Examining public transport usage by older adults with smart card data: A longitudinal study in Japan

Shasha Liu [a,*], Toshiyuki Yamamoto [a], Enjian Yao [b], Toshiyuki Nakamura [c]

[a] *Institute of Materials and Systems for Sustainability, Nagoya University, Nagoya 4648603, Japan*

[b] *Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China*

[c] *Institute of Innovation for Future Society, Nagoya University, Nagoya 4648603, Japan*

Abstract: Understanding public transport usage by older adults is necessary to develop senior-friendly public transport and improve the mobility of older persons. Although extensive literature has examined the travel patterns of older adults, very limited efforts have been invested to explore the longitudinal variability in public transport usage by different age groups of older adults. To address this limitation, we developed user-monthly profiles to explore the seasonal variability in public transport usage by older adults and defined user-based time slots of the day and geographical user areas to represent daily trip patterns and examine day-to-day variability. Using one-year smart card transaction data and an anonymous cardholder database from Shizuoka, Japan, we evaluated the seasonal and day-to-day variability in public transport usage by older adults. We also analyzed the role of age and living environment in travel pattern variability. The results indicate that older adults in highly developed areas and younger-old group (aged 65–74) are more likely to be characterized by high-frequency public transport usage and low seasonal variability. Additionally, the day-to-day variability in public transport usage by older adults is greater in more developed areas and appears to increase with age. This study enhances our understanding of public transport usage by older adults, which may contribute to the development of senior-friendly public transport policies and services.

Keywords: Aging society; Public transport; Older adults; Seasonal variability; Day-to-day variability; Smart card data

* Corresponding author.
E-mail addresses: liu.shasha@e.mbox.nagoya-u.ac.jp (S. Liu), yamamoto@civil.nagoya-u.ac.jp (T. Yamamoto), enjyao@bjtu.edu.cn (E. Yao), tnakamura@mirai. nagoya-u.ac.jp (T. Nakamura).

1 Introduction

Population aging has become a notable and common demographic phenomenon in most countries. The proportion of the population aged 60 years or over is growing faster than other age groups (Shao et al., 2019; Szeto et al., 2017; Wong et al., 2018). According to a population division report (United Nations Department of Economic and Social Affairs, 2017), the global population aged 60 or over is projected to reach nearly 2.1 billion by 2050, more than twice as large as in 2017 when there were 962 million older persons worldwide. Japan has the highest proportion of older adults in the world and is experiencing a “super-aging” society in both rural and urban areas (Muramatsu and Akiyama, 2011). According to the Japan Statistical Yearbook (2020), 34% of the Japanese population is above the age of 60, and 28% is aged 65 years or older. The proportion of the population aged 65 or over is estimated to reach a third by 2050.

With the aging population growing, the mobility needs of older adults are drawing increasing attention. For older adults, mobility is essential for general independence and ensuring good health and quality of life (Whelan et al., 2006; Wong et al., 2018). However, the trend toward car dependence is not necessarily positive in an aging society (Currie and Delbosc, 2010), because it may contribute to road accidents, traffic congestion, and environmental pollution (Rosenbloom, 2001). According to the Japanese National Police Agency, drivers aged 75 or over caused 460 fatal road accidents in Japan in 2018. More worryingly, the proportion of such accidents increased from 8.7% to 14.8% in ten years. Meanwhile, for older adults, lack of access to a car and loss of ability to drive may lead to a dramatic reduction in mobility and possibly physical and mental health problems as well (Cui et al., 2017). Public transport, as a low-cost and low-emission mobility alternative for older adults who cannot drive or choose not to drive, can enhance the mobility of older adults and bring social benefits to disadvantaged people at risk of social exclusion (Burkhardt, 2003; Currie and Delbosc, 2010; Engels and Liu, 2011). To promote public transport use among older people and to reduce the risk of social exclusion, it is important to understand the public transport usage by older adults (Truong and Somenahalli, 2015).

Although extensive research has explored the travel patterns of older adults over a range of geographic scales and contexts, most studies have focused on trip frequency, travel distance, trip purpose, mode choice, etc. (Föbker and Grotz, 2006; Ipingbemi, 2010; Ranković Plazinić and Jović, 2018; Shoval et al., 2010; Szeto et al., 2017). Meanwhile, existing studies on the topic have typically relied on travel survey data and examined interpersonal variability in travel patterns, whereas intrapersonal variability (i.e., longitudinal variability in travel behavior over time) in public transport usage by older adults has received very limited attention. In contrast to conventional travel surveys, which are costly and thus limited to short observation periods and small sample sizes (Chu and Chapleau, 2010), smart card automated fare collection systems automatically and continuously record public transport trip information of a large number of users, making it feasible to explore travel pattern variability through longitudinal analyses. Based on one-year smart card transaction data and an anonymous cardholder database (including home address, age, and gender) from Shizuoka, Japan, we attempted to address the limitation and explore the seasonal and day-to-day variability in public transport usage among older adults in different age groups.

The contributions of this study are twofold. From a methodological perspective, we developed user-monthly profiles to explore public transport use frequency and seasonal variability in public transport usage. Further, we defined user-based time slots of the day and geographical user areas to represent daily trip patterns and examine the day-to-day variability in public transport usage. From an empirical perspective, we examined the heterogeneity of travel patterns among older adults through a large-scale application of the proposed methodology to Shizuoka's public transport system. We exhibited the seasonal and day-to-day variability in public transport usage by older adults of different age groups in different residential regions.

The remainder of this paper is organized as follows. The next section reviews previous work on older adults and their mobility. The third section describes the study area and the data used. A detailed description of the methodology is presented in the fourth section. The fifth section analyzes the results of seasonal and day-to-day variability in public transport usage by older adults. A discussion of the results and conclusions are presented in the final section.

2 Literature review

2.1 Travel patterns of older adults

Population aging is the dominant demographic phenomenon in the 21st century, because of declining fertility and increasing longevity (Bloom and Luca, 2016). With the aging population growing, the mobility behavior of older adults is drawing increasing attention. For older adults, mobility is essential for general independence and ensuring good health and quality of life (Whelan et al., 2006; Wong et al., 2018). A lack of mobility may discourage older adults from participating in social activities, which may lead to reduced morale, increased depression, and loneliness (Musselwhite et al., 2015; Wong et al., 2017). Therefore, it is important to maintain the mobility of older people to ensure their social participation, which would in turn contribute to their physical and mental well-being and quality of life (Dickerson et al., 2007; He et al., 2018).

To understand older adults' travel needs and improve their mobility, an increasing number of studies have examined the mobility patterns of older adults. Most such studies have focused on trip frequency, travel distance, trip purpose, and mode choice over a range of geographic scales and contexts. Compared to younger adults, older persons tend to be less mobile, as they make fewer trips and travel shorter distances (Collia et al., 2003; Miranda-Moreno and Lee-Gosselin, 2008; Schwanen and Páez, 2010; Szeto et al., 2017). Meanwhile, some studies have revealed that older adults appear to be more mobile than ever before, particularly the "new old generation" born in the post-World II period (He et al., 2018; Hjorthol et al., 2010), because of their better health status and more active lifestyles than previous generations (Arentze et al., 2008). Van den Berg et al. (2011) found that older citizens in the Netherlands take as many social trips as young adults and that the average travel distance does not decrease as people get older. Choi et al. (2014) indicated that the trip frequency and travel distance of older adults in the Seoul metropolitan area increased from 2002 to 2006, but decreased from 2006 to 2010.

