EPIDEMIOLOGICAL-SURVEY-BASED STUDY FOR UNDERSTANDING DAILY MOBILITY OF ELDERLY IN SOUTHEAST CHINA

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ABSTRACT:

China's aging population has brought both opportunities and challenges to the society and economy. Promoting healthy aging is crucial to sustainable social and economic development. Learning the daily mobility pattern and health status of the elderly can provide references for the formulation and implementation of policies such as urban planning and social welfare. We derived key mobility indicators from the epidemiological survey data and then applied exploratory factor analysis to identify latent factors that can significantly affect mobility of the elderly in Southeast China. The study found that: quantity of out of home activities, extent of life space and stability of life space are three important factors that affect elder's mobility; gender gap is small in elders' mobility while the urban-rural differences in extent of life space and stability of life space are significant. The maximum distance from home for the rural elderly is significantly higher than urban elderly, while rural elder's extent of activities is narrower and longer, and the repetition is low. There were significant differences in both the quantity of out of home activities and the extent of living space between elderly in China and Switzerland, and the activities of the elderly in China are more consistent, while the mobility pattern of the elderly in Switzerland are extremely divergent. Epidemiological survey data can be used as a data source for the elder's daily mobility studying, and the results of this paper provide references for the policy formulation of policies to cope with aging, such as building an elderly-friendly community and caring for the physical and mental health of the elderly.

1. INTRODUCTION

The accelerating aging brings China both challenges and opportunities in various socio-economic aspects. Promoting healthy aging of the population is crucial to the sustainable development of the society and economy, so it is urgent to understand the physical and mental health of the elderly in China.

Elders' health is closely related to their daily activities and interacts with their social needs. Daily travel behavior is an important aspect of social needs (Feng and Yang 2015a), which reflects elders' basic daily movement ability (Crowe *et al.* 2008a), and social activity participation. Besides, the number and destination of daily activities can also have an impact on physical and mental health conditions such as happiness and well-being (Nordbakke and Schwanen 2014a). Therefore, with the acceleration of China's aging process, the study of the elders' daily travel behavior can help understand their daily life, needs and health status, thus providing scientific support for policy formulation in an aging society (Feng and Yang 2015a).
The Hu Line was proposed in 1935, dividing China into a densely populated southeast region and a sparsely populated northwest region (Hu 1935, Wang and Deng 2016a). Nowadays, the growing number of elderly people in the southeast region has put forward higher requirements for social infrastructure construction and services. Therefore, it is of great significance to study the elder mobility in southeast China.

Epidemiological survey data released by the government during the COVID-19 pandemic can be used as a data source for mobility research. In previous studies, many types of data sources are widely used, including travel dairy surveys, trajectories from GPS-embedded devices, call detail records (CDRs), and their combinations. However, every data source has its limitation: the travel dairy survey data is less time-sensitive (Yang and Fang 2018a), and is susceptible to bias due to the subjective factors(Fillekes *et al.* 2019a, Ho *et al.* 2020, Simões *et al.* 2018b); the GPS data has a higher spatio-temporal resolution than the survey, and can avoid the bias caused by subjective factors such as forgetting and social expectation deviation (Canzian and Musolesi 2015b, Isaacson *et al.* 2016b, Lin *et al.* 2015c), but the data does not contain information about the purpose and location of the trip, and typically are limited on a small scale(Brusilovskiy *et al.* 2016c, M. *et al.* 2018c); in addition, the individuals may change their travel behavior due to the influence of social expectations, which has an impact on the accuracy of travel dairy surveys and GPS-based surveys(Fillekes *et al.* 2019b, Johnson and White 1971); CDRs data set will be affected by the user's mobile phone usage habits, and its spatial accuracy is limited by the distribution density of the base station, so it cannot well reflect the individual's travel behavior(Burkhard *et al.* 2017a, Zhao *et al.* 2016d, Yang and Fang 2018a).

