere transportation, carrying emotional significance and supporting societal connection. However, age-related mobility decline creates barriers to OOH activities, affecting wellbeing and social integration. In the UK, many older adults report feeling "trapped" at home due to inadequate transportation options (WRVS, 2013).

Detailed spatiotemporal studies of mobility practices and the experiences of older people are still rare. Traditional methods, such as travel surveys, often lack the detail needed to fully capture the context and complexity of travel behaviours. In this study, we employ a Track and Trace (T&T) smartphone application that captures the daily mobility of older people over 12 weeks, providing high spatiotemporal detail and contextual information like timestamp, travel purpose and travel mode. Unlike studies based on single-day diaries, the extended passive tracking captures motif stability and uncovers patterns may be missed by traditional surveys, such as short walking loops and the gradual accumulation of diverse destination types within recurring mobility network structures. We employ the novel concept of *mobility motifs* and develop a sample matching framework linking out-of-home mobility profiles found in the English Longitudinal Study of Ageing (ELSA) with the mobility motifs generated from T&T data. We identify key recurring daily patterns of travel and offer new, detailed insights into common routines and variations of older people's mobility and its situation in more durable lifestyle routines.

2. Background

Creating age-friendly environments and transportation systems requires a thorough understanding of older people's mobility patterns and needs. Research shows older people are more likely to remain at home, make fewer trips, and travel shorter distances compared to younger cohorts. There is also a higher reliance on non-car transport, and less travel at night (Schwanen and Páez, 2010). However, these patterns vary significantly depending on sociodemographic characteristics and personal preferences (Siren and Haustein, 2013, 2016). Beyond biological age, mobility practices are shaped by individual lifestyles, social networks, and living environment (Siren and Haustein, 2016; Kandt and Leak, 2019; Ryan et al., 2019).

Recent research has leveraged the idea of 'network motifs' to examine recurring mobility patterns among older people (Su et al., 2021, 2021b) and the general population (Ma et al., 2024). The concept of mobility motifs is derived from complex network science (Milo et al., 2002), identifies recurrent patterns within sequences of mobility practices, which can be represented as networks of nodes and links representing the different locations individuals visit and the associated travels. This approach is particularly useful for highlighting variations within complex mobility networks and understanding interactions between individuals and their environments.

Research (Ma et al., 2024) has demonstrated the stability of mobility motifs over time, indicating consistent patterns in people's daily routines in urban environments. However, the study by Ma et al. (2024) lacks detailed sociodemographic information, limiting their applicability in explaining individual-level variations. Cao et al. (2019) explored the distance influence on motif choices using mobile phone positioning data based on cell tower, but the approach made it difficult to capture intermediate stops or link motifs to travel modes and demographic factors. For more nuanced insights, Su et al. (2021a,b) used self-reported travel survey data from California to examine the effects of sociodemographic and built environment factors on motif choices among older people. Despite providing valuable insights, this approach is limited by single-day data collection and potential recall bias.

Self-reported travel diaries often have lower spatial and temporal resolution, leading to less precise measurements of mobility patterns. Recall bias can be particularly evident for shorter or more frequent travels that are easily overlooked or omitted. This limitation may be more pronounced among individuals facing memory-related challenges, such as those with dementia. To overcome the limitations, some studies have employed GPS travel loggers to investigate mobility patterns of older people. GPS logger-based methods tend to require extensive post-processing, and the data collection periods are typically short (e.g. 1–14 days) for older people due to the burden of using dedicated tracking devices for participants (Chung et al., 2021; Shoval et al., 2011). Recently, smartphone Track and Trace (T&T) data, obtained for example from an advanced automatic travel diary app (Prelipcean et al., 2018), has emerged as a promising tool for exploring mobility behaviours with high spatiotemporal granularity and contextual richness (Harrison et al., 2020). An immediate advantage is the low burden on users, as it relies solely on apps installed on personal devices (e.g., smartphones), making long-term data collection easier and automatic. Additionally, T&T apps can capture detailed mobility data and be linked to the phone user's behavioural choices and other individual contexts (Harrison et al., 2020).

In this paper, we identify and systematically compare older people's mobility practices through motifs in the West Midlands Combined Authority, the largest metropolitan area in the United Kingdom outside London. We match mobile Track and Trace (T&T) data collected in summer 2023 to segments of mobility practices derived from the English Longitudinal Study of Ageing (ELSA) and discuss the mobility variations among different groups of older people.

3. Data and method

3.1. Study area and data

Our case study region, the West Midlands Combined Authority (WMCA), is the United Kingdom's second largest metropolitan region and comprises seven local authorities, including Birmingham and Coventry. The area has an extensive bus network, a light rail line known as the Midlands Metro and a local railway network.

The English National Concessionary Transport Scheme (ENCTS) offers older residents free travel on most local bus and rail services within the region after 9.30 a.m. during weekdays and at all times during weekends and public holidays (Department for Transport, 2024). The scheme is administered by local transport authorities, often through concessionary travel cards.

The primary data for this research was collected using a T&T app with participants from the WMCA. The recruitment of older people to surveys is generally challenging, and as a result this group can be under represented without proactive initiatives to enable their participation. For this study, recruitment was supported by Transport for West Midlands, the transport arm of WMCA. Transport for West Midlands distributed an invitation to participate in the study on behalf of the project to their large database of individuals who have previously given consent to take part in research and consultation activity. Individuals who contacted the university of Leeds in response to the invitation were screened by the university of Leeds research team for age category and the use/availability of a smartphone device for themselves. The university of Leeds research team offered participants a £25 e-shopping voucher at the end of the study. All participants were recruited during one month from June 28 to July 28, 2023 to start using the app. Upon enrolment, participants completed a registration process and maintained the app on their smartphones for three months. To ensure data reliability,

Table 1
participants sociodemographic and mobility characteristics.

Variable	Category	*Participants*		*Census 2021*	
		n	%	Expected n	%
Age	55–64	25	58.1	17	39.7
	65–74	15	34.9	14	31.7
	75 and above	3	7	12	28.6
Sex	Female	11	25.6	23	52.6
	Male	32	74.4	20	47.4
	Non-binary	0	0	0	0
Ethnicity	White	38	88.4	38[a]	88.6[a]
	Black, African, Caribbean or Black British	3	7	1[a]	2.8[a]
	Asian or Asian British	2	4.6	3[a]	6.9[a]
	Mixed and other ethnicities	0	0	1[a]	1.7[a]
Highest Educational Attainment	No formal qualifications	1	2.3	9[b]	21.1[b]
	Formal education up to 16 years old	2	4.7	4[b]	10.3[b]
	A Levels, BTEC - formal education up to 18 years old	3	7	6[b]	13.9[b]
	College or technical diploma	10	23.3	10[b]	22.4[b]
	University Degree (BSc, BA etc)	13	30.2	13[b]	29.4[b]
	Graduate Degree (Masters, MPhil, PhD)	13	30.2		
	Foreign or other	1	2.3	1[b]	2.9[b]
Approximated social grade by occupation types	AB: Higher and intermediate managerial/administrative/professional occupations	26	60.5	8	18.4
	C1: Supervisory, clerical and junior managerial/administrative/professional occupations	10	23.3	13	31.3
	C2: Skilled manual occupations	2	4.7	10	23.5
	DE: Semi-skilled and unskilled manual occupations; unemployed and lowest grade occupations	5	11.5	12	26.8
Annual Household Income	75,001 and above	2	4.6	N/A	
	50,001–75,000	7	16.2		
	38,001–50,000	6	14		
	25,001–38,000	11	25.6		
	15,001–25,000	7	16.3		
	Less than 15,000	5	11.6		
	Prefer not to say	5	11.6		
Car access in household	No	15	34.9	9[c]	21.5[c]
	Yes	28	65.1	34[c]	78.5[c]
Driving license	No	10	23.3	N/A	
	Yes	33	76.7		
Concessionary Travel card	No	23	53.5	N/A	
	Yes	20	46.5		
Health Status	Excellent	10	23.3	27	62.4
	Very Good	16	37.2		
	Good	11	25.6		
	Fair	5	11.6	16	37.6
	Poor	1	2.3		
Number of persons in household	1	15	34.9	10[a]	23.3[a]
	2	24	55.8	33[a]	76.7[a]
	3+	4	9.3		
Limiting Long-Term Illness	No	37	86	29	69.2
	Yes	6	14	13	30.8

[a] based on UK Census 2021 in WMCA, all usual residents aged 50 years and over.
[b] based on UN Census 2021 in WMCA, all usual residents aged 16 years and over.
[c] based on UN Census 2021 in WMCA, all households.

this study assessed data consistency and quality and verified continuous app usage. The final sample included 43 participants aged 55 and over, each of whom contributed data continuously for at least 12 weeks (84 days).

