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How spatial fixity of individual daily activities evolves in the long-term: A life course and multi-scale behavior explanation

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ABSTRACT

Spatial fixity, measuring the extent to which individual activities are confined to specific locations, is central to geographical studies on daily activities. Although recent studies have identified factors contributing to the variability of daily activity spatial fixity, there is a dearth of longitudinal observations to understand its evolution over extended timeframes. Addressing this research gap, the study introduces a framework that integrates multi-scale individual behaviors to investigate the long-term evolution of peoples daily activity spatial fixity, offering insights from a life course perspective. Using mobile phone data of 290,679 individuals across different age groups, the study assessed changes in their activity patterns from October 2019 to October 2020 and from October 2019 to May 2023. Three major findings were derived from Difference-in-Difference modeling and behavior grouping: (1) Individual daily activity spatial fixity exhibit a U-shaped distribution with age, revealing the 30–34 age group with the lowest fixity. Consistent levels of spatial fixity are observed as time progresses and individuals transition into specific age stages. (2) The multi-scale behavior framework elucidates over 40 % of the variation in daily activity spatial fixity over one and four-year intervals, and the result highlights the significance of integrating higher-scale behavioral dynamics over extended period. (3) Distinct behavioral change trends before and after the age of 35 result in the U-shaped curve of spatial fixity evolution. The study advances our comprehension of the long-term dynamics of human mobility. The findings provide valuable insights for enhancing individual behavior modeling, addressing delays in demographic data collection, and informing targeted social policies.

1. Introduction

While a large body of current research reveals the increasing mobility of urban residents, related studies also find that the set of spaces in which individuals perform their daily activities is to some extent fixed. The concept of spatial fixity constraints in daily life, which bind activities to specific places, has long been recognized as a key area of interest for geographers (Kwan, 1998; Weber and Kwan, 2002). The concept is also primary in transportation and urban planning practice, as it delimits the opportunities for individuals to engage in various activities and influences their accessibility to specific facilities (Kim & Kwan, 2003; Ren et al., 2014). Indicators of spatial fixity are playing integral roles in travel modeling (Rasouli & Timmermans, 2014; Yoon et al., 2012; Zhang et al., 2024), activity forecasting (Alexander et al., 2011; Chen & Kwan, 2012; Ren et al., 2014), social inequality measurement (Chen & Yeh, 2021b), and other significant research areas.

However, the spatial fixity of individual daily activities may change over time. Recent seminal studies on human mobility have demonstrated that individuals constantly exploit a small set of repeatedly visited locations in the short term, but the location set undergoes a gradual and partial replacement after a longer period of time spanning several months (Alessandretti et al., 2018; Pappalardo et al., 2015). This implies a subtle evolutionary process concerning individual daily activities when considered over an extended period. In light of this, the extant knowledge on the spatial fixity of daily activities, predominantly derived from observations at the daily (Schneider et al., 2013; Su et al.,

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2020) or weekly (Gonzalez et al., 2008; Shen et al., 2015) time scales, may be biased. The regularities observed in the studies can be time-sensitive, thereby posing challenges to their broader application.

Previous research has identified a variety of factors contributing to the variability of daily activity spatial fixity, spanning different spatial and temporal scales (Chen & Kwan, 2012; Chen & Yeh, 2021a; Savcisens et al., 2024; Schneider et al., 2013; Shen et al., 2015; Winata, 2024; Zhou et al., 2021). This means that individuals' current activities are not simply a consequence of their everyday routines, as higher-level behavioral changes—such as home relocations, job changes, variations in work flexibility, and multi-location living—coming to the fore when extending the research timeframe (Alessandretti et al., 2020; Ellegård & Vilhelmson, 2004). However, these fragmented findings were primarily drawn from cross-sectional comparisons or observations of selective groups. The collective impact of multi-scale constraints and their progressive manifestation over time remain poorly understood. This also impedes a comprehensive grasp of the long-term dynamics of daily activity spatial fixity.

The aim of this study is to establish an analytical framework that integrates long-term behavioral changes at various scales, thereby enhancing our understanding of the evolutionary process of daily activity spatial fixity. To achieve this goal, we introduce the life course perspective, which delineates an individual's biography from birth to death as an age-graded sequence of roles, opportunities, constraints, and events (Alwin, 2012). The age stratification framework allows for a continuous understanding of the nature of human lives and the processes of individual behavioral changes. Through life course analysis, the research aims to elucidate how multi-scale behavioral changes progress with age and ultimately lead to the evolution of their daily activity spatial fixity. The results will enrich our understanding of human mobility in long-term contexts and provide guidance for monitoring the population's daily activity dynamics, as well as for promoting people-oriented urban planning and governance.

2. Research context

2.1. Space-time fixity of daily activity and its variability

The fixity concept stems from Hägerstrand's time geography framework, where a person's activities are characterized as fixed or flexible to distinguish whether they are spatially or temporally modifiable (Hägerstraand, 1970). The binary distinction notion was later developed into a self-rated or objectively measured fixity index to reveal the extent to which the person's activities are confined in space and time (Miller, 2018; Schwanen et al., 2008). The fixity of activities can be both spatial and temporal. Activities with higher fixity have a higher priority in the daily schedule and act as pegs around which other activities are planned, while activities with lower fixity are fragmentarily distributed in space and time (Alexander et al., 2011; Schwanen et al., 2008). Typically, the objective fixity index is obtained by measuring the degree of variation in when and where activities occur over a certain time-span (Kim & Kwan, 2003). Hence, the fixity index actually reflects the individual's activity preferences over the recent period.

In recent studies, the spatial and temporal dimensions of activity fixity have been examined separately, revealing that they are not entirely synchronized. Spatial fixity, which has garnered significant attention in geography and urban studies, has been found to be more variable and sensitive to changes in the built environment (Chen & Yeh, 2021a). Moreover, it is believed that the rise of digital life presents additional challenges to the spatial fixity effect (Shen et al., 2020). The evolution of spatial fixity may warrant increased scrutiny and attention.

It's generally believed that the fixity of people's daily activities varies with the roles they play in the family and society. Household and childcare responsibilities are crucial factors imposing spatial and temporal fixity on daily activities, especially for women (Schwanen et al., 2008; Zhou et al., 2015). Older adults may become isolated as their activities become increasing confined to the home (Frantál et al., 2020). Studies have compared the fixity of activities among people with different occupations, and their general conclusion is that individuals on the higher occupational ladder tend to have more sovereignty over activity time and space (Breedveld, 1998; Liao et al., 2013; Winata, 2024). Although there is less direct discussion on the long-term changes of activities, the above studies indicate that the fixity of individual activities may evolve with their role transitions.

2.2. Daily activity spatial fixity governed by multi-scale behavior patterns

Spatio-temporal behavioral studies seek to explain the spatial fixity of individuals' daily activities by examining their behavior patterns. It's commonly assumed that people's everyday routines define their space-time constraints in activities. People who follow a simple 'home-work-home' routine are highly fixed to the two anchor points, and those with lower spatial fixity exhibit more complex activity sequences (Lu et al., 2021). Some studies have also identified the potential types of individual activity sequences and have revealed their relationships with spatial constraints (Huang & Li, 2016; Lu et al., 2023; Shen & Cheng, 2016; Wilson, 2008). These studies focus on people's diurnal activity patterns, but people can maintain regular activities over multiple days. For example, a case study in Wuhan, China found that while people have a primary residence and workplace each day, about 25 % of the population maintain alternate residences or workplaces that are visited regularly (Zhou et al., 2021). Similar multi-day visit patterns were also observed in other cities around the world (Breedveld, 1998; Su et al., 2020; Wang et al., 2021). In these studies, despite individuals having constant activity sequences, they may visit varied locations on different days, which complicates the spatial fixity of their daily activities. Recent research, however, has uncovered that individual activity patterns are also influenced by behaviors that unfold over much larger time scale spanning multiple years. During these periods, individuals may experience changes in their living environment and job-housing relationships that can reshape their activity patterns, as well as their everyday routines and regular activity arrangements (Ren et al., 2014). For example, relocation to more densely populated areas or city centers tends to enhance the flexibility of daily activities (Chen & Yeh, 2021a; Schwanen et al., 2008).