Epidemiological survey data is released by local government to prevent and control the infectious diseases. It records the time and place of individual behavior in detail (Cheng *et al.* 2021a). The availability of epidemiological survey reports opened up new avenues for studying daily human mobility. It is screened by the government relying on big data to reduce data bias caused by subjective factors (Shi *et al.* 2021b); the epidemiological survey data can cover a wider geographical range compared with GPS-based survey data. In addition, the location of the epidemiological survey data is usually recorded as POI, so its spatial resolution is better than CDRs data.

The existing research mostly study elder's mobility qualitatively or descriptively, while there are few quantitative studies. Quantitative analysis of the daily mobility can help characterize the daily activity behavior pattern of the elderly more macroscopically and accurately. In the future, it can also help predict the physical and mental health of the elderly based on mobility indicators (Fillekes *et al.* 2019c). There are 19 commonly used indicators, such as: number of locations, Distance in vehicle, Number of trips on foot, etc., these indicators can further be characterized as a combination of six main characteristic aspects: space, time, range of movement,

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attributes, time scale and statistical properties of the six aspects(Fillekes et al. 2019c). For example, Fillekes et al.(Fillekes et al. 2019c)introduce quantitative mobility indicator systems, and quantitatively analyze the mobility of 95 elderly people in Switzerland (average age 70.5 years) based on verified GPS positioning device data. Switzerland has more than 30 years of development experience of aging society. The infrastructure construction for the elderly is relatively complete. So their elder_mobility research results can be used as the baseline for the study of the elder's behavior in the aging areas. What's more, by comparing the differences in mobility patterns between China and Switzerland, we can know the gap and learn more experience to deal with aging.

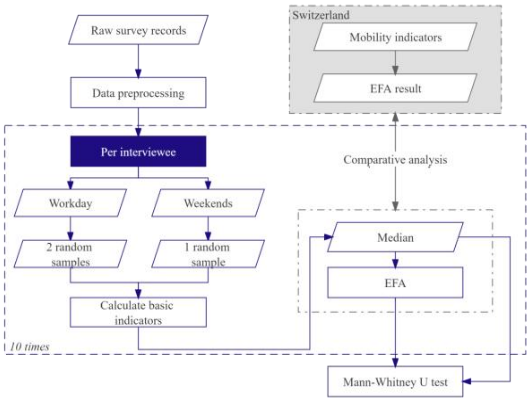

Figure 1. The overall workflow of the study

This study selects mobility indicators from Fillekes et al. (Fillekes et al. 2019c) conducted quantitative research on the mobility of the elderly in southeast China, and compared the results with the elderly in Switzerland.
This study tries to answer three research questions (RQ):
RQ1: What is the minimal comprehensive mobility indicator set to reflect elderly mobility in southeast China?
RQ2: Whether and to what extent do the mobility patterns of people in southeast China vary by gender and across the urban-rural gradient?
RQ3: What are the differences in mobility patterns between the elderly in China and Switzerland?

2. RESEARCH DATA AND METHODOLOGY

2.1 Workflow

Raw mobility indicators in this study are adapted from the following (Fillekes et al. 2019c), which suggest a set of basic mobility indicators and use an exploratory factor analysis (EFA) to find a minimal set of latent mobility indicators synthesized from the basic mobility indicator.

2.2 Data collection and preprocessing

To answer the proposed research questions, we investigate a novel data source: the time-place-annotated trajectories reported in the epidemiological surveys published by China's CDC.

The collected survey reports initially include 126 interviewees spanning from 2020.12.24 to 2021.08.04 over 15 provinces in China. In the context of the normalization of epidemic prevention and control, the Chinese government takes 3 tier restrictions. Thus, not every travel behavior would be restricted. In order to minimize the impact of COVID-19 and epidemic prevention policies on personal mobility, the samples selected in this study are people who can travel freely without restrictions. One trajectory record includes the time, place name, and transportation mode of daily trips of an anonymized interviewee. Depending on scenarios, some records can be up to 14 days before the date that the person is identified as a positive case. However, these reports are not published on a national platform, and they have no uniform format. Therefore, we had to manually collect the survey reports and extract information from the raw reports. At the data filtering stage, we aimed to keep interviewees who are local residents for their cities with enough observed dates by removing individuals who are: imported cases from foreign countries, travellers for business trips or inter provinces, interviewees with no home place or less than four days records.