Travel mode choice preferences of older adults vary among different countries and regions. Car (as driver or passenger) is the dominant travel mode for older adults in most Western countries (Whelan et al., 2006). In Denver, Colorado, USA, 88.6% of trips are made by private cars, 8.3% of trips are made by active modes (walking, biking), and 2.9% of trips are made by public transport (Boschmann and Brady, 2013). Similarly, in Denmark, car is the most common travel mode for 66.2% of older adults, followed by active modes; only 3.0% of older adults use public transport as their primary mode of travel (Siren and Haustein, 2013). Unlike car-dependent cities and countries, transit-oriented cities and countries (e.g., Hong Kong and Singapore) provide more frequent and reliable public transport services (Wong et al., 2018), and public transport is a more common travel mode for older adults. For example, in Hong Kong, public transport is the most frequently used mode of travel by all age groups, accounting for more than 92% of the total transport ridership (Szeto et al., 2017).

Travel patterns also differ among older adults in different age groups. Trip frequency and travel distance show downward trends with age (Boschmann and Brady, 2013; Olawole and Aloba, 2014). Truong and Somenahalli (2015) concluded that younger groups (65–74 and 75–84) exhibit more frequent public transport use, whereas the oldest group (85 and over) is more likely not to use public transport. Additionally, the temporal distribution of trips varies among different age groups. Boschmann and Brady (2013) found that the trips (primarily work-related and shopping trips) of the 60–64 age group are most dispersed throughout the day; the 65–74 age group has a broad daylong trend without a single major peak; the 75–84 and 85+ age groups have sharp mid-day peaks and most trips are for errands or social activities.

2.2 Public transport and older adults

Car dependence among older adults may contribute to road safety issues (Chandraratna and Stamatiadis, 2003), traffic congestion and environmental pollution (Rosenbloom, 2001). Moreover, driving gradually becomes more difficult for older adults, because of age-related declines in physical and cognitive functions (Chihuri et al., 2016). Not being able to drive may reduce the mobility of older adults and increase the risk of social exclusion if there is no appropriate alternative travel mode (Engels and Liu, 2011). Public transport not only provides older adults with a low-cost and low-emission alternative to car but also has many benefits for their physical and mental health: promoting participation in social activities; offering more walking opportunities that contribute to physical activity and health; alleviating mental health problems (e.g., depression and loneliness) that may result from lack of access to facilities, services, and social support; and improving feelings of self-worth and well-being (Burkhardt, 2003; Cui et al., 2017; Currie and Delbosc, 2010).

To promote mode shift and improve the mobility of older adults, many countries are implementing schemes to develop senior-friendly and barrier-free public transport systems. For example, in Singapore, various schemes, such as priority queue initiatives, wheelchair-accessible buses, and discount travel fare, have been implemented to create a senior-friendly transport system. The Japanese government has also introduced a range of innovative programs, including barrier-free design for facilities, low-floor buses, and standardization of walkways (Akiyama and Kim, 2005). In western countries, many public transport concession fare schemes are designed for older adults. For example, senior card holders over the age of 70 travel free on Transport Canberra bus and light rail services in Canberra, Australia; the Older Persons Freedom Pass for over-60s in London, England allows free travel across London and free local bus journeys nationally; and older adults aged 65 and over get discount fares in the Washington metropolitan area. Further, door-to-door minibus services are available for older people in some cities and towns (such as Norwich and Rotherham in England).

Although significant effort has been invested in developing senior-friendly public transport, there is mixed evidence about the trends in public transport use in aging societies. Based on data from the United States, Australia, Germany, New Zealand, Norway, and the United Kingdom, Rosenbloom (2001) stated that public transport use among older adults is in decline due to increased health, wealth, and car dependence. However, Currie and Delbosc (2010) reported that the Baby Boomers (born between 1946 and 1964) in Melbourne, Australia show a trend toward increased public transport use compared to the existing over-60s generation. Many factors influence public transport use among older adults. Kim and Ulfarsson (2004) used the multinomial logit model to examine the travel mode choice of older adults based on two-day activity-travel diary data in Washington State. They reported that high population density and short distances from home to bus stops increase the likelihood of public transport use. Moniruzzaman et al. (2013) investigated the factors affecting the transport mode choice and trip length of seniors using a joint discrete–continuous model framework based on Montreal's household travel survey data. They found a decline in the probability of public transport use with increasing age, lower income, lower density of employment, and population. Truong and Somenahalli (2015) collected one-day travel diary data and explored factors influencing the frequency of public transport use among older people in Adelaide, Australia. They revealed that more frequent use of public transport is related to higher perceived importance of public transport to residences and easier access to public transport in neighborhoods.

A satisfactory public transport trip for older adults typically includes: an acceptable walk to public transport stops or stations along a well maintained and lit sidewalk, a short and safe wait for bus or train which arrives reliably, a safe and comfortable journey that takes travelers to a drop-off location near to the final destination, and a timely return service (Metz, 2003). Problems at any stage of trips may discourage older adults from using public transport. In most western countries (e.g., the United States), car is the most common travel mode among older adults, and a small proportion of them use public transport. Ritter et al. (2002) reported that unavailable destinations, fear of crime, unreliable public transport service, and difficulties in accessing public transport stops/stations and transfers contribute to infrequent use of public transport among senior Americans. In contrast to car-dominate cities, transit-oriented cities (e.g., Hong Kong) provide more frequent and reliable public transport services, and public transport is a more common travel mode among older adults. Wong et al. (2018) found that lack of seats, long walking and waiting time for public transport services, and high travel cost are associated with a low probability of older adults using public transport in Hongkong.

Most studies on the mobility of older adults have relied on travel survey data and have examined interpersonal variability in travel patterns, whereas intrapersonal variability in public transport usage by older adults has received limited attention. In contrast to conventional travel survey data, smart card data provide continuous information on public transport trips of numerous users, making it feasible to explore travel pattern variability through longitudinal analyses. Extensive literature has examined travel patterns of public transport users using smart card data (Egu and Bonnel, 2020; Morency et al., 2007; Shao et al., 2019). For example, based on four-day smart card data, Shao et al. (2019) recognized older adults according to smart card types and investigated their spatiotemporal characteristics of public transport usage in terms of travel distance, travel frequency, travel start time on weekdays and weekends, and spatial distribution. However, because sociodemographic information (e.g., age) pertaining to individuals is usually not included in smart card data, these studies fail to fully capture the differences in travel patterns among older adults in different age groups.

3 Study area and data

Shizuoka Prefecture is located in the central region of Honshu in Japan, with a geographic area of 7,777 km^2 and a population of 3,656,487 (October, 2018). It is a car-dominated prefecture with a public transport share of about 3%. Drivers aged 75 or over are required to pass a strict cognitive function test when they renew their driving licenses every 3 years. If a driver shows signs of deficiency in memory and judgment, he or she must see a doctor, and if he or she is diagnosed with dementia, his or her license will be either revoked or suspended. Driving cessation may lead to a dramatic reduction in mobility and increase the risk of social exclusion. Meanwhile, with the increasing proportion of older adults in the population, the number of older drivers in Shizuoka is increasing and is resulting in a commensurate increase in their involvement in traffic accidents. To decrease car use but not reduce mobility, it is important to provide an alternative travel mode for older adults. Given that public transport is a low-cost and low-emission alternative to car, understanding public transport usage of older adults would help Shizuoka to develop a senior-friendly public transport system and promote public transport usage among older adults.

People aged 65 or over are commonly defined as older adults in Japan: they are eligible to buy senior passes (discount public transport passes for older adults), and the retirement age is typically 65. Therefore, we refer to public transport users aged 65 or over as the primary sample. Shizutetsu Bus and Railway is the urban public transport system of Shizuoka city (the capital of Shizuoka Prefecture) and neighboring cities. To examine the impact of living environment on public transport usage by older adults, Shizuoka city and neighboring cities were classified into three types of areas based on their socioeconomic conditions: highly developed areas, moderately developed areas, and poorly developed areas (Fig. 1 and Table 1). Older adults account for 25% of the population in Yoshida and make up approximately 30% in the other cities. In Shizuoka city, the city planning area accounts for a significantly smaller proportion because the northern part of the city is covered with mountains and forests. The service sector (e.g., educational, health care, social assistance, professional, and business services) is the largest contributor to GDP, accounting for over 69%. This indicates that the city's service sector is well developed. With easier access to a wide variety of facilities (e.g., shopping, recreational, and health care facilities), older persons are more likely to make trips and participate in social activities. Therefore, compared to other cities, Shizuoka city is more likely to be a senior-friendly city. We regard this city as highly developed areas (HDAs). Similarly, we classified Yaizu and Fujieda as moderately developed areas (MDAs) and classified Makinohara and Yashida as poorly developed areas (PDAs).