A hierarchical framework is commonly used to integrate multi-scale behavioral patterns. Earlier time geography studies have assumed that an individual's current activities are embedded within and constrained by a nested hierarchy of local orders, where orders at lower spatial and temporal scales are subject to those at higher scales. Therefore, individual activities occur within 'pockets of local orders' (Hägerstrand, 1985). This concept elucidates how people's spatio-temporal behaviors are shaped by constraints imposed by daily routines, work regulations, and broader social norms that operate at different time scales. People's current activities are not only determined by the immediate situation but are also governed by activity patterns at broader scales (Ellegård, 2018; Ellegård & Vilhelmson, 2004). Sharing a similar viewpoint, Alessandretti et al. (2020) propose that day-to-day human mobility is constrained by a series of spatial containers that exhibit nested scales. Their nested scale model is able to generate highly realistic trajectories without overfitting. And focusing on the hierarchical structure of tourism behaviors, a recent study has developed a cross-scale approach to represent tourists' travel trajectories. Their approach has also shown enhanced effectiveness in explaining the evolution of tourist activity spaces (Chen et al., 2023). These studies provide a solid foundation for constructing a hierarchical framework to elucidate current individual activity patterns, however, there is an ongoing need for a nuanced design to explore the dynamics of multi-scale behavioral changes among individuals. The right-hand side of Fig. 1 provides a schematic representation of how the spatial fixity of individuals' current activities is shaped by three hierarchical scales of behavioral changes. On the cross-year scale, individuals may experience changes in their living

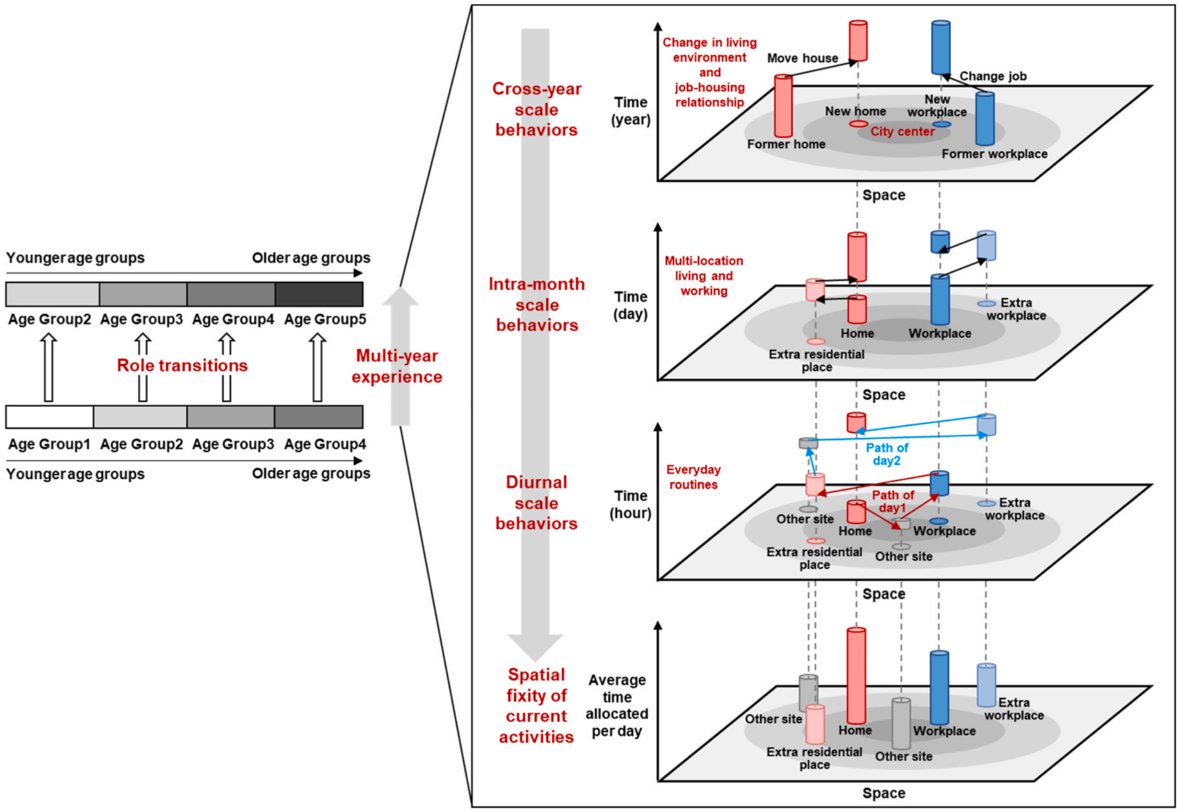


Fig. 1. The life course and multi-scale behavior framework to examine daily activity spatial fixity.

environment and job-housing relationships as they relocate their homes or workplaces. As illustrated in the top spatio-temporal frame in the right part of Fig. 1, individuals may move to locations closer to the city center (as indicated by darker shaded circles) and pursue closer job-housing distances after several years, or the opposite. As a direct consequence, the way they allocate their time to home and workplace is subject to evolve. On the intra-month scale, people may maintain extra residential or workplace locations that they visit on various days (as illustrated in the middle spatio-temporal frame). This multi-location living and working pattern amplifies the variability of individuals' residential and occupational sites. On the diurnal scale, individuals can maintain a repertoire of activity sequences that are performed alternately (as illustrated in the lower spatio-temporal frame). Everyday routines dictate their time allocation across a broader array of activity sites beyond their residential places and workplaces. Therefore, the spatial fixity of people's current activities, indicated by the variation in time allocated across different activity sites (as illustrated in the bottom spatio-temporal frame), is regulated by the three scales of behavioral changes.

2.3. *The life course perspective to understanding long-term behavioral changes*

The term 'life course' has a breadth of interpretations. Alwin (2012) offers an integrated framework particularly within the realms of aging and human development. This framework posits that aging refers to changes to individuals that occur over time, and people's life course is an age-graded sequence of roles, opportunities, constraints, and events, lasting from birth to death. Therefore, the process of aging involves a series of role transitions and corresponding behavioral changes (Alwin, 2012). Research on life courses of large population samples has revealed that the life trajectories of individuals within the same ethnic group may exhibit an *interlocking structure*. This implies that the social and familial roles assumed by populations at each age group are relatively stable, and individuals advancing from one specific age stage to the next undergo similar role transitions. When viewed from a collective perspective, people's life courses are interlocking (Hu & Zheng, 2022). Hence, long-term human behaviors can be examined within an age stratification-life course framework that incorporates historical and biographical time. The long-term changes in individuals' behaviors are thus attributed to role transitions that occur at specific historical periods and age stages. As illustrated in the left part of Fig. 1, the horizontal arrows indicate the progression of age groups from younger to older, while the vertical arrows represent the passage of time over multiple years. Over time, everyone ages and progresses from one age group to the next (as indicated by the darker-shaded squares). Alongside this aging process, populations within each age group experience specific role transitions. We assume that these age-group-specific role transitions can explain the multi-scale behavioral pattern changes in individuals. Therefore, by integrating the life course and multi-scale behavior perspectives, the framework is expected to provide explanations for people's long-term behavioral changes. Moreover, comprehending the multi-scale behavioral patterns across different age groups enables us to anticipate potential behavioral shifts in subsequent life stages, leveraging the interlocking structure of population life courses.

2.4. *Research questions*

Existing research on the spatial fixity of daily activities has recognized its variability among different populations but has not sufficiently investigated its long-term changes within individuals. Recent studies suggest that variations in the spatial fixity of an individual's current activities stem from changes in multi-scale behavioral patterns. The role transition perspective within the life course framework could potentially explain these changes. Thus, we introduce a framework that integrates individuals' life courses with multi-scale behaviors to examine the long-term evolution of their daily activity spatial fixity. To be specific, the study addresses the following questions: (1) How does the spatial fixity of daily activities evolve over time for people at different age stages? (2) Can changes in people's multi-scale behaviors explain the evolution of their daily activity spatial fixity? (3) How do these changes unfold over people's life courses?

3. Data and method

3.1. Study area and data set

We conduct a case study in Guangzhou, China, to demonstrate the efficiency of the proposed analytical framework. As one of China's nine national central cities, Guangzhou possesses a robust economic growth and favorable conditions in education and healthcare, effectively catering to the life needs of its residents throughout their life course. From 2010 to 2023, the permanent population of Guangzhou increased from 12.7 million to 18.8 million, indicating a substantial influx of individuals seeking long-term development opportunities. These characteristics make Guangzhou an appropriate case for life course research.