In this study, the age of 55 is chosen as the threshold for defining 'older people', since, at this age, UK citizens can begin accessing private pensions, which may mark shifts in lifestyle and travel choices as some consider early retirement. Although open to debate, the threshold provides a balanced, practical framework for analysing the diversity of aging experiences and mobility in the UK.

In addition to T&T data, participants provided self-reported information about their sociodemographic characteristics and out-of-home activities (e.g., frequency of eating out) in the registration. These survey questions were adapted from Carney and Kandt (2022),

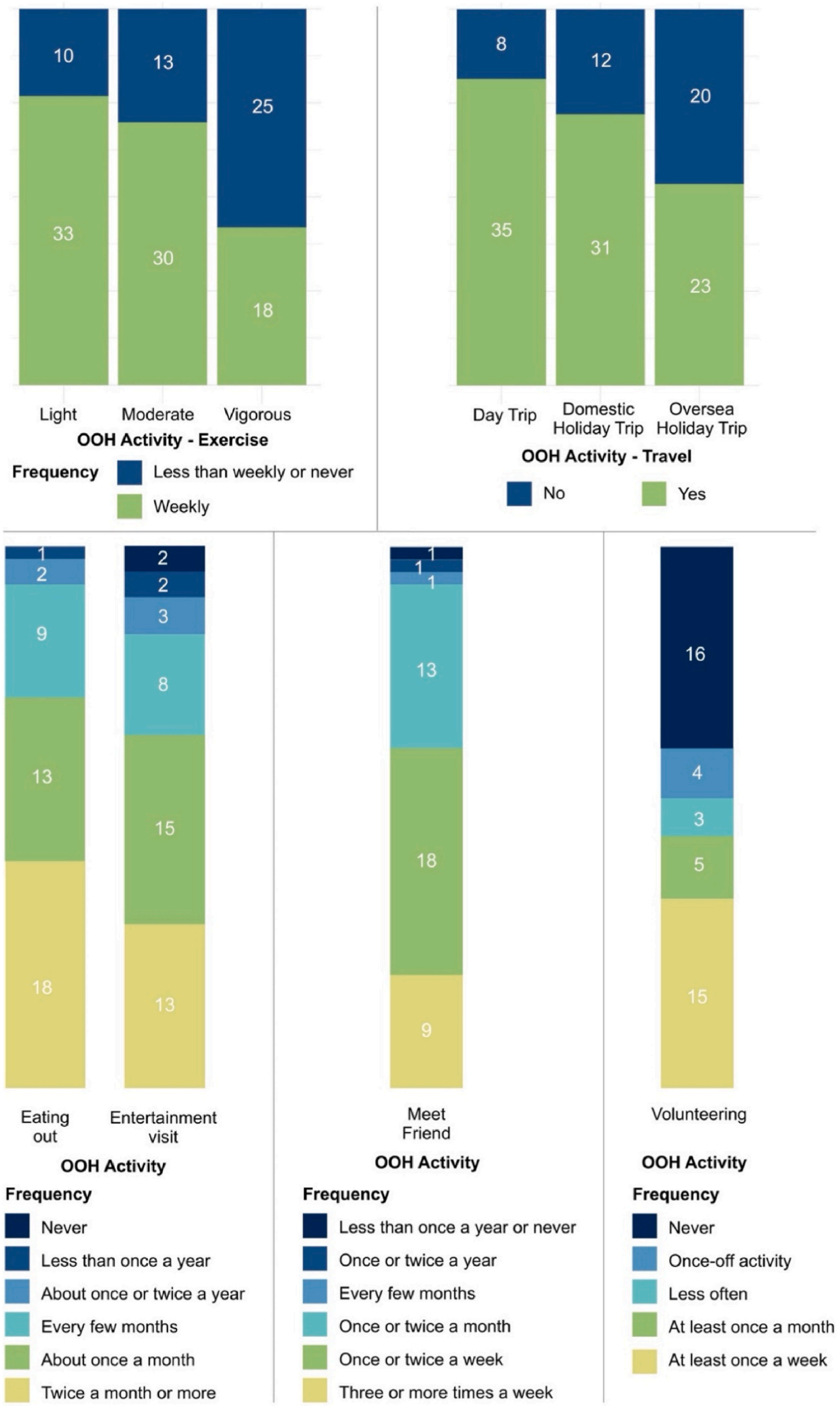

Fig. 1. OOH activity and self-reported frequencies.

drawing on variables from the English Longitudinal Study of Ageing (ELSA). An example question asked: “Thinking of the year before the pandemic, on average, how often did you eat out of the house?”. The questions allows profiling of participants and their daily short-term routines within more stable and long-term lifestyle practices. It also ensures that the degree of self-selection and sample distortion due to low participation rates can be assessed through linkage to a nationally representative sample.

Once the app was installed and registration completed, the T&T app, Sesamo, automatically recorded travel behaviours using GPS and other phone sensors (e.g., accelerometer). The app captured detailed travel data, including timestamps of each journey, co-ordinates, and contextual information such as weather and destination type. Temporal information and timestamps provide valuable data for analysing the rhythmic patterns of travel behaviour (Harada et al., 2023; Tang et al., 2024), enabling the analysis to identify departure and arrival times within individuals' daily mobility routines. Such temporal information and analysis can facilitate the examination of activity scheduling patterns, peak travel periods, and the temporal distribution of trips throughout the day, thereby offering insights into how older people structure their daily activities and coordinate their movements within broader temporal constraints.

The app also included a travel mode detection module based on a finely tuned probabilistic Bayesian model. Thomas et al. (2018) reported that its accuracy depends on trip distance, ranging from 78 % for short trips to 95 % for long trips. The detected travel mode is then further validated using the Google Maps API. (Geurs et al., 2015; Huang et al., 2021; van der Drift et al., 2022). This study examines travel mode variations to understand the diverse patterns of mode adoption among different groups of older people in their daily travel. The analysis of travel mode choice employs a dual analytical approach: first, by measuring the share of each transport mode in the total distance travelled; and second, by calculating the frequency with which each primary travel mode appears in individual journey sequences that comprise a complete daily mobility profile. This methodological framework enables a comprehensive understanding of both the extent and distribution of modal preferences across the study participants.

Journey purposes are inferred based on the origin and destination types (e.g., shop), provided by OpenStreetMap tags for the approximate location. This T&T app has been previously used in other studies to explore mobility patterns in various contexts (Mitas et al., 2023; Pronello and Kumawat, 2021; Huang et al., 2021; van der Drift et al., 2022).

The sociodemographic information of participants collected in this study is summarised in Table 1; alongside the expected number and proportion according to the UK Census 2021 in WMCA. Not all variables are available in the Census, and some variables lack detailed age cross-tabulation (which would help filter and focus on older people); consequently, some census data cells are marked as N/A or labelled with * mark (see footnote of Table 1).

Most participants (25 out of 43) are aged 55–64 and 15 are aged 65–74. There is an evident gender imbalance, with three in four participants being male, which contrasts with what would be expected, since there are more women in this age group according to Census. This provides evidence of self-selection, which we further investigate through our sample matching approach.

Similarly, while most participants identify as White, there is also a higher-than-expected level of educational attainment when compared to the Census, with the majority participants holding a university degree or higher. More than half belong to social grade AB, representing those in higher or intermediate managerial, administrative, or professional occupations. One-third lack household access to cars, a proportion exceeding Census expectations, while three in four hold a driver's license. Just 20 out of the 43 participants own a travel card that allows free use of public transportation. Regarding health, 37 participants report good to excellent health, while only 6 have a Limiting Long-Term Illness. These figures differ from Census expectations of 27 and 13, respectively. Participants tend to have better health and are in a younger age group, which may lead them to be more active than the general older population. Hence, this study may be overestimating their activity levels and OOH participation.Finally, 15 participants reside in single-person households, higher than the Census-expected figure of 10.

A majority of 33 participants reported engaging in light exercise weekly, while this decreased to 30 for moderate exercise and 18 for vigorous exercise (Fig. 1).

Regarding recreational travel, 35 took day trips, 31 had domestic holidays in the past year (before the pandemic), and 23 travelled overseas. Over half of the participants reported dining out and visiting entertainment venues (e.g., museum, theatre, cinema) at least once a month. Social interactions were more frequent, with 27 meeting friends at least once or twice a week. In contrast, volunteering was less common; 16 had never volunteered, and 4 participated in a one-off activity.

3.2. Group allocation

To ascertain the impact of self-selection and sample size, we match participants to a clustering model developed by Carney and Kandt (2022). Based on the nationally representative ELSA data, their model identified distinct groups of older people with varying types of out-of-home activities, which allows assessment of the extent to which groups (as characterized by daily activities) are over or underrepresented in our T&T sample. Key variables included the frequency of activities related to (1) entertainment, (2) dining out, (3) socializing with friends, (4) volunteering, (5) exercise, and (6) recreational travel, all of which were derived from ELSA questionnaire responses.