In original epidemiological survey report, some of the samples had records of staying in medical facilities in the last few days, which is a measure policy taken by the government to control the spread of the virus, rather than the autonomous behavior of the samples, so we also removed such records. Finally, 61 individuals were remaining, with an average age of 69.1.

Mobility indicator	Definition of daily mobility indicator
LengthPerTrip	Average length of a trip
MaxDist	Length of the straight line connecting home and the point furthest away from home
MeanDist	Average length of straight lines connecting home and places away from home
CHull	Area of convex hull enclosing all places
GravCompact	$K = \frac{P}{2\sqrt{\pi A}}$ Gravelius compactness of a convex hull, where P is the perimeter of a convex hull and A is the area of the convex hull. The higher, the more elongated is the life space.
NumLoc	Number of out of home places visited
RevisitedLS	Percentage of the daily convex hull that has overlap with any convex hulls of the other included study days (% revisited area of daily life space)
AvgRevisitiedLS	Average percentage overlap of the daily convex hull with the convex hulls of the other included study days
Entropy	$Entropy = -\sum_i p(y_i) log_{10}^{p(y_i)}$ where yi a unique place, including home, and p is the percentage of time spending on a place.
EntropyOH	$Entropy_{OH} = -\sum_i p_{OH}(y_i) log_{10}^{p_{OH}(y_i)}$ where yi stands for an out-of-home place and p_{OH} is the percentage of time in out-of-home places.

Table 1. Description of the computation of the selected basic mobility indicator

2.3 Basic mobility indicators

This study selected 10 basic mobility indicators(Table 1) whose calculation can be supported by the epidemiological survey data, adapted from the suggested list in(Fillekes et al. 2019c), In addition, we added EntropyOH with the hope of better describing the heterogeneity of place visitation out of home during the pandemic. Since not all interviewees have daily records for a whole week, we randomly sampled two weekday records and one weekend record from an individual's available records, selected the median value as the representative value of his/her daily mobility indicator, and used this value for future analytics, aligning the day selection in the referred study.

2.4 Analytics

2.4.1 Exploratory factor analysis

In case, the contribution has been accepted for publication, a camera-ready manuscript must be submitted at the due date. In this camera-ready manuscript the name(s) and affiliation(s) of the authors(s) must be identified, and acknowledgements can be personalized.

Elder's mobility might be influenced by only a few but complex driven factors whose output might be caught up by various mobility indicators. Exploratory factor analysis (EFA) has been used as a powerful tool for modelling latent factors from observed simple indicators to generate a theory about underneath driven factors. EFA, therefore, was applied to find possible latent factors as a linear combination of the raw indicators that can describe human mobility with rich semantic meaning but fwer indices. The result can be formulated as:

$$F_i = \sum_k Q_k \times W_k$$

where F_i is the score of the resulted i^{th} factor, Q_k is the value of the k^{th} raw indicator, and W_k is the loading of the k^{th} raw indicator to the resulting factor. The output of the EFA is expected to answer RQ1.

Particularly, we used the minimum residual method as the extraction method with varimax for factor rotation to accomplish the factor analysis using the implementation in psych package in R.

Before the EFA procedure, we also tested if our sample data are suitable for the method by employing Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The tests on the sample resulted in 0.7 for KMO and $p < 0.05$ for Bartlett's Test, which suggests that the sample is feasible for the factor analysis. To achieve more robust conclusions, the sampling was repeated 10 times and exploratory factor analysis was applied to each sampled set.

2.4.2 Statistical analytics on raw indicators and latent factors

As preliminary tests showed that the values of the raw indicators do not follow a normal distribution, we applied non-parametric tests to explore the difference in the raw indicators regarding the groups by the two driving factors: gender and urban-rural gradient. This was expected as human mobility and socioeconomic indicators typically follow highly skewed distributions. As our observations are not paired, we thus employed the Mann-Whitney U test for two-group comparisons.