To investigate individuals' daily activities, we employ an anonymized mobile phone dataset provided by a major mobile communication service supplier in China, which holds approximately 30 % of the market share in Guangzhou. The data originates from signal exchanges between users' mobile phones and cell towers. The data providers have located users' real-time positions with an accuracy of 250 m, based on the cell towers that captured the user signals and the relative strength of those signals. The data also encompasses basic individual attributes, including gender and age.

As discussed in the literature review, individuals' habitual daily activities remain stable only for a certain period, after which they start to change. Specifically, a span of 3–8 weeks serves as the time frame during which individuals can maintain a relatively stable set of preferred locations (Alessandretti et al., 2018; Pappalardo et al., 2015). Therefore, from the long-term individual mobility data, we selected three one-month segments to investigate the spatial fixity of individuals' habitual daily activities within these segments. To examine the effect of changes in individuals' age stages, we set two long-term intervals: one year, during which the majority of people had not yet transitioned to the next age group, and four years, during which most individuals had entered the next 5-year-segmented age group. Specifically, we focused on data collected in October 2019, October 2020, and May 2023, months in which no COVID-19 cases were reported in Guangzhou.

To mitigate the influence of irregular activities during weekends and holidays, we focus on the workday activities of individuals aged 19 to 64. This age range is commonly regarded as the working-age population in demographic studies in China (Shen et al., 2018; Tong et al., 2021). We identified individuals' longest-stayed locations during the period from 22:00 to 5:00, which is typically associated with rest and sleep, as their residences. Additionally, locations where individuals had an average daily total stay duration exceeding 3.5 h between 10:00 and 17:00, accounting for more than half of the primary working hours, were identified as their workplaces. This criterion has also been employed in other studies to identify individual residences and workplaces (Gonzalez et al., 2008; Lu et al., 2021). Since each mobile user registers a unique identity ID, this enables us to continuously track and identify individuals who have remained in Guangzhou over multiple years. To track individuals' activities across multiple years, we filtered the data to include only users who were present at both their residence and workplace in each of the three periods and who exhibited movement on at least nine out of seventeen consecutive workdays per month. After applying these filters, the data of 290,679 individuals was retained for subsequent analysis. The sample exhibits a higher prevalence of males and individuals aged below 30 compared to the 2020 Census of Guangzhou, yet the overall distribution is consistent (see Table S1 in Supplementary Materials for detailed information).

3.2. Methodology

(1) Measure spatial fixity of individual daily activities

We commence the daily activity analysis by identifying primary activity sites where individuals stay continuously for over 30 min. Individuals were identified to have a daily average of 4.1 primary activity sites in October 2019, 4.0 in October 2020, and 4.4 in May 2023, across workdays. Aligning with previous studies used similar criteria (Alessandretti et al., 2018), our analysis indicated that the majority of travels were made among the top six sites with the most extended dwell times each month, representing 96 % in October 2019, 97 % in October 2020, and 89 % in May 2023. Accounting for this, we examine the daily activity spatial fixity among the top six stayed sites for each individual.

We examine people's daily activity spatial fixity by quantifying the variability of their activity locations as indicated in previous fixity research (Kim & Kwan, 2003; Schwanen et al., 2008). A Spatial Fixity Index (SFI) is introduced as follow:

$$SFI = 100 \times \left(1 - \frac{\sum_{i=1}^{n} p_i \bullet \ln\left(\frac{1}{p_i}\right)}{\ln(n)}\right) \tag{1}$$

where n represents the number of locations visited by an individual during each month of the three years, p_i is the percentage of time spent at site i during the month. This index is inversely related to the commonly used entropy index and is standardized to a range from 0 to 100, where higher index values indicate greater spatial fixity in daily activity. If individuals spend their time equally across all activity sites throughout the month, they get a 0 SFI. If they spend all of their time at a single activity site, they get a 100 SFI.

(2) Identify multi-scale behavioral changes

We introduced a series of categorical variables to measure whether individuals experienced specific behavioral changes from October 2019 to October 2020 and May 2023. On the cross-year scale, we examine the relocation of individuals' residences and workplaces. We identified the longest-stayed residential and workplace locations as individuals' homes and primary workplaces during each of the aforementioned three periods. On this basis, two categorical variables were derived. The first variable assesses whether individuals' homes were relocated 2 km or more (exceeding the conventional walking distance) closer to the city center, moved 2 km or further away, or remained within a 2 km range, categorized as HM_Center, HM_Suburb, and HM_NoChange, respectively. Given that Guangzhou is a highly populated monocentric city, we define the city center as the location of the population center of gravity. If individuals relocate their homes away from the city center, this is considered a movement towards the suburbs. The second variable measures whether the distance between individuals' homes and primary workplaces has increased, decreased, or remained constant (also taking 2 km as a threshold) with CD_Increase, CD_Decrease, and CD_NoChange.

On the intra-month scale, we examine changes in the number of residences and workplaces of individuals during each period. One variable measures whether the number of residences within one month increased, decreased, or remained the same, with categories R_Increase, R_Decrease, and R_NoChange. Another variable measures similar changes in the number of workplaces, with categories W_Increase, W_Decrease, and W_NoChange.

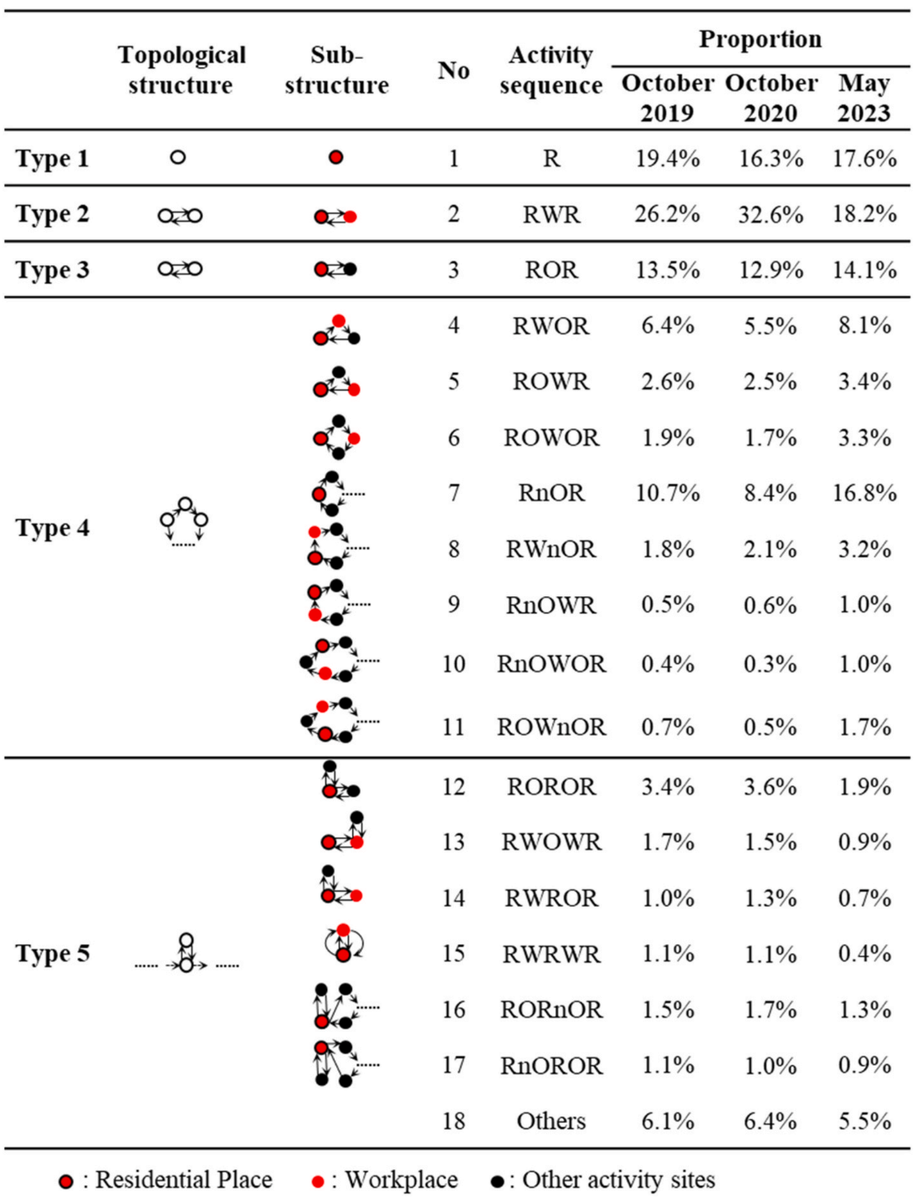
On the diurnal scale, we examine changes in people's activity sequence. We assigned three labels to people's activity sites: R for residential place, W for workplace, and O for other places. In this way, a person's daily activity sequence is represented as a chronological series of labels. For instance, a sequence of RWR indicates that an individual starts and ends the day at the residential place, with a period of work in between; A sequence of RWnOR signifies that after starting at the residential place and working, the individual visits n (n $\geq$ 2) additional activity sites before returning to the residential place. We categorized the variety of daily activity sequences into five distinct types based on the topological structure of their activity networks (Schneider et al., 2013). As illustrated in Fig. 2, Types 1, 2, and 3 correspond to the sequences R, RWR, and ROR, respectively. Type 4 is characterized by a loop structure sequence that includes at least three distinct activity sites, each visited once, with the residence acting as both the origin and the destination. Type 5 represents a repetitive visit sequence where one of the activity sites functions as a central hub, revisited multiple times throughout the day. Based on the daily activity sequence representation, we also generated a variable to measure the changes in people's diurnal scale behaviors. The variable measures which type of activity sequence showed the most significant proportional increase. T1_Increase, T2_Increase, T3_Increase, T4_Increase, and T5_Increase denote that, over the years, the most significant proportion increase within individuals' monthly daily activities were observed in Type 1, Type 2, Type 3, Type 4, and Type 5 activity sequences, respectively. T_NoChange represents the proportions of each type of activity sequence remained stable over the years.