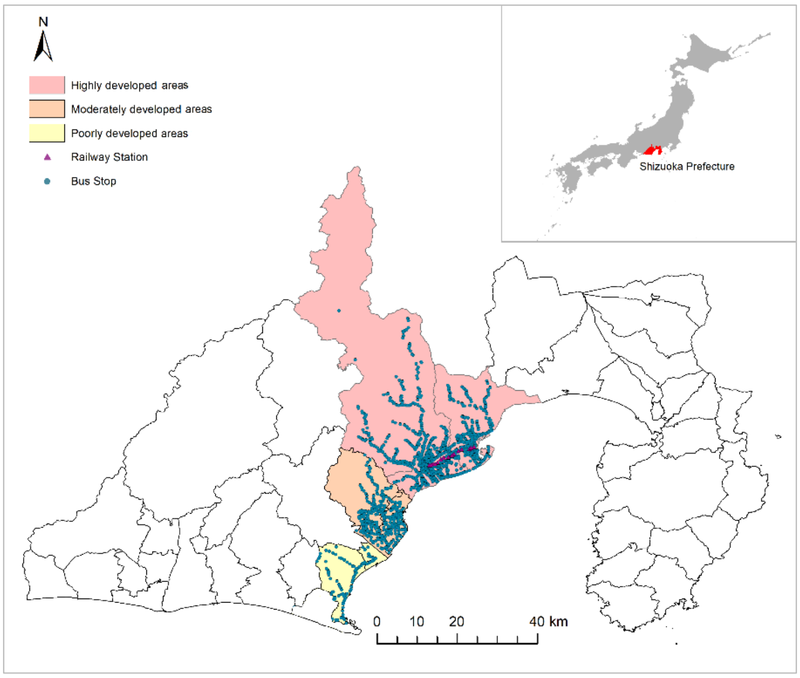


Fig. 1 Study area in Shizuoka

Shizutetsu Bus operates an extensive bus network with approximately 1600 bus stops spread over HDAs, MDAs, and PDAs, whereas Shizutetsu Railway runs one urban railway line with 15 stations spanning HDAs only. Compared to bus, urban railway is faster and more dependable. Coupled with bus accessibility, public transport appears the most attractive in HDAs, followed by MDAs, and the least friendly to older adults in PDAs (Fig. 2). With better public transport accessibility, older people are more likely to travel by public transport.

Table 1 Statistics of socioeconomic conditions in the three types of areas

Variables	HDAs	MDAs		PDAs	
	Shizuoka	Yaizu	Fujieda	Makinohara	Yoshida
Area (km^2)	1411.83	70.31	194.06	111.69	20.73
City planning area (km^2)	234.83	70.31	112.22	80.03	20.73
Population	695,416	137,193	142,689	44,392	29,017
Proportion of older adults (%)	30%	29%	30%	31%	25%
GDP (10^6 yen)	3,300,365	606,873	559,395	612,858	190,586
Manufacturing (% of GDP)	30%	48%	44%	81%	74%
Services (% of GDP)	69%	49%	55%	18%	25%
Per capita income (10^3 yen)	3,643	3,139	3,203	4,061	3,813
Number of hospitals and clinics	929	143	164	58	28

The Shizutetsu Bus and Railway agency issues a smart card named LuLuCa, which can be used to pay for public transport trips. Each smart card has a unique ID, and more than 90% of public transport users have included personal information (e.g., age, gender, and home address) in their registered smart card data. We collected smart card transaction data from April 1, 2018, to March 31, 2019. The full dataset included approximately 194,346 smart cards and 23.54 million transactions, 72% of which were bus transactions and the rest of which were railway transactions. Each transaction record contains card ID, tap-in date and time, tap-out date and time, origin and destination names, travel cost, bus line, and bus route. Apart from smart card transaction data, we also collected smart card registration data, including card ID, home address, age, and gender.

After data cleaning and filtering, there were 26,039, 2,329, and 805 older public transport users in HDAs, MDAs, and PDAs, respectively. The distribution of the distances from their homes to the nearest public transport stops or stations is illustrated in Fig. 2. The access distance to public transport is the shortest in HDAs and the longest in PDAs, suggesting that public transport has greater accessibility in more developed areas. In addition, as shown in Table 2, the number of older female users was significantly higher than the number of male users, indicating that older women are more likely to use public transport than older men. Furthermore, the number of public transport users seems to decrease with age, with the oldest group (85+) having the lowest number of public transport users. Young adult users, aged 18–64, were used as the comparison group to examine differences in travel patterns between older and younger users. There were 50,529, 4,216, and 1,965 younger users in the HDAs, MDAs, and PDAs, respectively, after data cleaning.

Table 2 Demographic characteristics of older adults in the three types of areas

Living area type	Number of older adults	Gender (%)		Age (%)				
		Male	Female	65–69	70–74	75–79	80–84	85+
HDAs	26,039	29%	71%	25%	22%	22%	18%	13%
MDAs	2,329	34%	66%	24%	22%	22%	19%	13%
PDAs	805	39%	61%	31%	29%	17%	13%	10%

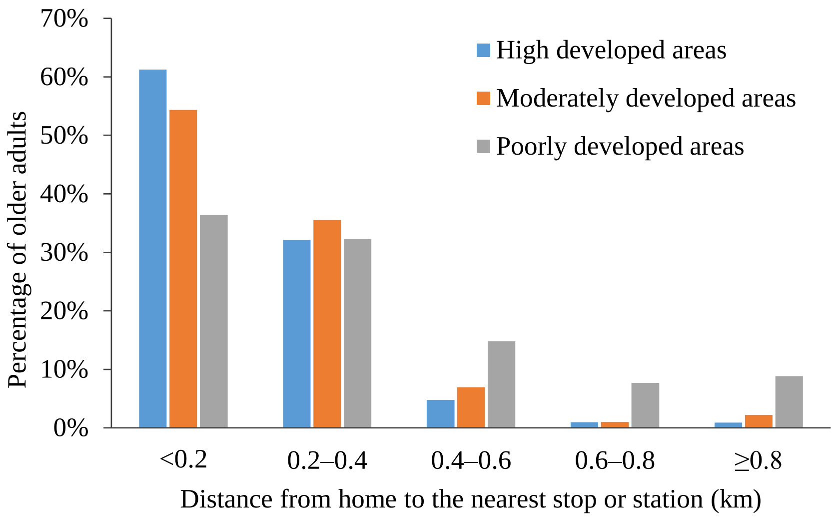


Fig. 2 Distribution of distance from home to the nearest stop or station

4 Methodology

Before exploring the variability in public transport usage, we constructed trips by linking trip legs between which the transfer time was within 30 min. The threshold of 30 min was selected on the basis of the 4th Shizuoka Metropolitan Area Person Trip Survey conducted in 2012, which revealed that more than 94% of transfer activities took less than 30 min in the public transport network.