	Gender	Urban-Rural
Entropy	0.4806	0.2355
EntropyOH	0.3976	0.0543*
CHull	0.2330	0.2543
NumLoc	0.9535	0.1919
MaxDist	0.2056	0.0019**
MeanDist	0.3412	0.0015**
LengthPerTrip	0.3462	0.0842
GravCompact	0.2907	0.1276
RevisitedLS	0.7447	0.0275*
AvgRevisitedLS	0.9083	0.0330*

Table 2. The results of the Mann-Whitney U test for the raw indicators. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

3. RESULTS

3.1 Statistical tests of raw indicators per demographic feature and urban-rural gradient

The results of the MANN-Whitney U test (Table 2) show that there is no gender gap in southeast China, while there are differences between the urban elderly the rural, especially in terms of the distance from home and the overlapping area of daily travel activities. This shows that the difference between urban and rural areas will significantly affect the travel patterns of residents, and there may be information redundancy between basic mobility indicators, so it is necessary to conduct exploratory factor analysis.

	Latent factor		
%explained	Quantity OH activities	Extent of life space	Stability of life space
variation	27%	37%	18%
Entropy [a]	0.93		
EntropyOH [a]	0.83		
CHull[b]	0.75		
NumLoc [b]	0.66		
MaxDist [a]		0.97	
MeanDist [a]		0.96	
LengthPerTrip [a]		0.95	
GravCompact [b]		0.76	
RevisitedLS[a]			0.97
AvgRevisitiedLS[a]			0.89

Table 3. Factor loadings for the set of mobility indicators listed in Table 1 to uncover latent mobility dimensions. As the indicator co-appearance in the factors is almost the same for the 10 EFA runs, we randomly selected one result without loss of generality. a: value without transform, b: value log-transformed. Indicators' factor loadings are displayed for the factor that they correlated mostly. The three factors capture over 72% of the variance of the raw indicators.

3.2 EFA results

The EFA procedure resulted in three latent factors (Table 3). The composition of the latent factors has a very similar pattern as the latent factors in Fillekes et al(Fillekes et al. 2019c).

Therefore, we still used the factor labels in the referred study to summarize the semantics of the discovered factors, namely quantity out-of-home (OH) activities, extent of life space, and stability of life space. The factor quantity OH activities in general measures the quantity and diversity of the place visitation. The factor extent of life space is more about the geometry perspective of life space. The factor stability of life space describes how stable the place visitations are. The explored assignments are stable as the raw indicators are almost consistently co-appear in the same group of latent factors in the 10-run repetition (Figure 2). There are a few notable differences in the latent factor composition from the referred study. Firstly, CHull is assigned to the quantity OH activities factor rather than the extent of life space. Secondly, the Gravelius Compactness of CHull (GravCompact) is assigned to the extent of life space, in the same factor as LengthPerTrip, MaxDist, and MeanDist. However, the analysis results of the two studies have the same order of variance for the variances: the explanatory space range is the most explanatory, and the stability of the living space is the least explanatory.

Factors	Quantity OH activities		Extent of life space		Stability of life space	
Driving factor	Gender	Urban-rural	Gender	Urban-rural	Gender	Urban-rural
p-value	0.2676	0.7818	0.2631	0.0020 **	0.9916	0.0367 *

Table 4.The results of the Mann-Whitney U test for the factors.*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

As shown in Table 4, the results of the inter-group comparison of each factor are similar to the results of the raw mobility indicator. The quantity out-of-home (OH) activities did not differ under the two factors of gender and urban-rural gradient; The extent of life space, and stability of life space factors have no difference across gender, but there was a certain difference across the urban-rural gradient factor. The post hoc one-tail test showed that the living space of the rural elderly was larger ($p=0.0010$), while the urban elderly had higher stability of living space ($p<0.05$).