Table 1 shows the multi-scale changes from October 2019 to October 2020 and from October 2019 to May 2023, as measured by the variables we introduced. It is shown that a significant proportion of individuals experienced behavioral changes across various scales from October 2019 to October 2020. The proportion has further increased when the observation period is extended to May 2023.

(3) Examine the effect of age growth on people's daily activity spatial fixity

We use a Difference-in-Differences (DID) model to examine the effect of age growth at different stages on individuals' daily activity spatial fixity. The DID model evaluates the impact of a treatment or intervention by comparing the changes in outcomes over time between a treatment group and a control group. In this study, the transition through various age stages is treated as a sequence of interventions targeted at the respective age groups. The DID model is formulated as follows:

$$Y_{it} = \alpha + \beta T_{ij} + \gamma P_t + \delta (T_{ij} \times P_t) + \varepsilon C_i + \epsilon_{it} \quad (2)$$



	Topological structure	Sub-structure	No	Activity sequence	Proportion October 2019	Proportion October 2020	Proportion May 2023
Type 1			1	R	19.4%	16.3%	17.6%
Type 2			2	RWR	26.2%	32.6%	18.2%
Type 3			3	ROR	13.5%	12.9%	14.1%
Type 4			4	RWOR	6.4%	5.5%	8.1%
			5	ROWR	2.6%	2.5%	3.4%
			6	ROWOR	1.9%	1.7%	3.3%
			7	RnOR	10.7%	8.4%	16.8%
			8	RWnOR	1.8%	2.1%	3.2%
			9	RnOWR	0.5%	0.6%	1.0%
			10	RnOWOR	0.4%	0.3%	1.0%
			11	ROWnOR	0.7%	0.5%	1.7%
Type 5			12	ROROR	3.4%	3.6%	1.9%
			13	RWOWR	1.7%	1.5%	0.9%
			14	RWROR	1.0%	1.3%	0.7%
			15	RWRWR	1.1%	1.1%	0.4%
			16	RORnOR	1.5%	1.7%	1.3%
			17	RnOROR	1.1%	1.0%	0.9%
			18	Others	6.1%	6.4%	5.5%

●: Residential Place ●: Workplace ●: Other activity sites

Fig. 2. Representation of five types of daily activity sequence.

Table 1
Statistics of variables measuring multi-scale behavioral changes (October 2019 to October 2020 and October 2019 to May 2023).

Variables	October 2019 to October 2020	October 2019 to May 2023
Cross-year scale		
House move		
HM_Center = 1	13.9 % (n = 40399)	18.7 % (n = 54356)
HM_Suburb = 1	16.9 % (n = 49013)	26.6 % (n = 77277)
HM_NoChange = 1	69.2 % (n = 201267)	54.7 % (n = 159046)
Change in commuting distance		
CD_Increase = 1	23.7 % (n = 68775)	29.2 % (n = 84972)
CD_Decrease = 1	26.0 % (n = 75618)	39.8 % (n = 115628)
CD_NoChange = 1	50.3 % (n = 146286)	31.0 % (n = 90079)
Intra-month scale		
Change in residential place number		
R_Increase = 1	11.0 % (n = 31851)	29.3 % (n = 85097)
R_Decrease = 1	9.5 % (n = 27756)	7.6 % (n = 22158)
R_NoChange = 1	79.5 % (n = 231072)	63.1 % (n = 183424)
Change in workplace number		
W_Increase = 1	15.5 % (n = 45002)	34.5 % (n = 100211)
W_Decrease = 1	20.3 % (n = 58976)	13.6 % (n = 39668)
W_NoChange = 1	64.2 % (n = 186701)	51.9 % (n = 150800)
Diurnal scale		
Change in activity sequences		
T1_Increase = 1	13.7 % (n = 39957)	17.8 % (n = 51722)
T2_Increase = 1	38.9 % (n = 112961)	17.4 % (n = 50484)
T3_Increase = 1	6.4 % (n = 18560)	10.3 % (n = 29822)
T4_Increase = 1	19.9 % (n = 57944)	42.7 % (n = 124040)
T5_Increase = 1	20.2 % (n = 58614)	11.2 % (n = 32678)
T_NoChange = 1	0.9 % (n = 2643)	0.7 % (n = 1933)

where Y_{it} represents the Spatial Fixity Index (SFI) for individual i at period t. T_{ij} is a treatment effect variable, which equals 1 if individual i is in age group j, and 0 otherwise. P_t is a time effect variable, marking the post-intervention period t with 1 and the pre-intervention period with 0. $T_{ij} \times P_t$ is the interaction term between the treatment and time effect variable, which captures the DID estimate. C_i represents other control variables for individual i, ϵ_{it} is the error term. The DID model provides an estimation of the effect of age growth on spatial fixity, net of time-related interferences.

(4) Explain the temporal variation of people's daily activity spatial fixity with multi-scale behavioral changes

We explain the variations of people's daily activity spatial fixity from October 2019 to October 2020 and from October 2019 to May 2023 with their behavioral changes throughout the two periods. Considering that the SFI variations between the two periods exhibit typical normal distributions (see Fig. S1 in Supplementary Materials for detailed information), we use an analysis of variance to examine how the variations response to different behavioral change groups. The analysis of variance, often abbreviated as ANOVA, is a core technique for testing causality in life science and health research (Doncaster & Davey, 2007; Zhang et al., 2019). It decomposes the total variance of the response variable into two components: the variance between groups and the variance within groups. If the grouping effectively explains the response variable, then a larger proportion of the total variance will be attributed to the between-group variance (indicating that the mean value of each group represent the response variable well), with a smaller proportion left as the within-group variance, representing the unexplained part (Doncaster & Davey, 2007). Based on the variables in Table 1, individuals are divided into 486 distinct groups according to behavioral change combinations (3 × 3 × 3 × 3 × 6). Fig. 3 illustrates partial examples of the grouping process. It can be observed that the behavioral change grouping effectively reduces the within-group variance for the top 3 groups by individual count.

For each group, we determine a variance explanation rate to quantify the proportion of SFI variation explained by the grouping process:

$$VER_i = \frac{Var_0 - Var_i}{Var_0} \tag{3}$$

where VER_i is the variance explanation rate for group i, Var_0 is the variance of SFI variation of the total sample, Var_i is the variance of SFI variation of group i. Thus, the overall variance explanation rate can be calculated as:

$$VER_{overall} = \sum_{i=1}^{n} \left(\frac{N_i}{N} \times VER_i \right) \tag{4}$$

where $VER_{overall}$ is the overall variance explanation rate, N is the total sample size, N_i is the sample size of group i. The rate will be calculated for the variations between the two periods: from October 2019 to October 2020 and from October 2019 to May 2023.