4.1 Seasonal variability in public transport usage

As smart card transaction records of users who use public transport over a short period are not sufficient to reveal seasonal variability in public transport usage, non-recurrent users were identified first by grouping users according to their public transport usage characteristics. Each user was characterized by the number of travel days over a one-year analysis period and the spread of travel days between the first and last days (Goulet-Langlois et al., 2016; Liu et al., 2020). Using these two features and the k-means++ algorithm, three clusters of users were identified: non-recurrent users who travel on a few days spread over a short period (average of 8 days traveled and 79 days spread), intermittent users who travel on a few days spanning most of the analysis period (average of 34 days traveled and 326 days spread), and frequent users who travel on many days spread over the analysis period (average of 208 days traveled and 359 days spread). Removing the non-recurrent users, we considered the remaining 23,614 older adults as the primary sample in exploring the seasonal variability in public transport usage.

For each user, we built a monthly vector of 13 elements, including the number of trips per month (from January to December) and the average number of monthly trips. The number of trips per month was transformed monthly trips as percentages of annual trips, capturing the monthly variability in public transport usage. Average numbers of monthly trips were normalized to values between 0 and 1 using min–max feature scaling, where the minimum and maximum values were defined based on all users' average monthly trips. Hence, the normalized average monthly trips reflected how often users take public transport. Based on the normalized user-monthly vectors, we applied the k-means++ algorithm to identify users with similar monthly patterns. The k-means++ algorithm (Arthur and Vassilvitskii, 2007) improves the initialization process using a randomized seeding technique, which outperforms the standard k-means method in terms of both accuracy and speed.

After determining the clusters of all users, we linked the cluster membership of each user to the cardholder anonymous database. Odds ratio analysis was conducted to evaluate the association between socioeconomic characteristics and cluster membership. As summarized in (1), the odds ratio $OR_{c,k}$ measures how much more (or less) likely a user in cluster k to have a given characteristic *c* than a user in other clusters (Egu and Bonnel, 2020; Goulet-Langlois et al., 2016). A $OR_{c,k}$ value greater than 1 indicates a positive association and vice versa:

$$OR_{c,k} = \frac{N_{c,k}/N_{c',k}}{N_{c,k'}/N_{c',k'}} \quad (1)$$

where $N_{c,k}$ is the number of users with a characteristic *c* in cluster *k*, k' is the aggregation of all clusters other than *k*, and c' refers to the aggregation of demographic characteristics except *c*. The natural logarithm of $OR_{c,k}$ is normally distributed, and whether $OR_{c,k}$ is significantly different from 1 at a given confidence level can be tested using the logit method (Morris and Gardner, 1988).

4.2 Day-to-day variability in public transport usage

We investigated the day-to-day variability in public transport usage based on daily trip patterns. For each public transport user, a day was characterized by not only trip frequency but also the spatiotemporal characteristics of trips. More specifically, the pick-up time was used to characterize temporal patterns other than the drop-off time, considering that bus travel is affected by road conditions that add more uncertainty to the drop-off time. Spatial patterns were represented by the origins and destinations of trips. Two days were considered similar if they had the same number of trips and these trips shared similar spatiotemporal characteristics.

We developed an ordered set $T = \{T(1), T(2), ...\}$ for each user to represent temporal patterns. An item $T(i)$ consisted of $T_t(i)$ and $T_f(i)$, where $T_t(i)$ indicated a time slot and $T_f(i)$ was the trip frequency during the time slot. A time slot set T_t was determined for each user according to the user's pick-up time distribution. In other words, the time segmentation for a user depended on the user's travel habits. This addressed the limitation that conventional time segmentations, such as breaking down a day into discrete time bins (e.g., hourly intervals) or predefined time windows (e.g., morning peak, midday, and evening peak) may not be appropriate for everyone.

To identify user-based time slots of the day, we applied sequential, overlapped, and fixed-time-length slots to split a one-day period, based on the work by Zhao et al. (2017). The length of the time slots was set to 2 h because: (1) 98% of trips last no more than 1 h in the public transport system; (2) users may change their travel schedules and the varying trips are involved by adding 1-h floating-time intervals to extend time slots. In this way, a day was split into 24 time slots: 00:00–01:59, 01:00–02:59, 02:00–03:59, …, 22:00–23:59, 23:00–00:59. User-based time slot sets were then determined using the approach described below. An example is illustrated in Fig. 3.

T'	Time slots T_t'	00:00-00:59	01:00-01:59	…	06:00-06:59	07:00-07:59	08:00-08:59	…	23:00-23:59
	Trip frequency T_f'	0	0	…	5	67	118	…	2

T''	Time slots T_t''	07:00-08:59	18:00-19:59	08:00-09:59	19:00-20:59	17:00-18:59	6:00-7:59	…	11:00-12:59
	Trip frequency T_f''	185	130	122	81	79	72	…	1

T	Time slots T_t	07:00-08:59	18:00-19:59	21:00-22:59	16:00-17:59	9:00-10:59	13:00-14:59	…	11:00-12:59
	Trip frequency T_f	185	130	25	21	7	7	…	1

Fig. 3 Example of extraction of user-based time slots

Step 1: Based on smart card transaction data, trip frequency is counted by hour for each user, as shown in the top portion of Fig. 3.

Step 2: Trip frequencies during overlapped time slots T_t''= {00:00–01:59, 01:00–02:59, …, 23:00–00:59} are calculated. Zero-value items are then deleted, and the set T'' is arranged by trip frequency in descending order, as presented in the middle portion of Fig. 3.

Step 3: User-based nonoverlapping time slots are determined by the following algorithm.

```
Algorithm: Extract individual temporal pattern T
T = Null
for i in 1: length (T_t'')
    if T_t''(i) does not overlap with T_t
        add T''(i) to T
    end if
end for
# check whether all trips are involved
T' = T'(T_f' > 0) # keep only non-zero items in hourly set T'
for j in 1: length (T_t')
    if T_t'(j) does not overlap with T_t
        add T'(j) to the front adjacent item in T
    end if
end for
arrange T by trip frequency in descending order
return T
```

The algorithm iterates the ordered overlapped time slot set T_t'' and adds an item $T_t''(i)$ to the set T if $T_t''(i)$ has no overlap with the time slot set T_t. For example, as illustrated in the bottom portion of Fig. 3, we added $T''(1)$ (the time slot of 07:00–08:59 and corresponding trip frequency 185) and $T''(2)$ successively to the set T. However, $T''(3) - T''(6)$ could not be added to the set T, as $T_t''(3)$ –$T_t''(6)$ overlapped with the first two time slots. Sometimes the set T obtained through the above iterative process may miss some hourly intervals. For example, the time slots of 16:00–17:59 and 13:00–14:59 remained in the set T, whereas the time period of 15:00–15:59 was missed. Given that there may be trips made during the missed time periods, we conducted a check to see whether all trips were involved. If time periods with trips were missed, they were added to the front adjacent items in T; for example, the time slot of 13:00–14:59 was extended to 13:00–15:59, and trips made during 15:00–15:59 were added to the extended time slot.

To represent spatial patterns, we first grouped public transport stops and stations into user-based geographical areas. As there is usually more than one public transport stop or station around an activity location, a user may use different stops or stations to access the same activity location. Moreover, some passengers get off a bus before reaching the final bus stop when there is heavy traffic congestion (Yamamoto et al., 2021). Therefore, it is necessary to examine the spatial relationships between stops and stations. Based on smart card transaction data, we built an activity stop and station set (including all distinct pick-up and drop-off stops and stations) for each user. Given a 10-minute walk, if the distance between stops or stations was shorter than 800 m, these stops and stations were grouped into the same geographical area. Origin–destination (OD) pairs, represented by the geographical areas of origin and destination of trips, were used to characterize spatial patterns.