In this study, the same questions were posed to participants in the registration, allowing each individual to be assigned to the most similar group identified in Carney and Kandt ’s model. The main process involved recoding the survey responses into scores for the six activity domains, which were then standardized to z-scores based on the mean and standard deviation of all ELSA samples of each domain from Carney and Kandt (2022). Subsequently, the Euclidean distance to each cluster centre was calculated, and each participant in our study was matched to one of the original OOH clusters.

This matching approach offers a significant advantage, as it leverages the insights from the ELSA dataset to provide a more representative grouping of older people in England. Relying solely on T&T survey data for clustering could introduce higher bias due to limited sample size. The six clusters were further consolidated into three broader groups: Extensive, Selective, and Limited OOH participation group (Table 2). The term ‘Limited’ refers only to the level of engagement in out-of-home activities. It should not be automatically interpreted as the result of resource constraints; rather, it may also reflect individual lifestyle preferences and voluntary choices.

This simplification better supports meaningful analysis and comparison. Table 2 also provides the Expected number based on the proportion of different OOH clusters in Carney and Kandt (2022). Overall, participants of the Extensive group are over-represented, while those of the Selective and Limited groups members are under-represented. This is an expected outcome given the over-representation of more educated and younger groups, which have been found to pursue OOH activities more extensively. Further results on groups’ sociodemogrpahics characteristics is provided in the Appendix (Table A1).

Fig. 2 uses radar plots to display the participants in the three groups and their average z-scores in each OOH domain. Higher scores, represented by points further from the centre, indicate greater engagement and intensity in OOH activities. The Extensive group shows high z-scores across all domains, reflecting broad participation. The Selective group demonstrates high scores in entertainment visits and dining out, but lower scores in volunteering and exercise. In contrast, the Limited group exhibits low scores across most domains, indicating minimal participation in various OOH activities.

3.3. *Construction of mobility motifs*

A motif is a directed network (graph), and in the context of this study, the nodes in the motif represent visited locations, while directed edges (links) represent journeys (Su et al., 2021a,b; Schneider et al., 2013). The T&T app records the journey diary of each participant through a continuous period. To construct motif representations from the data, we used the origin and destination locations of each journey as nodes and connected nodes with directed edges if there is a trip between them.

A series of one-day mobility motifs are split based on 4 a.m., which means that all journeys departing between 4:00:00 a.m. on one day until 3:59:59 on the following day are summarised for analysis for one day. Since we captured the mobility behaviours for a continuous 84 days (12 weeks), each day for the individual is then converted to a mobility motif. For example, if an individual conducted a typical grocery shopping journey and a return journey on a given day, then a network with two nodes (home, grocery shop) and bidirectional edges between them depicts the daily mobility pattern of the person (Su et al., 2021a,b). This method is applied to each individual for each day in the T&T data. In many studies, to make most of the motif analysis and identify the key motifs, loop journeys (same origin and destination) are generally discarded (detailed discussion on this choice can be found in Su et al., 2021a,b), except for the case that only one loop journey is made in the whole day.

Fig. 3 shows an example of a mobility motif involving three nodes and two bidirectional links. It should be noted that the motif does not account for the sequence of the journey; hence, if the Home–Park and the Home–Mall bi-directional links are swapped in order, the motif remains the same. This is not a shortcoming; on the contrary, this level of abstraction is beneficial (Su et al., 2020) for identifying key mobility behaviours and allows similar patterns to be effectively grouped and analysed together.

To gain further insight into travel patterns, the origin and destinations within each motif node were categorized based on their type. Drawing on existing literature (Carney and Kandt, 2022; Yang et al., 2023) and the characteristics of the data, nine location categories were identified and recoded, as outlined in Table 3. Understanding these location types can offer a clearer perspective on journey purposes and the activities associated with each destination, thereby enriching the analysis of mobility behaviours and motifs.

4. Results

The matching and classification of participants into three groups facilitate a comparison of their travel patterns. T&T dataset further offers detailed journey information for insight on mobility behaviours and can serve as a resource for validation of the classification.

Fig. 4 presents box plots illustrating the total journey counts and journey counts by purpose across the three groups. The Extensive group shows the highest total journey count, with a median of 260, followed by the Selective and Limited groups, which have median values of 214 and 137, respectively. This pattern indicates that the Extensive group engages in more frequent travel activities overall.

Table 2
Clusters and group allocation.

OOH clusters	Number of participants matched	Expected number[a]	Recode OOH Group	Combined Number of participants	Expected number[a]
Extensive participation	17	7	Extensive	26	14
Extensive participation with low volunteering	9	7			
Selective engagement - Volunteering	1	7	Selective	12	18
Selective engagement – Travel and Eating out	11	11			
Low level of engagement and visiting friends	3	7	Limited	5	11
Low level of engagement	2	4			

[a] based on Carney and Kandt (2022), samples aged 50 and over.

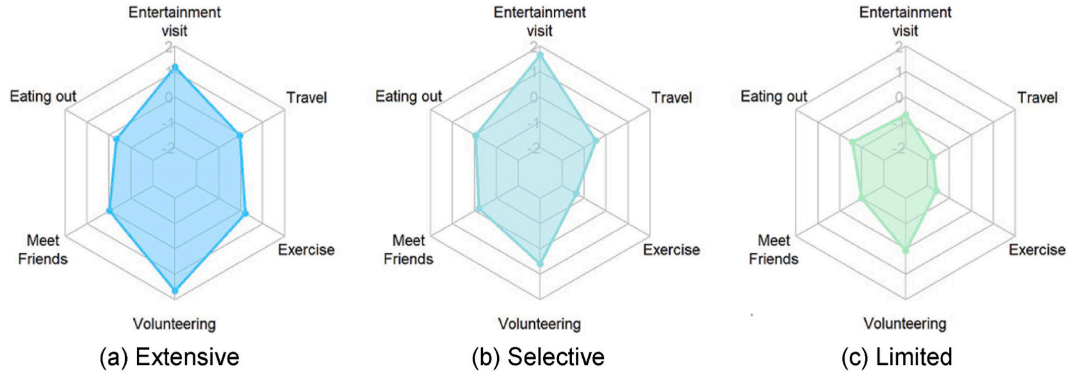

Figure: 2. OOH activity profile of clusters among participants.

Person ID	Origin ID	Destination ID	Origin Type	Destination Type	...
16	A	B	Home	Park	...
16	B	A	Park	Home	...
16	A	C	Home	Mall	...
16	C	A	Mall	Home	...

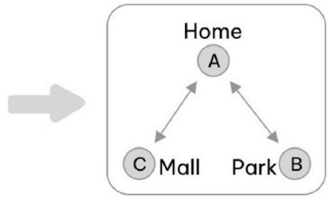

Fig. 3. Daily mobility motif example.

Table 3
Recoded categories of location types.

Recoded Category	Explanations and example OSM place tags
Home	Home is identified based on the individual's most frequent overnight stay location
Other residential	Care home, Hotel, Residential (other than home)
Shopping – Grocery	Supermarkets, Convenience shop, Marketplace, Butcher Shop
Shopping – Other retail	Toy shop, Shoe shop, Jewellery shop
Service and Appointment	Hairdresser, Pharmacy, Bank, Hospital, Petrol station, Recycling centre, Car wash
Entertainment Visit	Museum, Theatre, Cinema, Concert Hall, Gallery, Stadium, Exhibition centre
Leisure	Park, Recreation ground, Bowling alley, Theme Park, Canal, Forest, Garden, Pub, Social Club, Community Centre
Eating out	Restaurant, Fast food, Cafe
Other	Any other types and OSM tags, including for example, NA, place, church, university, industrial building, unclassified area (OSM), building

When examining specific activities, a notable trend emerges in entertainment visits. The Extensive group demonstrates a higher frequency, with a median of 4.5 over the study period and a broader range of engagement, as indicated by a higher third quartile. In contrast, the Selective group shows a lower frequency, while the Limited Group exhibits a narrow interquartile range and a lowest median value of 1.5, reflecting their minimal participation in entertainment OOH activities.

For eating out, a different trend is observed, with the Selective group leading in frequency. This aligns with the defining characteristics of this group, as many of its members belong to the "Selective Engagement – Travel and Eating Out" cluster identified by Carney and Kandt (2022). The finding highlights the distinct preferences of each group and supports the validity of their classification.

In addition to the above OOH activities, grocery shopping frequency was also analysed. As shown in Fig. 4, there is a clear decline in median grocery shopping frequency from the Extensive to the Limited Group. However, grocery shopping remains substantially more frequent than dining out or entertainment visits across all groups, highlighting its essential role in all daily life.