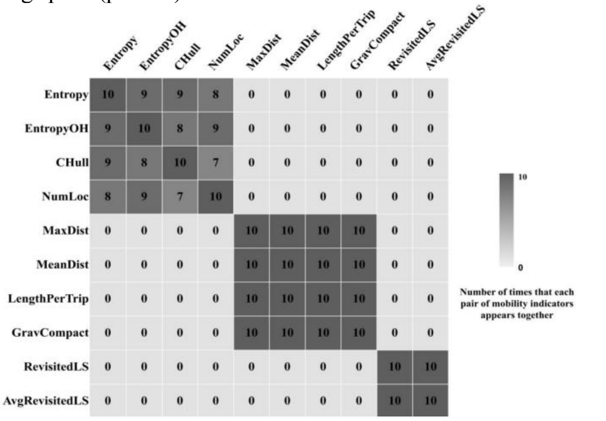

Figure 2. EFA summary matrix for the 10 runs of the random day selection. The counts indicate how often each pair of mobility indicators co-appears in a factor. The mobility indicators are organized as the same as Table 3.

4. DISCUSSION AND CONCLUSION

4.1 Elder's mobility

Through the results of exploratory factor analysis: quantity OH activities, extent of life space, and stability of life space consist of a minimal comprehensive mobility factor set to summarize elder's daily mobility. This suggests the capacity of generalizing the conceptual framework proposed by Fillekes et al. to identify and interpret the latent mobility factors from mobility indicators from a different form of mobility data(Fillekes et al. 2019c). At the same time, it also justifies the validity of the mobility indicators derived from the epidemiological survey as a possible source for understanding people's daily mobility.

The results of the non-parametric test show that no gender difference is observed among the elderly in southeast China. Although there are no relevant findings in the region, gender differences in mobility exist in the United States(Mitra *et al.* 2021c), rural China(Zhao and Yu 2021d), middle-income Latin America(Olivieri and Fageda 2021e) and developed countries such as France(Havet *et al.* 2021f), and Sweden(Frändberg and Vilhelmson 2011). These studies all reveal higher mobility in men than women (men have longer distances and travel times, more trips). Existing studies suggest that disparities in socio-economic and cultural status, access to medical care, legal age limits for driving and driver's license holders, community-built environments and the division of household jobs may be responsible for gender differences.

For example, different occupations may have an impact on mobility(Long and Reuschke 2021g), Due to the influence of traditional division of household jobs, some women will become housewives in order to assume family responsibilities(Havet et al. 2021f, Olivieri et al. e), which will influence their mobility. However, the gender gap in elder's occupations has narrowed, thus narrowing the mobility gap among the elderly. In addition, there is a gender-gap in travel purposes: men's leisure and entertainment travel account for a higher proportion than women's, while women's travel purposes are usually limited by responsible housework activities (He *et al.* 2017b), With the improvement of infrastructure, the life and leisure service functions will be more complete within a certain geographical range, thereby reducing the gender-gap in the mobility of the elderly.

In addition, there are large urban-rural gaps in the extent of life space and the stability of life space for the elderly in southeast China: rural elder extent of life space is wider, and urban elder's stability of life space is higher. The mobility of the elderly is mainly affected by individual characteristics such as health status, family composition, car ownership, and built environmental factors such as building density, road accessibility, and improvement of public transportation facilities (Wei *et al.* 2021i, Li *et al.* 2021h, Liu *et al.* 2018d). Building density, as well as the layout of basic living services, may be responsible for this result. The basic living needs of urban residents can be met in a smaller space because cities have higher architectural density. In addition, the perfection of public transportation may be a more important influencing factor, the elderly usually travel by public transportation and on foot due to their physical conditions(Song and Wang 2018e). During the epidemic period, the willingness of urban elderly to take public transportation has decreased because of the higher risk of infection, resulting in a reduction in their life space range.

4.2 Comparative analysis with Swiss elder

The calculation and comparison results show that the difference in elder MaxDist and NumLoc between 2 countries is large, while the difference in elder RevisitedLS is small (Table 5). Rural elder MaxDist is 4 times more than urban elder, while their convex hull area is very similar, indicating that rural elder life space is long and narrow, and may mainly along the rural road. Meanwhile, the urban elder life space is more compact, mostly around the patchy area near their home. The maximum distance from home for elderly in Switzerland is between urban and rural elderly in China, but the standard deviation is large. This shows that the Swiss elder life space is larger than Chinese urban elder, and there are great individual differences. The NumLoc and RevisitedLS of the Chinese urban elderly and Swiss elderly are relatively close, but the variance in NumLoc of Swiss elderly is still significantly higher than Chinese urban elderly. Meanwhile, Chinese rural elder's NumLoc and RevisitedLS are smaller than Swiss elderly and Chinese urban elderly.This shows the travel spaces of rural elderly are not repetitive, and the elderly go out of home seldom. However, the length of each trip is long, and the convex hull is in a narrow shape along the road.