Based on the identified temporal and spatial patterns, each trip was connected to a time slot and an OD pair to characterize the trip's spatiotemporal characteristics. If two days had the same number of trips and these trips shared similar spatiotemporal characteristics, we considered the daily trip patterns of these two days to be similar. Based on daily trip patterns, we explored the day-to-day variability in public transport usage using Shannon entropy and average similarity. Entropy is an expression of the disorder or randomness of a system that can be used to capture travel pattern variability and predictability (Deschaintres et al., 2019; Song et al., 2010). As summarized in (2), entropy measures the diversity of the distribution of daily trip patterns. Greater entropy indicates more diverse daily trip patterns and higher day-to-day variability in public transport usage.

$$E_\mu = -\sum_{k=1}^{H_\mu} P(R_k)\log_2 P\,(R_k) \tag{2}$$

where E_μ is the entropy of a user μ, H_μ is the number of distinct daily trip patterns of the user, and $P(R_k)$ is the probability that the user exhibits a daily trip pattern R_k.

Although entropy measures the daily variability in public transport usage, it cannot be used to compare the daily trip patterns between distinct days of the week, such as the travel pattern difference between Mondays and Tuesdays. Hence, we proposed the average similarity S_μ, as follows.

$$S_\mu = \begin{cases} \frac{1}{N_\mu \times M_\mu}\sum_{i=1}^{N_\mu}\sum_{j=1}^{M_\mu} S(D_i, D_j) \\ \frac{2}{N_\mu \times (N_\mu - 1)}\sum_{i=1}^{N_\mu}\sum_{j=i+1}^{N_\mu} S(D_i, D_j) \end{cases} \tag{3}$$

$$S(D_i, D_j) = \begin{cases} 1 & \text{if } D_i = D_j \\ 0 & \text{else} \end{cases} \tag{4}$$

where $S(D_i, D_j)$ is a Boolean variable that captures the similarity in daily trip patterns between day i and day j and N_μ is the number of days with same features (e.g., the number of Mondays), as is M_μ (e.g., the number of Tuesdays). More similar daily trip patterns result in greater values of the indicator.

5 Results

5.1 Seasonal variability in public transport usage

Based on smart card transaction data for older adults, aggregate numbers of monthly trips were calculated and are shown in Fig. 4. Shizuoka has a humid subtropical climate characterized by hot summers and mild winters. The number of monthly trips exhibits seasonal variation that is smaller when the temperature is higher than 24°C (from July to September) or lower than 8°C (from January to February). This suggests that the travel of older users is affected by the weather.

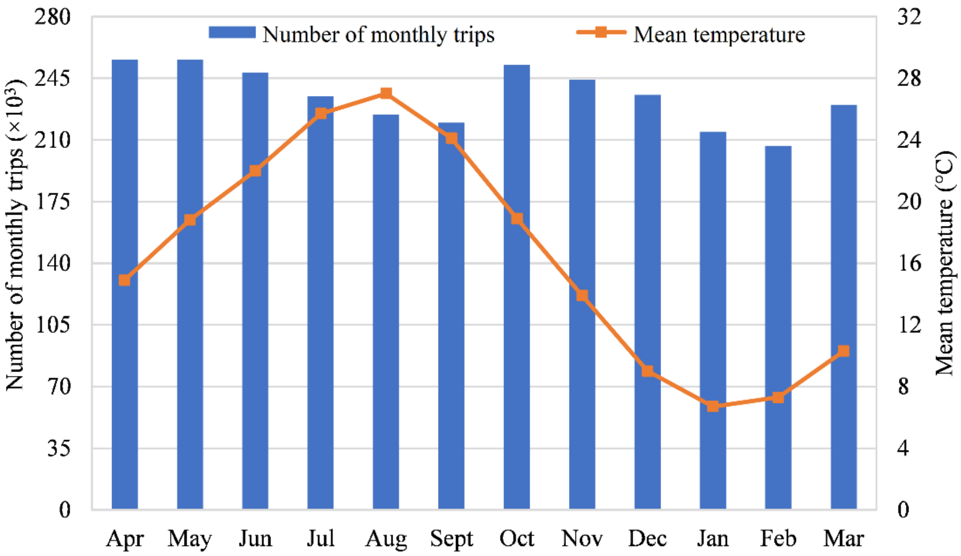


Fig. 4 Aggregate monthly trips in study area

Based on normalized user-monthly vectors, the k-means++ algorithm was used to group older adults with similar monthly patterns. Fig. 5 shows the Davies–Bouldin index, a measure of internal cluster validation based on the ratio of the within-cluster scatter to the between-cluster separation. A smaller Davies–Bouldin index value indicates better clustering results; hence, the optimal value of k is 2. We grouped older adults into two clusters, each characterized by a distinct monthly profile. Fig. 6 illustrates the centers of these two clusters, as well as the interquartile ranges (intervals between the 75th and 25th percentiles). The center of a cluster was calculated as the average of the user-monthly vectors that belong to the cluster, representing the average trip distribution by month and average monthly public transport use frequency.

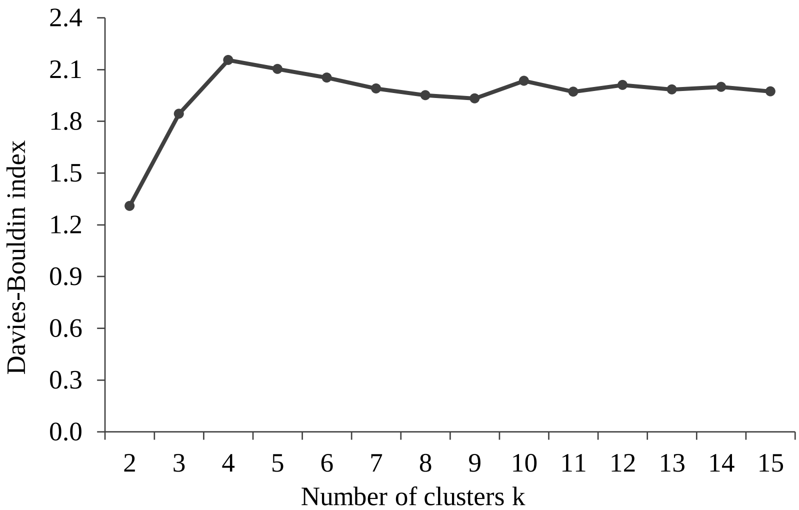


Fig. 5 Davies-Bouldin index for clustering

Cluster 1 accounted for 86.6% of older adults, characterized by low-frequency public transport usage (average of five trips made per month and 37 days traveled in the analysis period) and high seasonal variability. In line with the aggregate monthly trip analysis, older adults tended to take public transport less frequently in hot weather (from July to September) and cold weather (January and February). Further, according to the interquartile ranges, the distribution of monthly public transport usage showed a great variation among older persons. Based on the odds ratio statistics shown in Table 3, older adults in MDAs and PDAs were 1.24 times and 3.41 times more likely to be assigned to this cluster than to Cluster 2, respectively, which suggests that older adults in less developed areas take public transport less frequently and that their public transport use frequency is more likely to be affected by weather. Older adults aged 75 or over were positively associated with this cluster, indicating that older adults (75+) tend to use public transport less and exhibit greater variation in monthly trips than the younger-old group (65–74).