The ANOVA grouping as illustrated in Fig. 3 reflects the collective effect of five behavioral changes. As we have discussed in the theoretical framework of the research context section, individual behaviors at

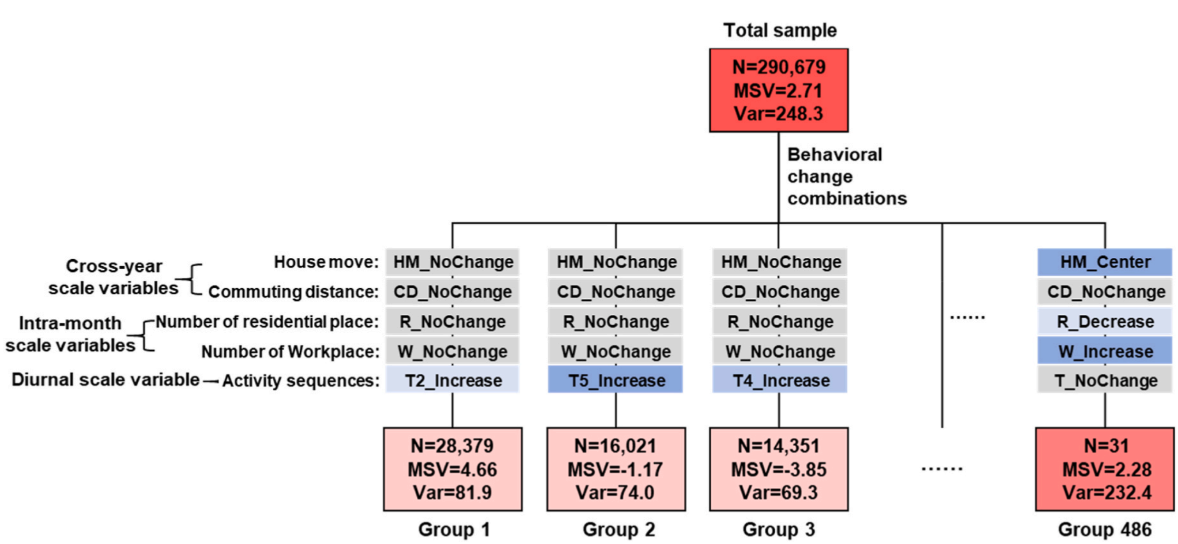


Fig. 3. SFI Variation from October 2019 to October 2020 for individuals with different behavioral change combinations (partial examples).
Note: N is the number of individuals, MSV is the mean value of SFI variation, Var is the variance of SFI variation, darker color in box represents greater variance. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

different scales influence each other and jointly determine people's daily activities. Therefore, we cannot isolate the contribution of each single behavioral change using simple linear models and control variable methods, as these variables may exhibit multicollinearity. To address this issue, we introduce a cooperative game theory method that can fairly allocate the contribution of each variable in the collective impact. The principle of the method is to consider all possible combinations of collective impacts among variables and calculate the marginal contribution of each variable in these combinations (Shapley, 1952). Based on the cooperative game theory method, we can use the Shapley Value to quantify the contribution of each single behavioral change in every behavioral change group:

$$\varphi_{x_i} = \sum_{S \subseteq N \setminus \{x_i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} \cdot [v(S \cup \{x_i\}) - v(S)] \tag{5}$$

where φ_{x_i} is the Shapley Value for behavioral change x_i. It represents the fair share of the contribution that x_i has on the SFI variation among all the five behavioral changes. N is the set of all behavioral changes. S is a subset of behavioral changes from N that does not include x_i. $v(S)$ is the mean value of SFI variation (MSV) of the behavioral change group delineated by S. $v(S \cup \{x_i\})$ is the MSV of the group delineated by S with x_i added. Therefore, $[v(S \cup \{x_i\}) - v(S)]$ represents the marginal effect produced by adding x_i to S. $\frac{|S|!(|N|-|S|-1)!}{|N|!}$ is a weighting factor. Here, $|N|$ is the total number of behavioral changes in each ANOVA group (which is 5 in this study), and $|S|$ is the number of behavioral changes in the subset S. The weighting factor ensures that the Shapley Value is calculated by averaging the marginal contributions of x_i over all possible orders in which variables can join the set.

Therefore, the average Shapley Value of each specific behavioral change can be calculated as:

$$\overline{\varphi_{x_i}} = \sum\nolimits_{j=1}^{n} \frac{N_{x_ij}}{N_{x_i}} \cdot \varphi_{x_ij} \tag{6}$$

where $\overline{\varphi_{x_i}}$ is the average Shapley Value of a single behavioral change x_i. φ_{x_ij} is the Shapley Value of behavioral change x_i in ANOVA group j, N_{x_i} is the total number of samples who exhibited behavioral change x_i, N_{x_ij} is the number of samples exhibited behavioral change x_i in group j. The Shapley Value inherently mitigates the effects of multicollinearity among variables. This is achieved by calculating the marginal contribution of each variable while averaging over all possible orders of variable inclusion. As a result, the Shapley Value provides a fair and comprehensive assessment of each variable's contribution, even in the presence of correlated features (Lipovetsky & Conklin, 2001). This method has been widely applied in contexts where the complex influence of multiple variables needs to be considered across various fields, such as financial risk assessment (Tarashev et al., 2016), climate change (Luqman et al., 2019), and medical diagnosis (Tang et al., 2021). The widely known SHAP (Shapley Additive Explanations) method also employs the same principle (Lundberg & Lee, 2017). The Shapley Value will also be calculated for the two periods: from October 2019 to October 2020 and from October 2019 to May 2023.

4. Results

4.1. *Long-term evolution of daily activity spatial fixity within different age groups*

The results of the DID model reveal how individual SFIs evolve from October 2019 to October 2020 and from October 2019 to May 2023 across different age groups. As shown in Table 2, males generally exhibit lower SFIs across all years. The age group variable coefficients reveal that in the baseline period (October 2019), individuals' SFIs exhibit a decline followed by an increase with advancing age, reaching the lowest pointing in the 35–39 age group (2.946 lower than the reference). The time effect variable's coefficients indicate a general increase in individuals' SFIs in October 2020 (by 5.166), suggesting that individuals may have proactively reduced the diversity of their activity locations due to the COVID-19 pandemic, even without local cases. In May 2023, SFIs generally decreased compared to October 2019. The time effect variable controlled for these temporal fluctuations. The coefficients of the DID estimates indicate the net changes in SFIs across age groups in October 2020 and May 2023, showing a further decrease compared to the reference group, with the 30–34 age group experiencing the most significant decrease.

Table 2
Variable coefficients of the DID model.

Variables	Coefficients	P>|t|
Intercept	52.979	0.000
Gender (male = 1), control variable	−1.848	0.000
Age group		
19–24 = 1	−1.495	0.000
25–29 = 1	−2.108	0.000
30–34 = 1	−2.428	0.000
35–39 = 1	−2.946	0.000
40–44 = 1	−2.908	0.000
45–49 = 1	−2.867	0.000
50–54 = 1	−2.377	0.000
55–59 = 1	−1.810	0.000
Reference (60–64 = 1)		
Time effect variable		
Post_period1 (month = October 2020)	5.166	0.000
Post_period2 (month = May 2023)	−3.219	0.000
Pre_period (month = October 2019)		
DID estimates		
Age group × Post_period1		
(19–24 = 1) × post_period1	−2.560	0.000
(25–29 = 1) × post_period1	−2.628	0.000
(30–34 = 1) × post_period1	−2.799	0.000
(35–39 = 1) × post_period1	−2.402	0.000
(40–44 = 1) × post_period1	−2.309	0.000
(45–49 = 1) × post_period1	−2.135	0.000
(50–54 = 1) × post_period1	−2.136	0.000
(55–59 = 1) × post_period1	−1.180	0.000
Reference (60–64 = 1) × post_period1		
Age group × Post_period2		
(19–24 = 1) × post_period2	−4.063	0.000
(25–29 = 1) × post_period2	−3.909	0.000
(30–34 = 1) × post_period2	−4.150	0.000
(35–39 = 1) × post_period2	−3.546	0.000
(40–44 = 1) × post_period2	−3.412	0.000
(45–49 = 1) × post_period2	−2.811	0.000
(50–54 = 1) × post_period2	−2.402	0.000
(55–59 = 1) × post_period2	−1.063	0.171
Reference (60–64 = 1) × post_period2		

Note: Age groups are based on individuals' ages in October 2019.