The area of convex hull can describe the life space quantitatively(Giannouli *et al.* 2018f, Sanchez *et al.* 2017c), In mobility studies of adults in the southern suburbs of India (Sanchez et al. 2017c), adults in the center of Paris(Perchoux *et al.* 2014b) and elderly in Switzerland(Fillekes et al. 2019c) the area of convex hull is assigned to the extent of life space. It is used in many studies to represent the extent of life space, and helps to explore the human mobility characteristics and the influencing factors. Shi et al. point out that the area of convex hull shows a power-law distribution(L. *et al.* 2017d), in addition to the convex hull area showing differences in gender (Tung *et al.* 2014c), age, and economic income status(Fan and Khattak 2008b). Some study look at the relationship between human health and extent of life space, Tung et al. find that the convex hull area is significantly different between Alzheimer's disease patients and the cognitively intact older adults, and it is related to the pace of the elderly and the mental health status (Tung et al. 2014c). Objective factors such as living environment and the improvement of its infrastructure construction have a significant impact on the elder's extent of life space: the elder who lives in a walk-friendly and high road accessibility neighborhood will have a wider extent of life space.(Chung *et al.* 2021j)

		Max Dist	CHull	Num Loc	Revisite dLS
Chinese Urban	Mean	5.00	3.91	1.61	0.52
	Median	1.53	3.89	1.75	0.50
	SD	7.25	1.50	0.61	0.41
Chinese Rural	Mean	21.65	4.07	1.35	0.28
	Median	28.50	4.48	1.00	0.03
	SD	16.06	1.66	0.74	0.38
Swiss	Mean	12.2	74.5	2.6	0.5
	Median	3.8	3.8	2	0.5
	SD	39.3	617.5	1.6	0.3

Table 5. The comparison of the raw indicators calculation results

In our study, the area of convex hull is assigned to the quantity OH activities, and there is a large gap of the value between China and Swiss. It may be caused by individual samples because the standard deviation of the Swiss elderly is large. In addition, the urban infrastructure, the elder's living conditions, and the impact of the epidemic on human mobility may also be the main reasons for this discrepancy. Switzerland has entered the ageing era in the 1980s, so it has a more complete experience in dealing with aging. Its urban infrastructure construction is also more friendly to elder daily travel and life, which has a positive impact on their travel. COVID-19 may have a negative impact on people's travel, especially for older people with poor immunity. To reduce the risk of infection, they may shorten the distance traveled and reduce the frequency of long trips; In addition, the epidemic prevention and control policy (eg., showing a health code or COVID-19 test certificate when taking public transportation) will also have a negative impact on people's willingness to travel.

Considering the gradual spreading of COVID-19, the samples of the study are not completely randomly selected, which is more similar to the snowball sampling used by Liu et al. in studies on qualifying the influence of COVID-19 on daily mobility (Goodman 1961, Liu *et al.* 2021k). However, as being infected by an airborne disease such as COVID-19 is not fully deterministic, being a sample in the epidemiological survey also has some degree of randomness. Considering the difficulty and workload of collecting human mobility data and information, the epidemiological survey is still extremely valuable for us to understand the patterns and geographical differences in elder mobility.

Based on epidemiological survey data released from December 2020 to August 2021, this study analyzes the mobility patterns of the elderly (60+) in southeast China. The results of the study prove that the epidemiological survey data can be used as a data source to study the daily travel activities of the elderly, and the elder's mobility can be quantitatively studied, so as to provide a reference for the construction of elderly-friendly communities and the physical and mental health care of the elderly to deal with aging policies.

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