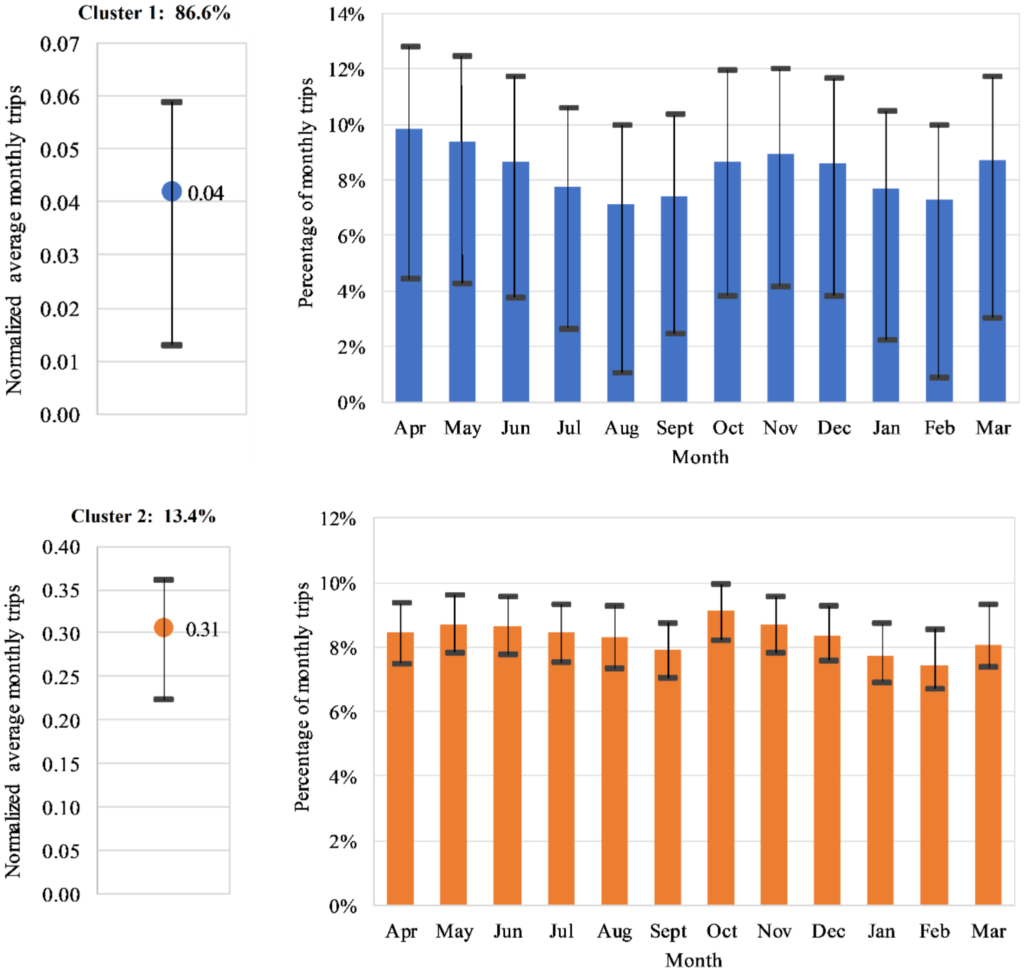


Fig. 6 Monthly profile cluster centers

Cluster 2 comprised 13.4% of older adults. The major features characterizing this cluster were high-frequency public transport usage (average of 38 trips made per month and 220 days traveled in the analysis period) and low seasonal variability. According to the interquartile ranges, the distribution of monthly public transport usage exhibited less variation among older adults than in Cluster 1. Based on the odds ratio statistics, older persons in HDAs were 1.50 times more likely to be classified into Cluster 2 than into Cluster 1, suggesting that older adults in HDAs tend to use public transport frequently and that their monthly trips vary slightly. Furthermore, those in the age cohorts of 65–69 and 70–74 were 1.37 times and 1.07 times more likely, respectively to be assigned to this cluster than to Cluster 1, which reveals that the younger-old group (65–74) are more likely to use public transport frequently and exhibit small variation in their monthly use frequency.

Table 3 Odds ratio statistics of older user clusters

Cluster ID	Living area type			Gender		Age				
	HDAs	MDAs	PDAs	Male	Female	65–69	70–74	75–79	80–84	85+
1	0.67	1.24	3.41	1.06	0.95	0.73	0.93	1.04	1.24	1.46
2	1.50	0.80	0.29	0.95	1.06	1.37	1.07	0.96	0.81	0.68

Note: All odds ratios are significant at the 95% confidence level.

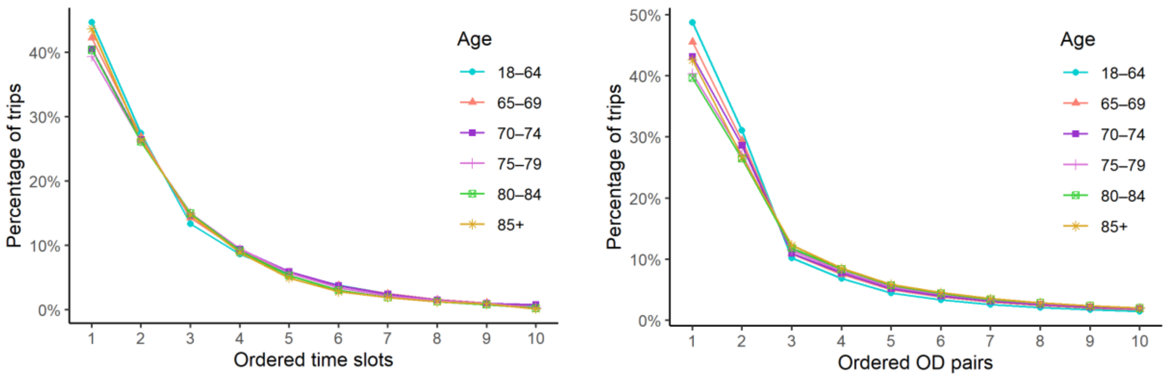
As in the analysis method for older adults, we selected 37,119 intermittent and frequent younger users to explore the seasonal variability in public transport usage among younger adults. As illustrated in Appendix A, compared to older adults, seasonal variability was lower among both low-frequency and high-frequency younger users. Moreover, according to odds ratio statistics, younger users in HDAs, MDAs, and PDAs were 1.16, 0.90, and 1.08 times more likely, respectively, to be assigned to Cluster 1 than to Cluster 2, which implies that regional living environment has less impact on the seasonal variability in public transport usage among younger adults than among older persons.

5.2 Day-to-day variability in public transport usage

There is a significant effect of age on trip frequency, $t\ (69{,}282) = 28.35$, $p < 0.001$, with younger adults using public transport more frequently than older persons. Table 4 summarizes the characteristics of public transport use by age. Compared to younger adults, older adults are characterized by reduced travel on weekdays and frequent trips on non-working days, which is consistent with the findings of Shao et al. (2019). Additionally, older adults tend to travel during fewer time slots of the day (Mean = 5.09, SD = 1.91) than younger adults (Mean = 5.51, SD = 2.30), $t\ (69{,}303) = 28.61$, $t < 0.001$; whereas they have significantly more activity locations (Mean = 7.07, SD = 4.86) than younger people (Mean = 5.96, SD = 3.94), $t\ (49{,}297) = -33.42$, $t < 0.001$. Moreover, we sorted the time slots and OD pairs by trip frequency for each user and calculated the average proportions of trips of ordered time slots and OD pairs. Fig. 7 shows that most trips were made during the top two time slots and between the top two OD pairs, which is consistent with the findings of Zhao et al. (2017). This can be explained by the fact that most riders have limited active places and travel during relatively fixed time slots. Further, older adults appeared to have fewer concentrated active time slots and OD pairs than younger adults, which suggests that the temporal and spatial distributions of trips become more diffuse as age increases.