The Kruskal–Wallis test results (Appendix Table A2) indicated variation across groups. For total journey count, the p-value was close to the conventional 0.05 threshold ($p = 0.052$), with a moderate effect size ($\varepsilon^2 = 0.098$). This suggests some evidence of group differences in overall journey frequency, though weaker than for purpose-specific journeys. In contrast, journey counts by purpose showed clear group differences (all $p < 0.001$). The effect was small for eating out ($\varepsilon^2 = 0.026$) and grocery shopping ($\varepsilon^2 = 0.049$), while it was moderate for entertainment visits ($\varepsilon^2 = 0.076$). These results suggest that different group members were more strongly associated with variation in entertainment-related journeys, while differences in eating out and grocery shopping were more modest.

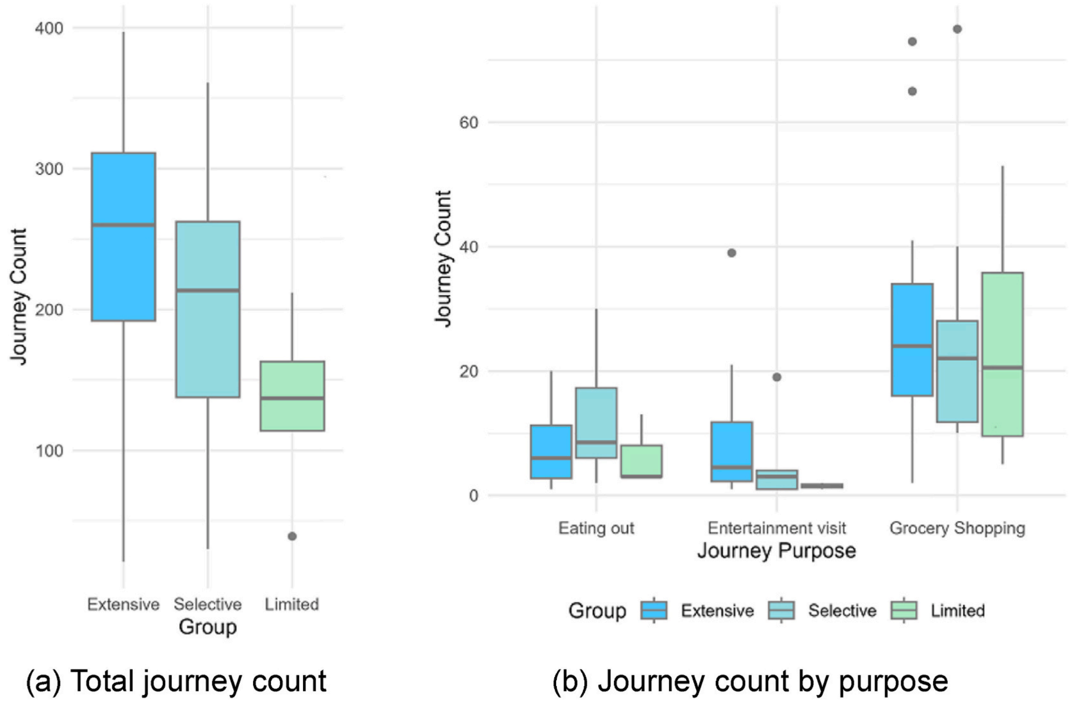

Fig. 4. Journey counts across OOH groups in T&T data.

4.1. *Journey rhythm*

Journey rhythm plots, visualized as heatmaps (Fig. 5), reveal the temporal patterns of journey behaviour. The x-axis represents the hours of the day (0–23), while the y-axis shows day type (weekday/weekend) with colour indicating the mean value of individuals' average journey departure frequency per day within hourly intervals. Higher journey activity is represented by brighter, more saturated yellow coloration.

Distinct temporal patterns emerge across the identified groups. The Extensive group demonstrates relatively uniform journey distribution across both weekdays and weekends, maintaining consistently high activity levels. In contrast, the Selective group exhibits a weekend-dominant pattern, with notably elevated activity during weekend midday periods.

The Limited group shows the lowest levels of journey activity (Fig. 5). Additionally, this group is less likely to have journeys in the early morning for example start between 6 and 7 a.m. Their overall travel is minimal, reflecting their reduced mobility and travel participation compared to the other two groups.

To sum, the Extensive group's consistent activity implies higher mobility and greater flexibility in making journeys, which would allow them to participate in a wide range of activities throughout the week. The Selective group's more focused travel may reflect a

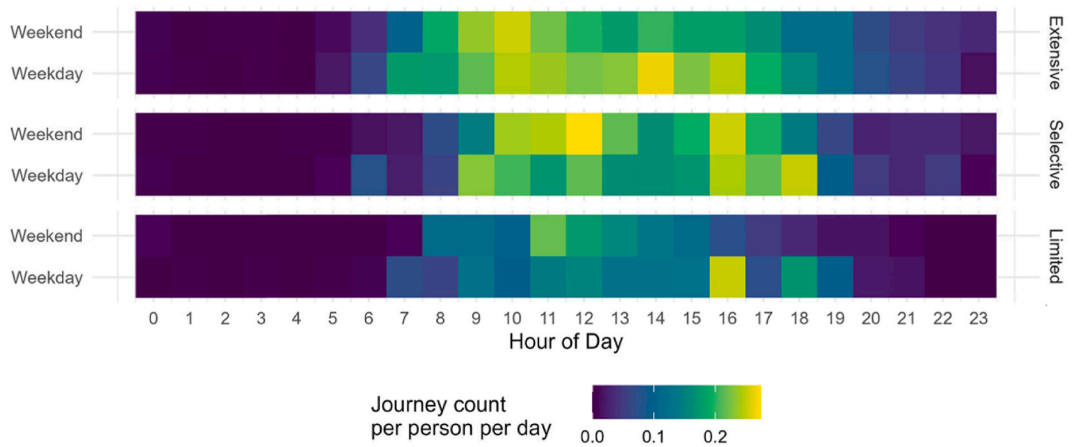

Fig. 5. Journey rhythm of journey departing time across groups.

pattern of planned and purposeful journeys, indicating a relatively moderate level of mobility. In contrast, the Limited Group's minimal travel activity highlights constraints in mobility and limited opportunities to engage in out-of-home activities.

4.2. Mode share

To better understand the travel patterns and choices of older people, Fig. 6 compares mode share based on the total travel distance covered using each mode. Mode share is calculated for each individual by dividing the total distance travelled using a particular mode by their total distance across all modes. The x-axis represents different modes, while the y-axis indicates the percentage of mode share by distance.

Car travel is the dominant mode across all groups. The Extensive groups show a median car mode share above 75 %, while the Limited group has a considerably lower median value, around 30 %, with a wider interquartile range. A notable difference appears in the use of public transport, particularly buses. The Limited group shows a higher median value, indicating greater dependence on bus, likely due to limited access to cars (as shown in Table A1 in the appendix) compared to Extensive group. Walking and cycling constitute only a small proportion of the total travel distance for all groups.

The presence of outliers in the Extensive and Selective groups in walking and bus indicates that, despite the heavy reliance on cars by most participants, some individuals have lower car usage.

Overall, the Extensive group tends to have the highest proportion of car travel, followed by the Selective and Limited groups. Conversely, bus usage is most prominent in the Limited group, reflecting its reliance on public transport. These findings highlight the distinct travel patterns, available options and preferences among the groups.

4.3. Mobility motifs patterns

Motif node count represents the number of places that an individual has visited/stayed in one day, and Fig. 7 presents the average frequency (per person) of node count in all identified mobility motifs in the study period. 0 node indicates a full day stay at one location (e.g. home), and in the study period of 84 days, the Limited group shows 34.6 days of 0 node days on average, greater than Selective (25.8) and Extensive (23.6) groups. When people do go out, the most common node count is 2, suggesting that staying in two distinct locations is typical among older individuals, and one of them is normally the individual's home. The Limited Group exhibits the highest frequency at 2 nodes, with an average of 28.0, followed by the Selective Group at 22.7 and the Extensive Group at 20.7.

The frequency distribution flattens considerably for node counts beyond 4 across all groups, indicating that only a small proportion of individuals visited 3 or more locations (excluding home) in a single day. For higher node counts (3 and above), the Extensive Group consistently demonstrates a greater frequency compared to the Selective and Limited Groups. Notably, at a node count of 8, only the Extensive and Selective Groups are represented, while at a node count of 9, only the Extensive Group is present.