Fig. 4 intuitively presents the variations in SFI across different age groups over the years, as depicted by the cumulative coefficients. It's shown that the coefficients for the baseline period (October 2019) indicate a U-shaped distribution across age groups, with the 35–39 age group at the bottom. The distribution of the cumulative coefficients remained U-shaped in both October 2020 and May 2023, but it gradually shifted to the left. By May 2023, the age group with the lowest expected SFI had transitioned to the 30–34 age group. Since the age groups were determined based on individuals' ages in October 2019, the majority of individuals initially in the 30–34 age group would have entered the 35–39 age group by 2023. The findings actually indicate that the relative levels of SFI among age groups are constant, with the 35–39 age group consistently being the one with the lowest SFI. Consistent with the *interlocking structure* hypothesis of life course theory, similar behavioral changes are anticipated as individuals progress through successive age stages.

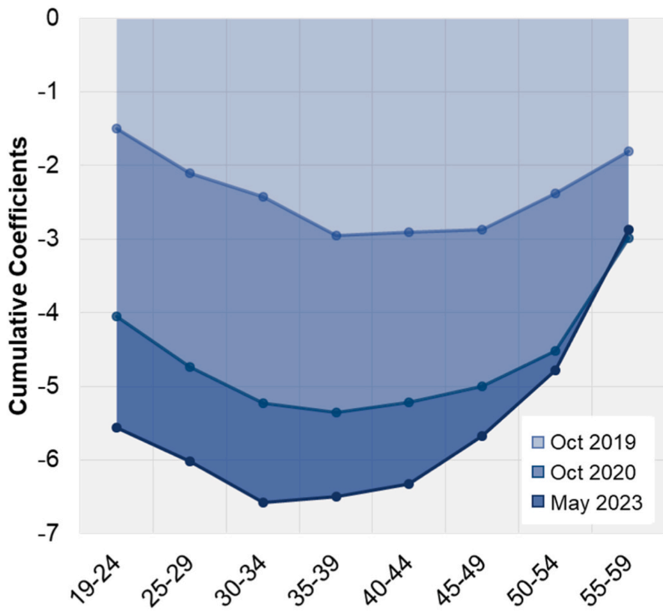


Fig. 4. Cumulative DID coefficients by age group: October 2019, October 2020, and May 2023.
Note: Age groups are based on individuals' ages in October 2019.

4.2. Multi-scale behavioral changes and daily activity spatial fixity variation

The temporal variation in individuals' daily activity spatial fixity across years is partly explained by their multi-scale behavioral changes. As shown in Table 3, the multi-scale behavioral change variables explain 49.0 % of the variance in SFI from October 2019 to October 2020 and 46.2 % from October 2019 to May 2023. We can also discern a shift in the variables predominantly influencing SFI variation with an increase in the time span. From October 2019 to October 2020, diurnal scale variables account for the largest proportion of SFI variation. And from October 2019 to May 2023, intra-month scale variables explain the most, with a significant rise in the proportion of SFI variation explained by cross-year scale variables. This highlights the importance of incorporating behavioral change variables at broader scales (Intra-month, Cross-year) rather than just at the diurnal level when examining the evolution of individual SFIs at extended timeframes.

Fig. 5 illustrates the contribution of each variable on SFI variation, measured by Shapley Values. Subfigures (A), (B), and (C) illustrate the contributions of each behavioral change to the SFI variation from October 2019 to October 2020, presented separately by scales. Subfigures (D), (E), and (F) display the analysis results of the variation from October 2019 to May 2023. It's shown that the increase in daily activity spatial fixity can be attributed to behavioral changes including reducing commuting distances, residing closer to the city center on the cross-year scale, maintaining fewer residential and workplace locations on the intra-month scale, and engaging in more Type 1 and Type 2 activity sequences on the diurnal scale. Conversely, a decrease in daily activity spatial fixity corresponds to behavioral changes including increasing commuting distances, residing further from city centers on the cross-year scale, maintaining a greater number of residential and workplace locations on the intra-month scale, and engaging in more Type 4 and Type 5 activity sequences on the diurnal scale. The above results clarify the specific behavioral changes that underline the evolution of the daily activity spatial fixity over one-year and four-year intervals. Based on these findings, we can trace the trajectory of SFI evolution throughout people's life courses by examining how their behavior patterns change through successive age stages.

Table 3
Performance of different scales of behavioral change variables in explaining SFI variation.

Variables introduced	Variance of SFI variation (ratio explained)	
	October 2019 to October 2020	October 2019 to May 2023
Null	248.3	426.7
Cross-year scale variables	242.3 (2.4 %)	390.8 (8.4 %)
Intra-month scale variables	195.7 (21.2 %)	356.7 (16.4 %)
Diurnal scale variables	190.9 (23.1 %)	363.9 (14.7 %)
Variables of all three scales	126.6 (49.0 %)	229.5 (46.2 %)

Note: The table presents the within-group variance sums for ANOVA groupings when considering behavioral change variables at individual scales and when considering variables across all three scales simultaneously. The ratios in parentheses indicate the proportion of variance explained relative to the Null model.

4.3. Behavioral changes in life course and daily activity spatial fixity evolution

As shown in Fig. 6, the differences in behavioral changes over one year and four years are primarily evident at the diurnal and intra-month scales. In October 2020, although no local COVID cases were reported, we can still observe that individuals reduced the diversity of their activity locations. A higher proportion of individuals adjusted their activity sequences to the simpler RWR type (indicated by a higher proportion of T2_Increase in Fig. 6C compared to others) and reduced visits to extra workplaces (indicated by a higher proportion of W_Decrease in Fig. 6B compared to others). However, by May 2023, the diversity of people's activity locations exceeded pre-pandemic levels. A higher proportion of individuals turned to loop-structured Type 4 activity sequences (indicated by a higher T4_Increase in Fig. 6F), which involve more activity locations and expanded the diversity of their workplace locations (indicated by a higher W_Increase in Fig. 6E compared to Fig. 6B). These changes in activity patterns explain why the SFI of individuals decreased in October 2020 and then increased in May 2023.

Individuals under the age of 35 exhibit unstable residence patterns and job-housing relationships, characterized by frequent house moves and changes in commuting distances (as shown by the lower proportions of HM_NoChange and CD_NoChange for the under 35 age groups in Fig. 6A). Their activity sequences also show a more significant response to the pandemic: from October 2019 to October 2020, a larger proportion of individuals under 35 adjusted their activity sequences to the most stable R and RWR types (indicated by higher proportions of T1_Increase and T2_Increase for the under 35 groups in Fig. 6C). By May 2023, the under 35 individuals had shifted to Type 4 sequences in the largest proportion (higher T4_Increase proportion for the under 35 groups in Fig. 6F), demonstrating a stronger rebound. Upon reaching the age of 35, individuals' primary residences and job-housing relationships tend to stabilize, with workplace diversity peaking (indicated by a higher proportion of W_Increase for the 30–34 age group than for all other age groups in Fig. 6E), making it the life stage with the lowest daily activity spatial fixity. This aligns with the widely observed '35-year-old effect' in Chinese society, where individuals often seek stable employment around the age of 35 to cope with the job market's preference for younger employees. After the age of 35, individuals' primary residences remain stable, but they tend to reduce their commuting distances (as indicated by higher proportions of CD_Decrease for the over 35 age groups in Fig. 6D), and increasingly adopt Type 1 (R) and Type 5 (repetitive visit) activity sequences (indicated by higher proportions of T1_Increase and T5_Increase for the over 35 age groups in Fig. 6F). This leads to a resurgence in their daily activity spatial fixity. Hence, the U-shaped distribution of daily activity spatial fixity observed across individuals'