Table 4 Descriptive statistics of public transport use characteristics by age

Public transport use characteristics	18–64	65–69	70–74	75–79	80–84	85+
Average number of trips on weekdays	105.74	80.39	77.21	77.77	74.57	64.32
Average number of trips on non-working days	19.72	20.55	21.83	21.57	20.42	17.16
Average number of distinct time slots	5.51	5.20	5.27	5.23	4.99	4.46
Average number of activity locations	5.96	6.48	7.05	7.59	7.58	6.63
Average entropy	2.56	2.76	2.99	3.18	3.23	2.98

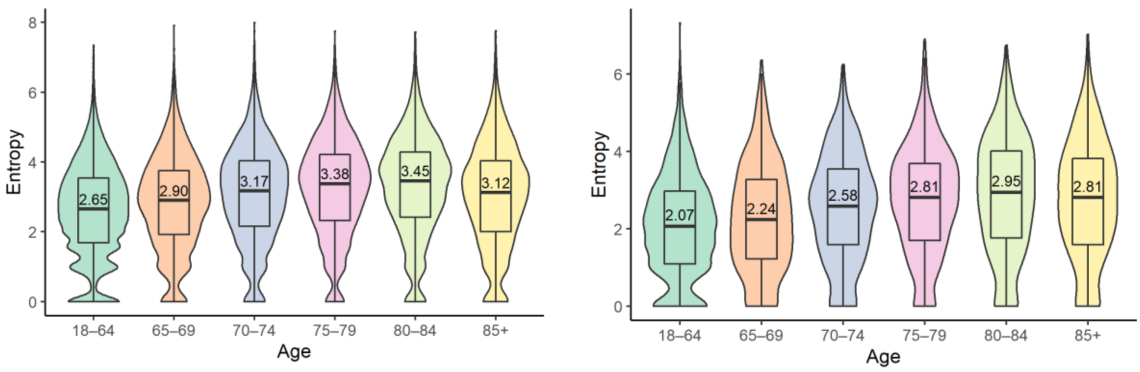


(a) Temporal distribution of trips

(b) Spatial distribution of trips

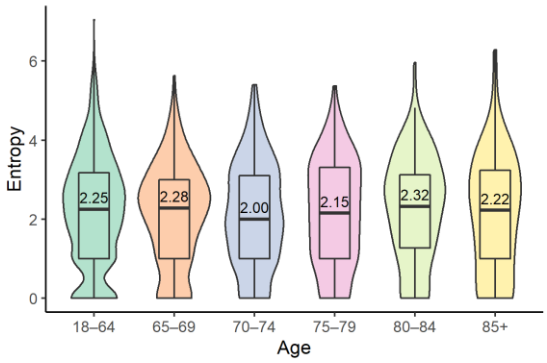
Fig. 7 Trip distributions of ordered time slots and ordered OD pairs

Based on daily trip patterns, we explored the day-to-day variability in public transport usage using entropy and average similarity. Entropy results indicate that older adults (Mean = 3.01, SD = 1.43) show significantly higher entropy values than younger adults (Mean = 2.56, SD = 1.34), t (55,401) = -45.46, p < 0.001, suggesting that older adults tend to exhibit higher day-to-day variability than younger adults. We used violin plots to represent the comparison of the entropy distribution across different age groups and different types of living areas, as shown in Fig. 8. Violin plots not only indicate median and interquartile ranges but also depict the distribution of the data using density curves. The width of each curve corresponds to the approximate frequency of the data points in each region. According to Fig. 8, the entropy values of transport usage by older adults were the largest in HDAs, followed by MDAs and PDAs, which indicates that the public transport usage by older adults shows higher day-to-day variability in more developed areas. Compared to the entropy in HDAs, the entropy values in MDAs and PDAs exhibited more elongated distributions without distinct peaks, suggesting that daily trip patterns are more diffuse among older adults in less developed areas. Regarding the day-to-day variability by age groups, in HDAs and MDAs, the day-to-day variability in public transport usage appeared to be higher among older adults than among younger adults, and the day-to-day variability among older adults aged 65–84 seemed to increase with age. In contrast, older adult users in PDAs do not show significantly higher day-to-day variability in public transport usage than younger adults, which may be a result of their lower frequency of public transport usage.



(a) HDAs

(b) MDAs



(c) PDAs

Fig. 8 Distribution of entropy by age and living area types

To measure daily trip pattern variability between days of the week, average similarity indicators were calculated for each user, and then a mean was evaluated within older adult group. The results are presented in Table 5 and Appendix B. Compared to younger adults, older adults showed less similarity in daily trip patterns between days of the week. Additionally, there was less similarity within the same weekend days than within the same weekdays. Moreover, weekdays were more similar within each other than with weekend days, and the same weekdays exhibited more similarity than distinct weekdays, which is consistent with the findings of Egu and Bonnel (2020). Regarding the regional differences, the mean similarity indicators of older adults between weekdays were the smallest in HDAs, followed by MDAs and then PDAs. In addition, the mean similarity indicators of older adults between weekend days in PDAs were greater than those in HDAs and MDAs. This suggests that the day-to-day variability of older adults is higher in more developed areas, which is consistent with the entropy results.

Table 5 Mean similarity between days of the week in HDAs

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
Mon.	0.168 (0.278)	0.126 (0.259)	0.125 (0.247)	0.127 (0.256)	0.125 (0.229)	0.080 (0.087)	0.084 (0.076)
Tue.		0.160 (0.286)	0.122 (0.252)	0.127 (0.261)	0.121 (0.234)	0.082 (0.086)	0.082 (0.070)
Wed.			0.161 (0.273)	0.123 (0.249)	0.120 (0.229)	0.084 (0.087)	0.083 (0.071)
Thu.				0.162 (0.278)	0.122 (0.234)	0.087 (0.090)	0.087 (0.076)
Fri.					0.153 (0.244)	0.085 (0.091)	0.084 (0.073)
Sat.						0.130 (0.133)	0.095 (0.098)
Sun.							0.113 (0.125)

Note: Mean similarity indicators of the younger comparison group are given in parentheses.

6 Discussion and conclusions

Using smart card data from Shizuoka, Japan, we explored the seasonal and day-to-day variability in public transport usage by older adults and analyzed the association between socioeconomic characteristics and travel pattern variability. Our methodological contribution resides in the novel representations of user-monthly profiles and user-based daily trip patterns. By representing each user as a monthly vector and using the k-means++ algorithm, we captured both public transport use frequency and seasonal variability in public transport usage. We defined geographical user areas and user-based time slots of the day based on users' trip distribution in space and time, and we characterized daily trip patterns by trip frequency and the spatiotemporal characteristics of trips. Based on daily trip patterns, we further investigated day-to-day variability in public transport usage using entropy and average similarity.

Our empirical contribution is that we revealed the seasonal and day-to-day variability in public transport usage by older adults in different age groups and in three types of living areas using a large sample. Regarding the seasonal variability in public transport usage in three types of living areas, older people in HDAs are more likely to be characterized by high-frequency public transport usage and low seasonal variability, suggesting that these older adults take public transport more frequently and that their public transport use frequency varies less with the season. This may be explained by the following facts. First, as found by He et al. (2018), older adults living in inner-city areas are the most active travelers. Older adults are more willing to make trips and participate in social activities with easier access to a wide variety of activities (e.g., shopping and recreation) in more developed areas. Second, public transport has greater accessibility in more developed areas, resulting in a higher probability of using public transport (Kim and Ulfarsson, 2004; Truong and Somenahalli, 2015). According to the 4th Shizuoka Metropolitan Area Person Trip Survey, among older adults, 3.8% of trips are completed by public transport and 49.4% are made by automobiles in HDAs, whereas public transport accounts for only 0.8% of trips in MDAs, while 62.7% are made by automobile. Older persons appear to be more dependent on automobiles in less developed areas. Although there are fewer public transport demands in MDAs and PDAs, older adults who cannot drive or choose not to drive are a disadvantaged group that requires special attention. To make the best use of limited public transport resources, increased door-to-door minibus usage should be considered for less developed areas.