Fig. 8 further illustrates the distribution of daily mobility motifs among different groups of participants when they made at least one journey (node count greater than 0). The x-axis categorizes motif types, with dashed lines indicating sections based on the number of nodes within each motif. The ordering on the x-axis follows a two-step logic: motifs with fewer nodes are placed on the left, and within

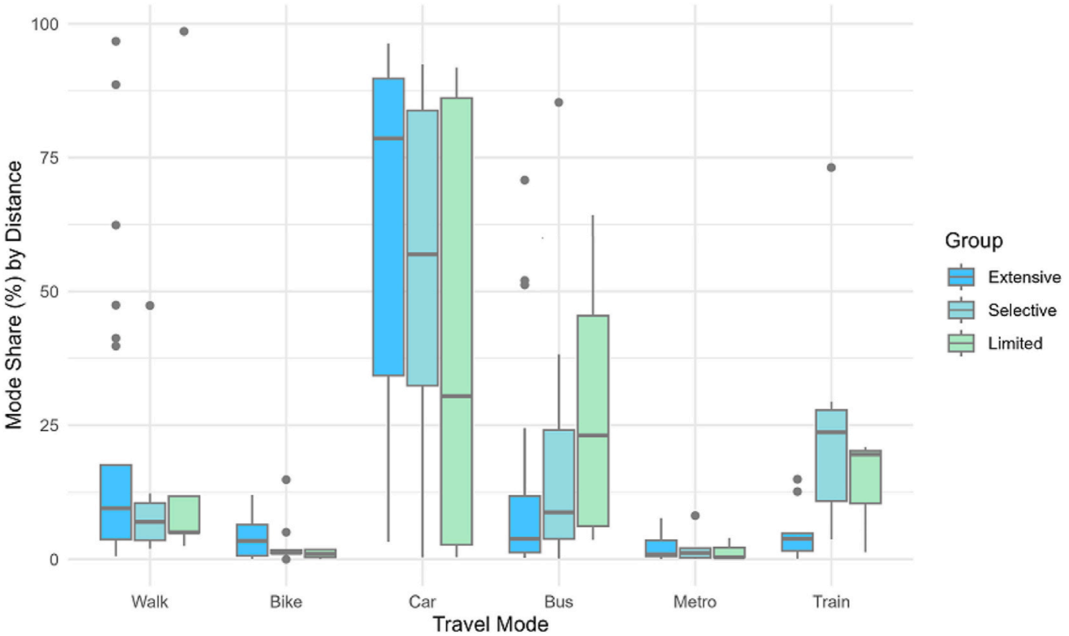

Fig. 6. Mode share by distance travelled.

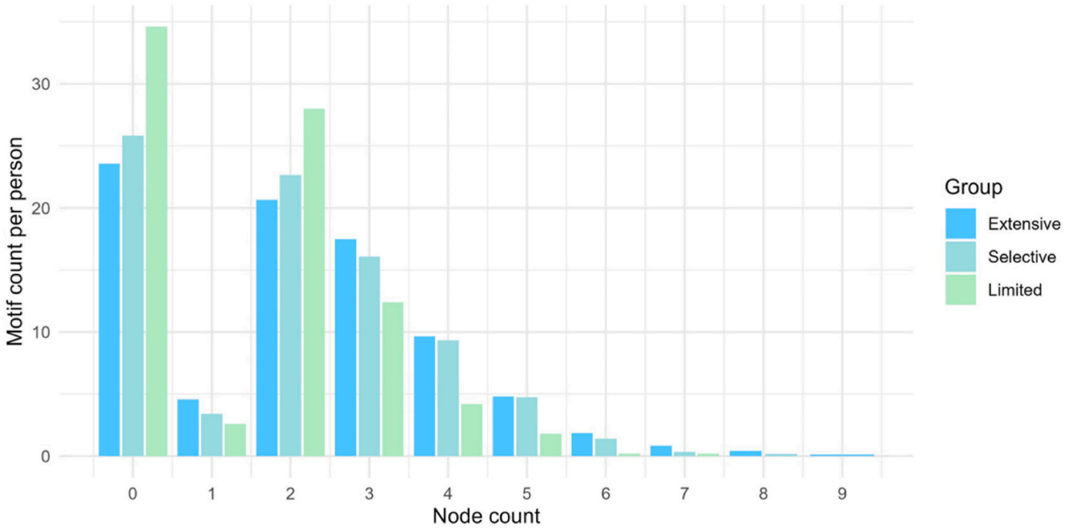

Fig. 7. Number of nodes in motifs and mobility profile count by group.

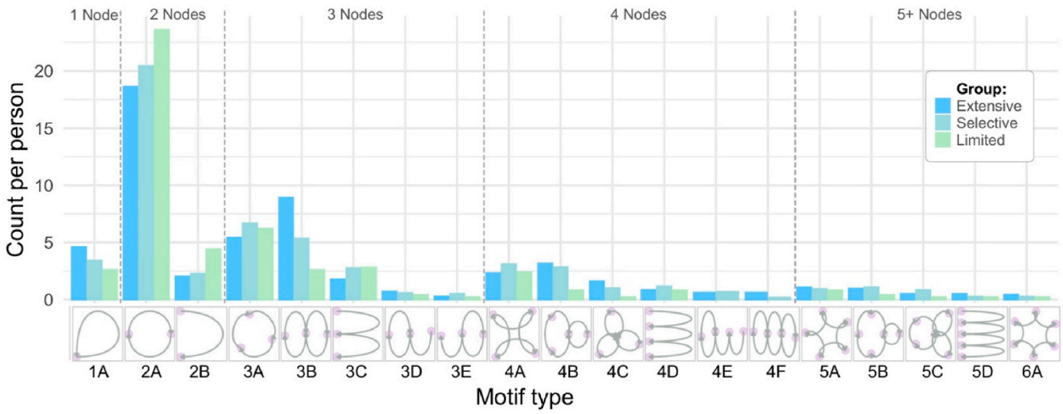

Fig. 8. Occurrence frequency of top 15 motif types for different groups of older people.

each node count, motifs with the highest sum of average frequency in each group are prioritised from left to right. The y-axis represents the average frequency per person, and the bars are shaded to indicate different groups.

The analysis identified 106 distinct motif types (excluding 0 node motif) from the daily mobility profiles when participants go out at least once. Fig. 8 highlights 19 unique motif types, derived from the 15 most frequent motif types in each group of older people. Together, these 19 motif types accounted for 92.2 % of the total frequency of all daily mobility profiles, while the remaining 87 motif types represented only 7.8 %.

A share of 6.9 % among identified daily motifs consists of single-node self-loops (motif 1A), primarily associated with home-to-home travel. Of these, 91.8 % occur at an individual's primary residence (home), with the remainder occurring in other residential locations (i.e. hotel, friends' or other family members' home). Activities related to 1A are primarily (over 80 %) associated with outdoor walking, likely for exercise or dog walking.

Motif 2A, characterized by two nodes with bidirectional links, is the most frequent motif, consistent with findings from previous studies by Lei et al. (2020), Cao et al. (2019), and Su et al. (2021a,b). This motif represents a simple round journey, where an individual leaves place (a) to visit place (b) and then returns to (a). the “Limited” group displayed the highest frequency of this motif, indicating a strong preference for this simple return journey chain.

Among the 3-node motifs, 3A, a circular motif with three unidirectional edges, has the highest average occurrence sum in all groups, with average counts of 5.4, 6.6, and 6.2 for the Extensive, Selective, and Limited groups, respectively. 3B, characterized by two bidirectional edges, occurs at an average frequency of 8.9 in the Extensive group, 5.3 in the Selective group, and 2.6 in the Limited group. While the frequency of 3A is similar across all groups, the Limited group shows a notably lower frequency of 3B. This suggests that when involving three locations, the Limited group tends to consolidate journeys, creating a chain of out-of-home activities to fulfil multiple tasks in a single outing. This pattern is also reflected in 4-node motifs, particularly in Motifs 4A, 4B, and 4C.

There are several motifs (e.g. 2B, 3C, 3D, 3E, 4D, 4E and 5D) where there is a node with the outgoing link (journey) but does not have the return link in a given day, which could happen when the individual does not return the first journey origin in the day, for example departing from home, and stay overnight elsewhere.

Fig. 9 provides a detailed breakdown of travel modes based on the number of nodes in a travel motif, focusing on the share of journeys by count rather than distance. Walking emerges as the dominant mode for single-node motifs, accounting for over 80 % of these journeys. However, as the number of nodes increases, the reliance on walking decreases notably, while the use of cars rises. This indicates a shift towards motorized transport (particularly cars) as travel patterns become more complex and involve multiple destinations. Moreover, the use of the metro and train remains consistently low across all levels of travel complexity in daily activities.

4.4. Attributed motifs

Examining the distribution of motifs provides valuable insights into older people's travel behaviour from a topological perspective. By differentiating motifs based on node attributes (Ma et al., 2024), it becomes possible to further understand the heterogeneity in lifestyle and travel choices among people. The chord diagrams in Fig. 10 illustrate participants' origin-destination (OD) patterns, focusing on several most frequent motif types. The segments represent various types of destinations, while the arcs between segments show the flow of journeys from one type of destination to another. The thickness of these arcs indicates the frequency of travel between the OD pairs.