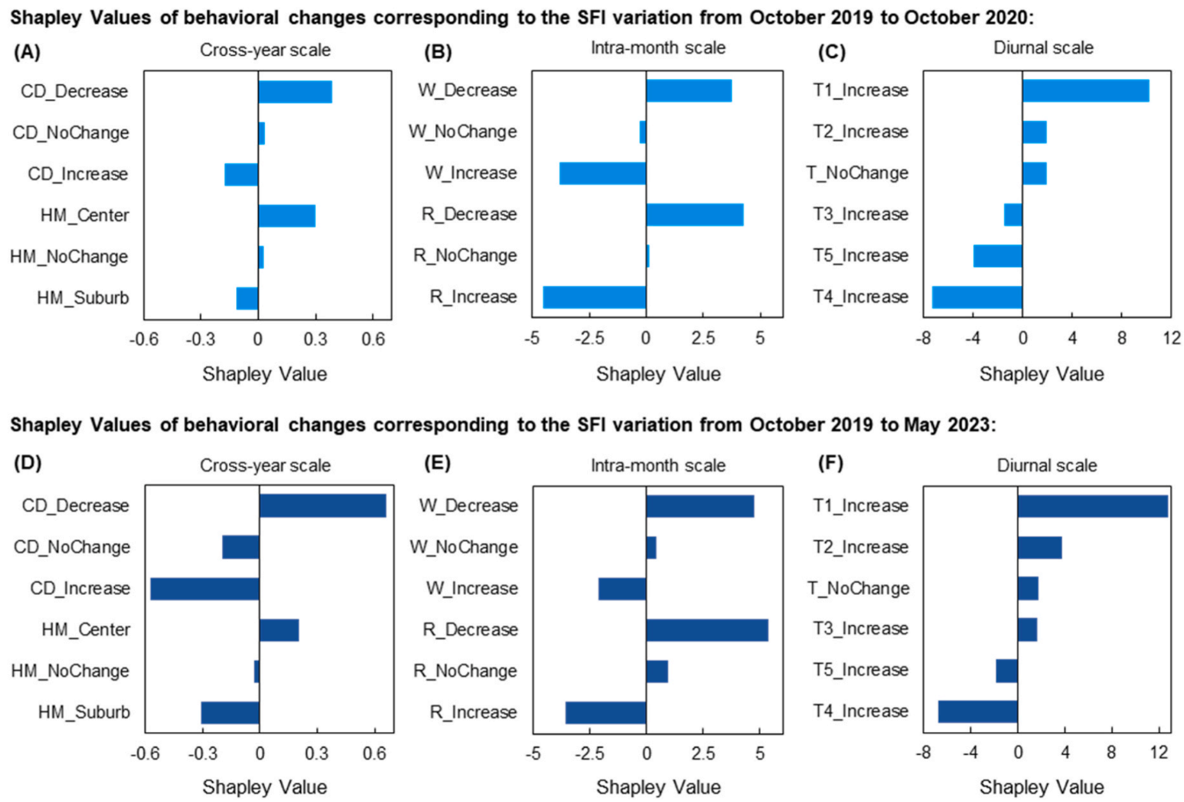


Fig. 5. Shapley values of behavioral changes at different scales: (A), (B), and (C) display the results corresponding to the SFI variation from October 2019 to October 2020; (D), (E), and (F) display the results corresponding to the variation from October 2019 to May 2023.

life courses is a consequence of the interplay of multi-scale behavioral changes occurring at different age stages.

5. Discussion and conclusion

The study introduces an analytical framework that integrates multi-scale individual behaviors to investigate the long-term evolution of people's daily activity spatial fixity and provides explanations for these changes from the life course perspective. By using mobile phone data of 290,679 individuals at different ages, the study assessed their behavioral changes from October 2019 to October 2020 and from October 2019 to May 2023, as well as the consequences of these changes on daily activity spatial fixity. The findings reveal a U-shaped distribution of daily activity spatial fixity with age, identifying the 30–34 age group as the period of lowest fixity. Moreover, it's found that the relative levels of daily activity spatial fixity among different age groups are stable, with similar levels of spatial fixity observed when individuals enter a particular life stage, indicating an *interlocking structure*. Within our framework, it's found that behavioral changes at the cross-year, intra-month, and diurnal scales explain over 40 % of the variance in daily activity spatial fixity variation, with broader-scale behavioral changes gaining prominence over extended period. Based on these research findings, we further discover that 35 years old is a crucial turning point in people's life courses. The distinct behavioral change trends observed before and after the age of 35 are responsible for the U-shape curve of daily activity spatial fixity. These findings provide innovative insights into the evolution of daily activities over time and carries significant theoretical and practical implications.

(1) Theoretical Implications

Recent human mobility research has uncovered fundamental patterns of individual daily activity, but there is an ongoing debate on how these patterns evolve with time. This study illuminates the substantial fixity effect that spatial constraints have on daily activities, showing that these constraints are intricately tied to an individual's life course. Throughout their life courses, individuals experience a succession of role transitions and behavioral changes that typically unfold with age. Consequently, as numerous studies have indicated (Alessandretti et al., 2018; Pappalardo et al., 2015; Yin & Chi, 2022), in the short term, individuals' daily activity patterns are stable and they are confined to specific locations due to the absence of significant life course events. However, as the time frame extends over a year or more, the progression of life course stages with advancing age precipitates changes in both behavior patterns and spatial constraints. These age-progressive changes explain the discrepancies between short-term and long-term findings in previous human mobility research. By bringing this pattern to light, we can attain a more expansive understanding of human mobility and its evolution across extended temporal dimensions.

The study also contributes to the field of time geography by developing a hierarchical framework for examining behavioral changes. Prior time geography research introduced the concept of 'pockets of local orders' to articulate the intricate interplay of human behavior across various scales (Ellegård & Vilhelmson, 2004). Although this concept has been employed to elucidate people's spatio-temporal behaviors within specific contexts, its broader application has remained constrained. The framework we proposed integrates pivotal findings across disciplines, with its explanatory power confirmed through analysis of a large-sample dataset. It serves as a conduit between foundational time geography theories and the expansive field of human mobility, thereby broadening the applicability of time geography concepts and hypotheses to a spectrum of real-world scenarios.

(2) Practical Implications

The most immediate application of this study lies in the field of

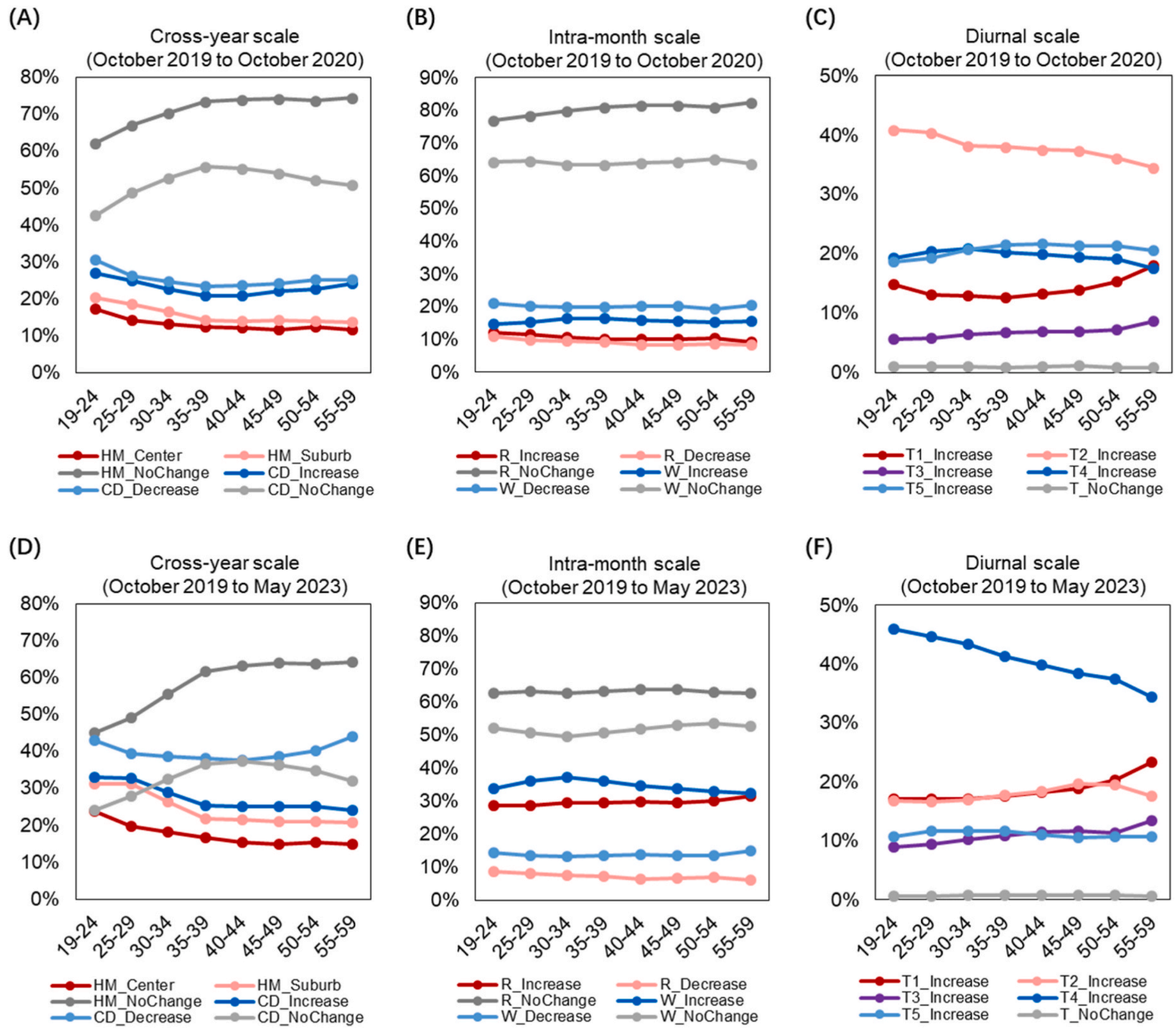


Fig. 6. Multi-scale behavioral changes among different age groups (October 2019 to October 2020 and October 2019 to May 2023).