In most diagrams, “Home” (HM) consistently appears as the central node, dominating the flow of journeys to and from other types of locations. Grocery shopping and services or appointments are among the popular destination types. This suggests that older adults’ travel needs are often associated with essential and utilitarian activities, such as purchasing food and attending medical or other necessary appointments. Leisure is also another important OOH activity, as evidenced by its large sections across most motif types in Fig. 10.

When the motifs involve at least three nodes and exhibit a one-directional circular structure, such as in 3A, 4A, and 5A, the flow into grocery shopping tends to be diverse, with journeys originating from multiple other types of locations, such as leisure site and food venues. This suggests that older people in this motif may combine grocery shopping with other activities, creating a more integrated mobility pattern. This behaviour reflects a strategy to maximize efficiency and convenience, likely to minimize travel burdens and optimize daily schedules.

In contrast, motifs featuring “bridge” nodes, such as 3B, 4B, and 5C, display fewer but thicker flows compared to motifs with the same number of nodes, such as 3A, 4A, and 5A. Additionally, the larger home section in 3B, 4B, and 5C suggests that home serves as an anchoring point, with individuals leaving and returning home for a single or simpler purpose in each outing. These motifs (3B, 4B, and 5C) are considerably less frequent among the Limited group (Fig. 8).

Fig. 11 compares the chord diagrams for motif 3A and 3B across the groups. Both motifs consist of three nodes, but their link structures differ. 3A is characterized by three unidirectional links, indicating that there is no return to an adjacent node within a single day. In contrast, 3B features two bidirectional links, suggesting that individuals return to a “bridge” node during the one-day travel, the “bridge” can be home or any other type of location.

For 3A (Fig. 11), the Extensive and Selective groups demonstrate a diverse range of visits, characterized by a relatively balanced distribution among destinations such as other residences, grocery shopping, other retail, and entertainment activities. In contrast, the Limited group shows a notably higher proportion of visits to service and appointment locations, which are typically utilitarian purpose. They rarely visit other residential areas or entertainment venues. This pattern suggests that daily travel within this motif for

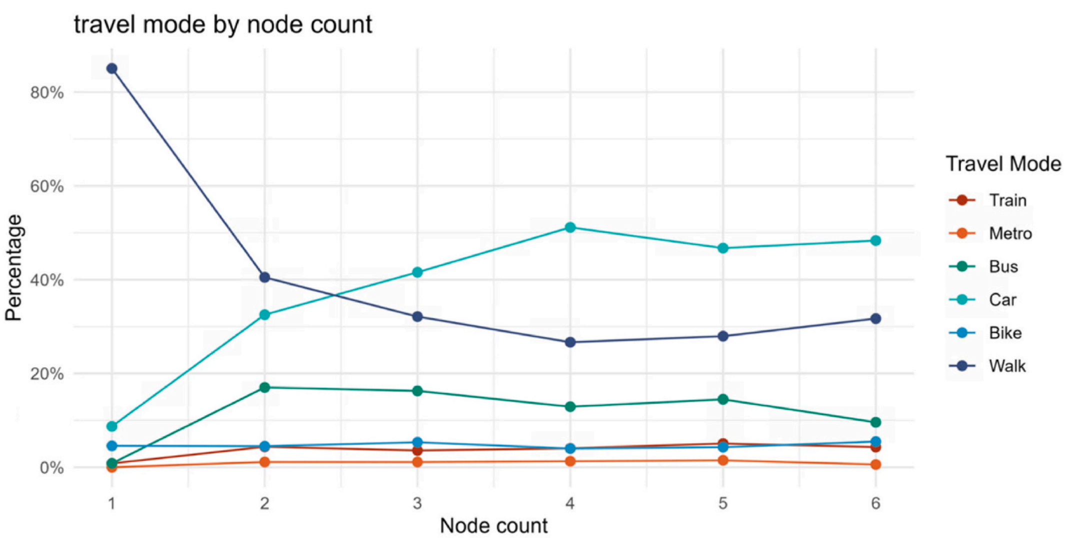

Fig. 9. Travel mode share by motif node count.

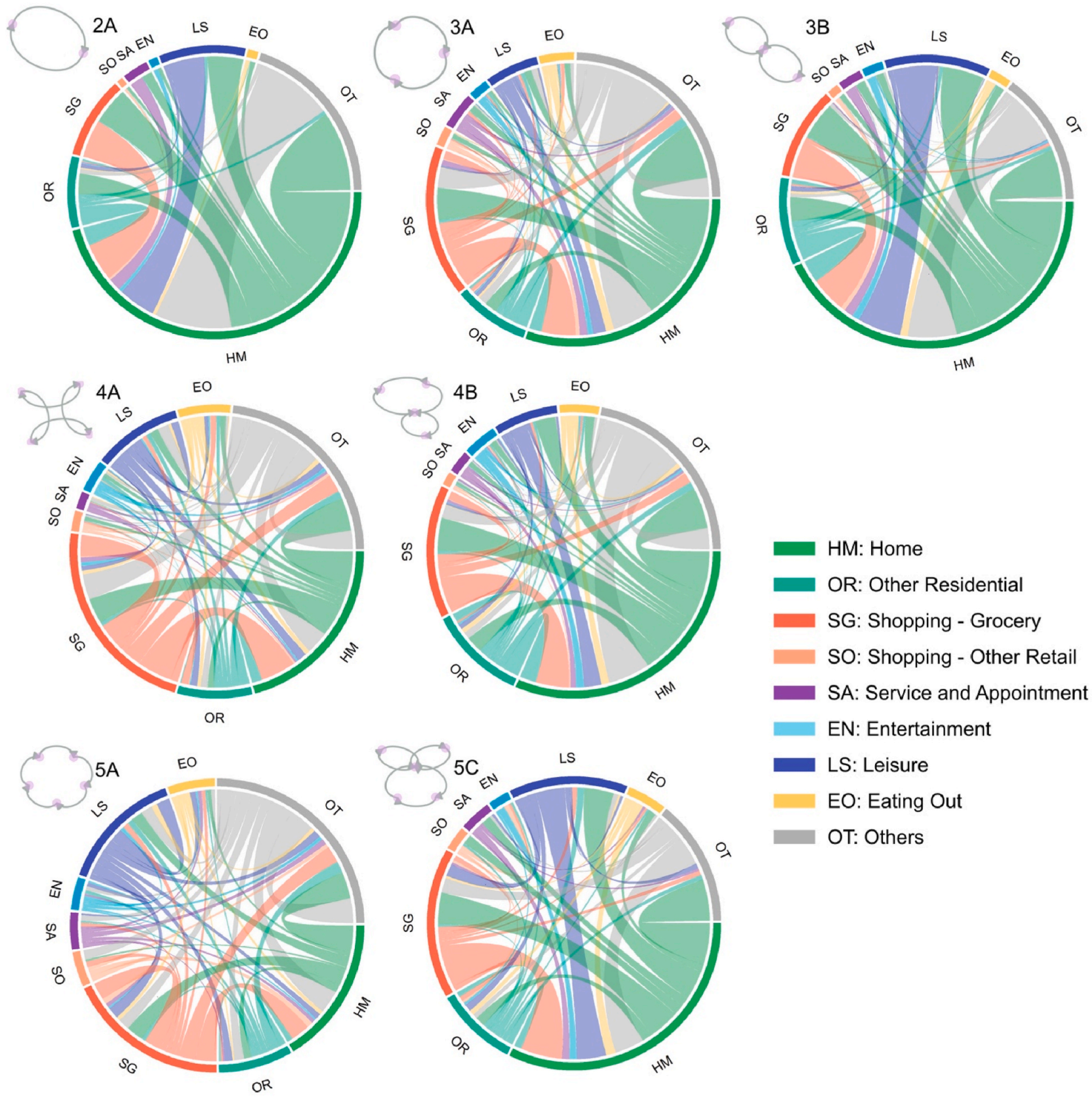

Fig. 10. Chord diagram for different motifs.

individuals in the Limited group contributes less to social engagement and well-being, as it lacks connections related location types and oppotunities.

For 3B (Fig. 11), the Limited group again exhibits a higher proportion of utilitarian journeys. The Selective groups display a distinct and evident flow between Eating Out and Other Residential locations, a pattern that is either absent or weak in the other groups. This implies that dining venues may play a key role in facilitating social interactions with family and friends for the Selective groups. In the Extensive group, leisure journeys primarily originate from and return to home, indicating that home serves as the anchor point, and leisure visits are often standalone journeys, with individuals returning home afterwards rather than combining leisure with other visits (for motif 3B type 5). A similar trend is observed with journeys related to service and appointments across all three groups, where these activities are typically isolated from other visits.