individual behavior modeling. When modeling individuals' behaviors in daily activities, researchers typically consider the behavioral patterns at the daily scale, an approach that faces increasing deviations as the temporal scale extends. Our study reveals that individual behavioral changes over longer time scales stem from life course progressions related to their age, and specifically identifies the primary shifts at various age stages. These changes have significant implications for individual behavior modeling. For instance, the quantity conservation law (Alessandretti et al., 2018) and motifs patterns (Schneider et al., 2013) of human mobility have been extensively applied in individual behavior modeling, which may operate well when there are no significant changes in the life course stages of individuals. However, it is expected that, over time, changes in activity sequences, workplace diversity, and job-housing relationships will gradually emerge, subsequently altering the daily activity spatial fixity of individuals. By taking these potential changes into account, we can enhance the credibility of individual behavior modeling in extended time scales.

The study also holds practical implications at the population level. City governments employ population level statistics, such as censuses, economic surveys, and traffic surveys, as the basis for resource allocation and planning decisions. However, due to the immense workload involved in data collection, these statistics are typically conducted every five or ten years, leading to a lack of understanding of changes in population attributes and behavior patterns between these years. This makes the information that urban governments possess often being outdated. Our findings are instrumental in extrapolating the annual change trends of the statistical data, thereby mitigating the bias caused by data lag. As shown in Fig. 7a, we have estimated the SFI levels for Guangzhou residents based on their gender and age using data from the 2020 census. Despite the absence of the most current statistical data, we can extrapolate potential changes in residents' behavioral patterns one year or four years after the census was conducted, based on the DID model. Fig. 7b presents the projected SFI estimates for the year 2024, considering the aging of the community population (see the section 'Estimating the SFI of Guangzhou Residents in 2020 and 2024' in the Supplementary Materials for detailed information). Notably, there is a significant discrepancy between these two estimates, indicating that substantial bias may arise if the government bases resource allocation decisions on census data that is four years out of date.

The broader practical implications of this research lies in its potential to inform social policies. As we have found, the age of 35 is a significant turning point for people's daily activity spatial fixity. The '35-year-old effect', a phenomenon also noted in studies on career progression and housing decisions, is linked to the pressures of the job market and societal expectations (Fang & Qiu, 2023; Huang et al., 2020). Our study revisits this effect from the vantage point of human mobility. The study's findings indicate that this effect is evident in the pre-35 instability of multi-scale behaviors, the workplace diversification occurring around age 35, and the post-35 adjustments in commuting distances and activity sequences. These insights highlight the interplay between people's spatial needs and constraints in their daily activities in response to the '35-year-old effect', offering valuable knowledge for future spatial

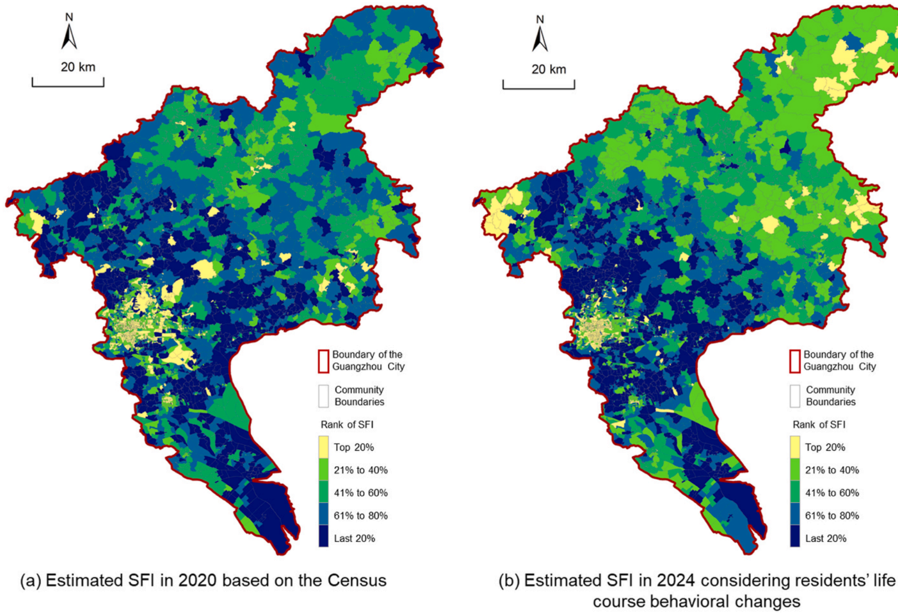


Fig. 7. Spatial fixity index (SFI) Levels Estimated for Individuals across Different Communities in Guangzhou.

governance, social resource distribution, and social policies tailored to individual needs. For instance, with the prior knowledge that after the age of 35, people's activity sequences will predominantly shift from the loop-structure type to the simple 'R' and the repetitive visit types, we can strategically optimize the organization of public transportation routes and the allocation of service facilities to accommodate these evolving needs.

(3) Limitations of This Research and Future Work

The study is not a full life-course longitudinal study tracking individuals from birth to death. Instead, we analyzed data from the same group of individuals over one month in 2019, 2020, and 2023. Our research identified patterns of behavioral changes within a year and over a span of four years, as well as the interlocking structure of these changes across different age stages. To project the behavior evolution over a longer period, one would have to assume that the interlocking structure remains constant. However, given the dynamic nature of socio-economic conditions, it's unlikely that this structure will remain static. Therefore, this study is simply an investigation from the life-course perspective, which discloses a trend in the evolution of spatial fixity of daily activities within the current context, rather than a comprehensive life-course study. Moreover, the study exclusively examines workday activities of individuals aged 19 to 65, potentially overlooking certain segments of the population and types of activities. There are also individuals aged 19 to 65 who do not have a workplace (for example, college students and retirees) or whose work involves non-fixed locations (for example, taxi drivers, delivery workers, and fieldwork professionals). In these cases, the 'workplace' we identify actually represents other primary activity locations during working hours (such as schools, public service centers, supply stations, charging stations, etc.), which also impose constraints on individuals during worktime. Similarly, as the study is exclusively focused on spatial fixity, it inherently neglects non-spatial work constraints, such as remote working. We observed in the results that a considerable proportion of individuals shifted towards activity sequences without explicit work locations in both October 2020 and May 2023 (as indicated by the increase in R-type activity sequences represented by T1_Increase). The underlying cause of this phenomenon may be attributed to possible work mode shifts. The grouping process accounts for 49.0 % of the variance in people's SFI from October 2019 to October 2020 and 46.2 % from October 2019 to May 2023, indicating that a substantial portion of the variance is yet to be explained. Because the primary objective of this study is to introduce a research framework, we have intentionally included only five basic categorical variables to ensure the interpretability of the results. We believe that a more sophisticated variable design will lead to substantial improvements in the model's performance in the future. In subsequent research, we plan to continue tracking the individuals in this study. With the collection of extensive long-term behavioral data, we believe we can provide a more comprehensive explanation of the long-term evolution of people's daily activities.

CRediT authorship contribution statement

Junwen Lu: Writing – original draft, Visualization, Funding acquisition, Formal analysis, Conceptualization. **Suhong Zhou:** Supervision, Funding acquisition, Data curation. **Yang Xu:** Writing – review & editing, Supervision, Methodology, 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 A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2025.103609.

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