5. Discussion

The Extensive and Selective groups demonstrate greater engagement in diverse OOH activities, which indicates that they are more

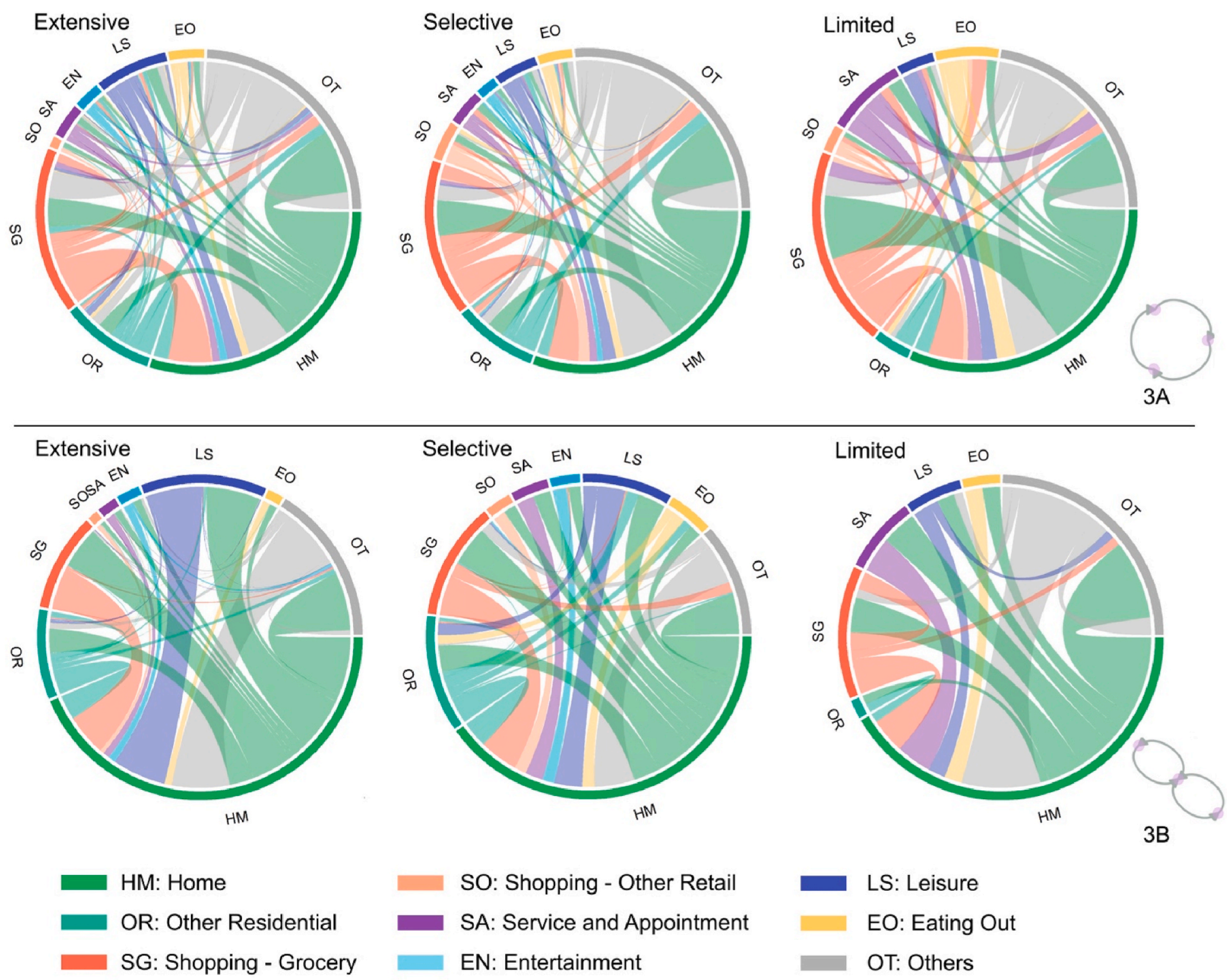

Fig. 11. Chord diagram for the three groups of older people regarding motif 3A and 3B.

able to access and participate in various social, leisure, and utilitarian journeys. This broad range of activities is associated with higher levels of social interaction and overall well-being, as these individuals can better maintain connections with friends, family, and their community through frequent outings. The presence of flows between destinations such as dining venues and other residences suggests the importance of public and commercial spaces in facilitating social interactions for these groups. These findings align with existing literature on the positive impact of diverse travel patterns on social connectivity and well-being among older people (Carney and Kandt, 2022).

Older people in the Limited group may face mobility barriers that limit their access to (and potentially willingness to engage with) various activities and venues, other than only grocery shopping and service appointments. These barriers could include limited transportation options, reduced physical capacity, or socio-economic factors restricting access to leisure and other activities. Addressing these barriers through targeted interventions, such as enhancing transportation accessibility or offering tailored support to help them navigate more complex travel routes to access a wider range of destinations, could encourage engagement in activities that promote greater well-being, rather than a predominant focus on utilitarian journeys.

Analysing mobility motifs may help planners to specify some of the characteristics associate with ‘age-friendly’ cities that have been debated in recent years (Davern et al., 2020, Plouffe and Kalache, 2010; van Hoof and Marston, 2021). For example, the motifs suggest which facitilies may be helpfully co-located to allow easier access in line with older people's daily routines, such as adding green space for leisure purpose closer to grocery shops and service and appointment type of locations. By strategically locating amenities, resources, and services based on these patterns, planners can create more opportunities for older people to engage with in their daily lives, enhancing their overall quality of life. In addition, improving pedestrian accessibility between nearby amenities along with the provision of age-friendly street facilities, such as benches near key destinations, may encourage more frequent visits and facilitate movement across different types of destinations for more mobility-restricted groups (Klicnik and Dogra, 2019). This aligns with the WHO Global Age-friendly Cities guide (World Health Organization, 2007), which highlights the importance of fostering local social relationships, creating opportunities for neighbours to meet, and ensuring that older people feel integrated and safe within their communities.

Despite the widespread availability of free public transport through concessionary travel cards, a key limitation of conventional modes such as buses is their inability to provide door-to-door service, which can be essential for completing more complex mobility motifs. This limitation may particularly affect those who have physical or cognitive challenges, which make the use of public transport less feasible or attractive (Sun and Lau, 2021). With advancements in digital technology and automation, there may be potential to support more complex travel needs (Golant, 2019; Klicnik and Dogra, 2019; Shrestha et al., 2017) and potentially enable those categorized as Limited OOH group to engage in more diverse and spontaneous journeys for purposes other than primarily on essential or utilitarian activities – although factors contributing to the digital divide among older people need to be addressed (Carney and Kandt, 2022; Li, 2023b).

There may also be opportunities in adjusting public transport services. Motif 2A (e.g., home–destination–home journeys) is most prevalent among the Limited group (Fig. 8), who show higher bus dependency (Fig. 6) and concentrated travel during specific time windows (Fig. 5). Improving public transport (bus) schedules to better align with the Limited group's temporal patterns could be particularly helpful, especially by focusing on mid-morning departures (09:30–11:00) and early afternoon returns (14:00–16:00), as shown in Fig. 5. In future scenarios where autonomous taxi/bus become available and affordable, similar targeted services could also be designed to accommodate the temporal travel needs of this group, offering more flexible, demand-responsive mobility options that complement traditional public transport (Golant, 2019).

Another significant implication of this research is the identification of 19 key motifs that account for up to 92.2 % of all daily travel patterns among participants. These dominant motifs and their frequency distributions provide valuable insights for simulation models aimed at replicating older people' daily travel behaviours. By converting these motifs into a list of potential travel sequences and probability of travel mode choice, modelers can develop more realistic agent-based or network models. For example, the differentiation of older people into specific groups allows for the creation of various agent types, which may simplify the model design while still accurately capturing essential differences in personal characteristics and mobility behaviours. Yet, in view of the novelty of such a modelling approach, requirements would need to be carefully specified and tested. Additional input parameter may include transition probabilities between motifs across consecutive days, duration distributions at different location types and distance decay functions for journey legs (Prédhumeau and Manley, 2025; Bastarianto et al., 2023). These could be derived from other travel surveys (Prédhumeau and Manley, 2025) or through further analysis of the data collected in this work, but such analysis lies beyond the present scope of this study. Further work is needed to fully understand the value and possibilities of incorporating mobility motifs into transport models.

While Su et al. (2021b) analysed single-day travel diaries of older people, the 12-week continuous tracking in this study reveals motif stability and variation over extended periods. The longer observation window makes it possible to distinguish habitual patterns from occasional deviations. This is further strengthened by linking our participants to more stable out-of-home profiles that have been identified from a national sample. By contrast, short-term studies may conflate temporary behaviour with enduring routines and have not always been able to find methods to link their sample to broader mobility patterns that can be found in the entire population. Such limitations may reduce the value of existing track-and-trace studies for long-term transport planning.

This study has several limitations that should be addressed in future research. First, the sample size is small and is subject to self-selection, which can limit the generalisability of the findings. These two sources of bias restricts the diversity of travel behaviours observed among older adults. Although this study collected data for a significantly longer duration (84 days) than other GPS-logger based research for older people (e.g. generally 7–14 days, some may extend to 28 days, as discussed in Chung et al., 2021) to allow more motifs emerges, having more participants has the potential to enrich diversity of motifs. We sought to address this issue by linking participants to representative out-of-home activity profiles, which allows us to assess the extent of over and under-representation of mobility patterns. Future studies should consider larger, more diverse or boosted samples for underrepresented groups, such as the Limited group, to strengthen the robustness and external validity of the findings.

Second, using a 24-h period as the temporal unit for dividing mobility profiles is relatively arbitrary. Although it is less likely for many older people to travel at 4 a.m., this cutoff may still create artificial breaks in continuous journey chains, potentially leading to missing or fragmented information about longer journeys or activities that extend beyond the time point. This limitation could hinder the accurate reconstruction of comprehensive mobility patterns and impact the interpretation of older adults' travel chains.

Additionally, the T&T data were obtained from participants' smartphones. This approach unfortunately excludes individuals who do not use smartphones, which may systematically underrepresent older people who are less digitally inclined. As this "digitally left behind" group may face greater challenges in social engagement (particularly through the internet), the findings should be interpreted with caution and not overly generalized. Future research should explore alternative data collection methods to include individuals with lower levels of digital literacy. Moreover, the motif construction ignores the self-loop links, although is the common practice in mobility motif analysis and considered as a necessary and practical approach (Su et al., 2021a,b), it might mask some interesting patterns in the travel patterns. Furthermore, the questionnaire does not collect information on the reasons for engaging or not engaging in out-of-home activities, we are unable to directly attribute activity levels to either resource constraints or voluntary lifestyle choices.

Despite these shortcomings, our study reveals a diversity of directly observed mobility patterns, which are derived from the app rather than "compiled" based on users' reporting. This approach, when linked to a representative sample, can provide a basis for a more accurate understanding of complex mobility patterns over short and long time frames.

6. Conclusion

This study highlights the diversity in older people's travel behaviours and emphasises the importance of targeted interventions to improve mobility and social engagement among vulnerable groups. This study blends traditional survey data with new forms of data

(T&T) for mobility behaviour analysis and leverages the motif analysis to identify and compare the key recurring travel patterns. Nineteen motifs are identified that can cover 92.2 % of daily travels networks among the participants. Linking these motifs to broader contextual information provides valuable insights that can inform policy and planning efforts that aim to promote 'age-friendly cities' and support older people's social connectedness, well-being and quality of life.

CRediT authorship contribution statement

Yuanxuan Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yanis Boussad:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Jens Kandt:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Babak Mehran:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Ed Manley:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Susan Grant-Muller:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix

Table A1 presents several key sociodemographic differences between the three OOH groups. The Extensive group is characterized by younger age, higher annual household income, better car access, and better self-reported health. These trends, when compared to the other groups, are overall consistent with the findings of Carney and Kandt (2022) using the ELSA data sample.

The Limited group consists predominantly of older people with lower household income, poorer car access, and generally worse self-reported health compared to the other groups. Additionally, 3 out of 5 participants in the Limited group are aged 65 or older, the highest proportion among the three groups. The Selective group generally falls between the Extensive and Limited groups across many variables, however, the proportion of living in one-person household is the lowest (3 out of 9). It is also important to note that due to the small sample size, particularly in the Limited group, some of the distributions may be distorted.

Table A1
Sociodemographic differences across OOH groups

Variable	Categories	Extensive (*n*)	Selective(*n*)	Limited (*n*)
Age	55–64	17	6	2
	65+	9	6	3
Gender	Female	8	2	1
	Male	18	10	4
Annual Household Income	Above 38001	9	5	1
	25,001-38000	8	2	1
	15,000–25,000	4	2	1
	Less than 15,000	2	1	2
	Prefer not to say	3	2	0
Car Access	No	6	6	3
	Yes	20	6	2
Travel Card	No	15	5	3
	Yes	11	7	2
Health Status	Excellent or Very Good	18	6	2
	Good and Fair	8	6	2
	Poor	0	0	1
Limiting Long-Term Illness	No	25	8	4
	Yes	1	4	1
Live alone	No	16	9	3
	Yes	10	3	2

Table A2 provide the Kruskal test results on different journey counts. A limitation of this study is the relatively small sample size, which reduces the statistical power of the Kruskal–Wallis test. As a result, the null hypothesis may be more easily retained, not necessarily because no true group differences exist, but because the test lacks sufficient sensitivity to detect them. This limitation should be taken into account when interpreting the results.

Table A2
Kruskal test on different journey counts

Journey counts	P-value	Effect size	Magnitude
Total	0.0522	0.09760	moderate
Journey count – eating out	<0.0001	0.0260	Small
Journey count – entertainment visit	<0.0001	0.0758	moderate
Journey count – Grocery shopping	<0.0001	0.0491	small

Table A3
Questionnaire survey questions and response options

Survey Questions	Response options
What is your gender identity?	• Male, • Female, • Prefer to self-describe • Prefer not to say.
What is your age? Select the appropriate band	• 55–59 years • 60–64 years • 65–69 years • 70–74 years • 75–84 years • 85 and older • Prefer not to say
Do you have a concessionary travel card for public transport?	• Yes • No
Do you have a valid driving license?	• Yes • No
Do have access to a car/van or other motorized vehicle you could drive for your own travel (regardless of whether you own it or not)?	• Yes • No
How many people are in your household, including yourself? [By "household" we mean "people who live together and share at least some financial resources" (housemates/roommates are usually not considered members of the same household).]	• 1 • 2 • 3 • 4+
Choose the category that contains your approximate 2022 annual household income before taxes. [By "household" we mean "people who live together and share at least some financial resources" (housemates/roommates are usually not considered members of the same household)]	• Less than 15,000 • 15,000–24,000 • 25,000–37,000 • 38,000–50,000 • 51,000–75,000 • 76,000–99,000 • 100,000–124,000 • 125,000–150,000 • >150,000 • Prefer not to say
How would you describe your health generally?	• Excellent, • very good, • good • Fair • poor
Do you have any long-term illness, health problem or mobility issue which limits your daily activities or how you choose to travel? (include problems due to old age)	• Yes • No • Prefer not to say
Think of the year prior to the pandemic: On average, how often did you visit any of the following: the cinema, theatre, concerts, operas, museums or art galleries?	• Twice a month or more • About once a month • Every few months • About once or twice a year • Less than once a year • Never
On average, how often did you eat out of the house?	• Twice a month or more • About once a month • Every few months • About once or twice a year • Less than once a year • Never
On average, how often did you meet up with friends?	• Three or more times a week • Once or twice a week • Once or twice a month

(continued on next page)

Table A3 (*continued*)

Survey Questions	Response options
	• Every few months • Once or twice a year • Less than once a year or never
How often did you volunteer through a group, club or organisation?	• At least once a week • Less than once a week but at least once a month • Less often • One-off activity • Never
On average, how often did you undertake light exercise?	• Weekly • Less than that or never
On average, how often did you undertake moderate exercise?	• Weekly • Less than that or never
On average, how often do you undertake vigorous exercise?	• Weekly • Less than that or never
Did you take any day trips?	• Yes • No
Did you take any holidays elsewhere in the country?	• Yes • No
Did you take any holidays abroad?	• Yes • No
How would you describe yourself?	• White • Mixed or Multiple Ethnic Groups • Asian or Asian British • Black, African, Caribbean or Black British • Any other Ethnic Group • Prefer Not To Say
What is your highest level of educational attainment?	• No formal qualifications • Formal education up to 18 years old • A Levels, BTEC – formal education up to 18 years old • College or technical diploma • University Degree (BSc, BA etc) • Graduate Degree (Masters, MPhil, PhD) • Foreign or other • Prefer not to say
Choose the option that best describes your current or most recent job.	• Professional occupations such as: accountant, solicitor, medical practitioner, scientist teacher, nurse, physiotherapist, social worker, welfare officer, artist, musician, police officer (sergeant or above), civil or mechanical engineer or software designer • Clerical and intermediate occupations such as: secretary, personal assistant, clerical worker, office clerk, call centre agent, nursing auxiliary or nursery nurse • Senior managers or administrators (usually responsible for planning, organising and co-ordinating work and for finance) such as: finance manager or chief executive • Technical and craft occupations such as: motor mechanic, fitter, inspector, plumber, printer, tool maker, electrician, gardener or train driver • Semi-routine manual and service occupations such as: postal worker, machine operative, security guard, caretaker, farm worker, catering assistant, receptionist or sales assistant • Routine manual and service occupations such as: HGV driver, van driver, cleaner, porter, packer, sewing machinist, messenger, labourer, waiter or waitress, or bar staff • Middle or junior managers such as: office manager, retail manager, bank manager, restaurant manager, warehouse manager or publican • Never had a job

Data availability

Data will be made available on request.

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