Our findings on the seasonal variability in public transport usage among different age groups indicate that the younger-old group (65–74 years) is more likely to be associated with high-frequency public transport usage and low seasonal variability, whereas older adults aged 75 or over have a higher probability of being characterized by low-frequency public transport usage and high seasonal variability. This indicates that different older age cohorts exhibit heterogeneous travel characteristics and that aging-related mobility tends to decline with age, which is consistent with the findings of previous studies (Alsnih and Hensher, 2003; Kim et al., 2020; Szeto et al., 2017; Truong and Somenahalli, 2015). Because users characterized by low frequency and high seasonal variability account for over 80% of older adults, close attention should be paid to their needs. A targeted survey can be conducted among these users to help public transport authorities better understand the obstacles to public transport usage by older adults. Additionally, to discourage older adults from driving, in Shizuoka, not only older people aged 65 and over but also those aged 60-64 who voluntarily return their driver's licenses are eligible to buy senior passes. Compared to commuter passes that are limited to a single spatial interval, senior passes are cheaper and can be used in most public transport routes. However, the currently available senior passes are more useful for high-frequency users than for low-frequency users. For example, the one-month senior pass is 5,100 yen, which is equivalent to the cost of 25 public transport rides at regular fares. Namely, if travelers use public transport less than 25 times a month, it is not a cost-effective option to buy the senior pass. Therefore, public transport concession fare can be designed for older adults, allowing low-frequency users to take public transport at lower fares. Moreover, free travel passes have been proved to have a positive effect on promoting public transport usage by older adults in Britain, Hongkong, and Beijing (Baker and White, 2010; Wong et al., 2018; Zhang et al., 2019). For the older-old group (aged 75+) at risk of driving cession and social exclusion in Japan, the introduction of free travel passes may improve their probability of using public transport, enhance their mobility and promote their participation in social activities.

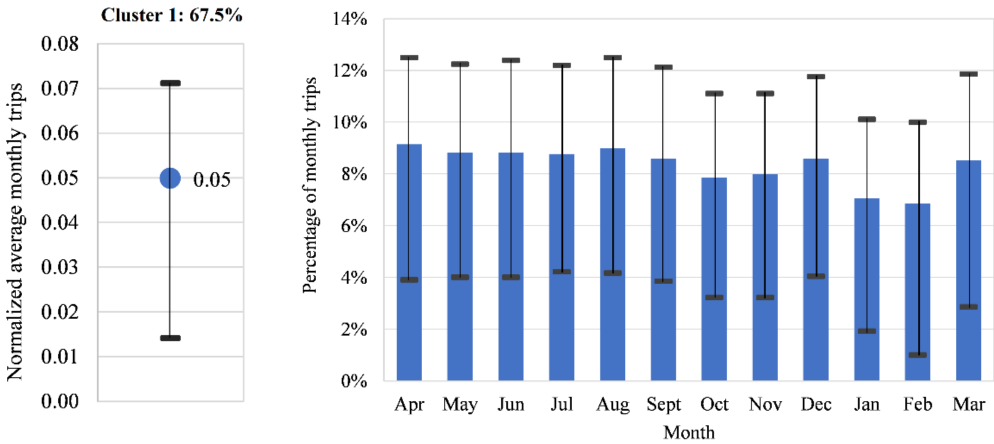
Our findings also shed light on the day-to-day variability in public transport usage by older adults. The public transport usage of older adults exhibits the highest day-to-day variability in HDAs, followed by MDAs and PDAs. This may result from the greater access to a wide variety of activities and more options for travel schedules in more developed areas. Meanwhile, entropy values seem to increase with age among older adults aged between 65 and 84 in HDAs and MDAs, suggesting that older adults tend to have more diverse daily trip patterns. Although the retirement age is typically 65 in Japan, many older persons continue to work for financial reasons or social participation. Based on the 4th Shizuoka Metropolitan Area Person Trip Survey, for the 65–69, 70–74, and 75+ age groups, 13.9%, 5.6%, and 3.0% of public transport trips, respectively, are made for work purposes. Decreased commuting may contribute to more diverse daily trip patterns. Meanwhile, the existence of commuting trips also explains why weekdays are still more similar to each other than to weekend days for older adults. Intrapersonal day-to-day variability can assist in identifying groups of older adults who are more likely to change their travel behavior with the introduction of new services (Egu and Bonnel, 2020). In addition, for the frequent older adults with low day-to-day variability, we can get the information about where and when users typically travel. If their trips are expected to be disrupted or highly crowded, not only an alert but also targeted suggestions related to alternative travel options can be sent to them. Compared to indiscriminately diffused messages, personalized information provision can increase the effectiveness of these messages and improve passenger experience.

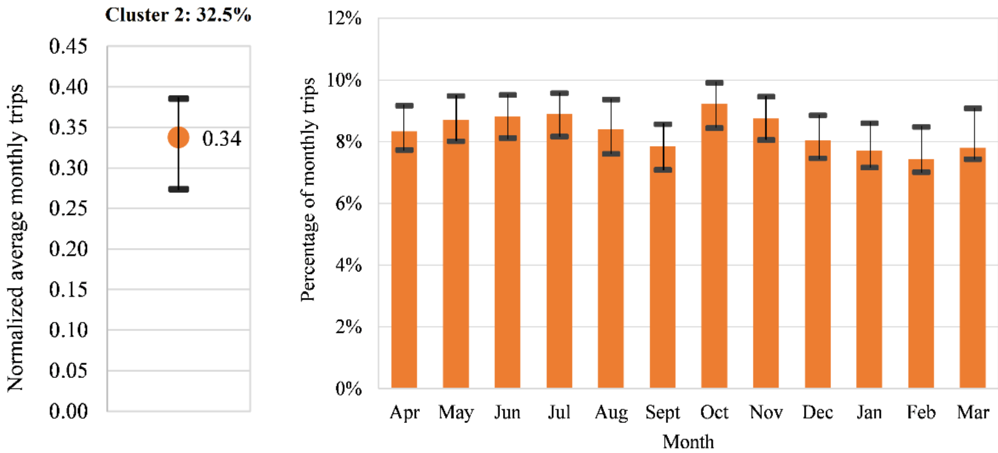
Although the results of this study advance our understanding of the seasonal and day-to-day variability in public transport usage by older adults, there are several limitations of the study. First, we focused only on public transport usage, neglecting competition with other modes (e.g., automobiles and taxis). The influence of access to alternative modes, destination choice, and trip purpose should be examined in future research. Second, we did not investigate the effects of socioeconomic characteristics (e.g., household structure, income level, and car ownership) and physical conditions on public transport usage by older adults. In the future, a survey distributed by mail to registered cardholders with registered home addresses can collect more information on socioeconomic characteristics and competitive modes. The impacts of competitive modes and more socioeconomic characteristics on public transport usage by older adults can then be evaluated.

Acknowledgements

We are grateful to the Shizutetsu Group for providing the data for this study. We also thank the editors and three anonymous reviewers for their valuable comments and suggestions. This work was supported in part by the National Key R&D Program of China (No. 2018YFB1601300).

Appendix A Representation of monthly profile clusters of younger users





Appendix B Mean similarity between days of week in MDAs and PDAs

(a) Mean similarity between days of week in MDAs

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
Mon.	0.179 (0.306)	0.149 (0.286)	0.148 (0.270)	0.140 (0.282)	0.144 (0.264)	0.078 (0.108)	0.086 (0.094)
Tue.		0.192 (0.318)	0.149 (0.277)	0.149 (0.292)	0.141 (0.272)	0.088 (0.111)	0.090 (0.093)
Wed.			0.177 (0.293)	0.139 (0.272)	0.140 (0.261)	0.082 (0.107)	0.088 (0.089)
Thu.				0.180 (0.310)	0.133 (0.268)	0.089 (0.110)	0.087 (0.093)
Fri.					0.165 (0.284)	0.086 (0.111)	0.086 (0.093)
Sat.						0.145 (0.184)	0.110 (0.137)
Sun.							0.142 (0.164)

(b) Mean similarity between days of week in PDAs

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
Mon.	0.200 (0.253)	0.161 (0.238)	0.170 (0.218)	0.157 (0.219)	0.168 (0.200)	0.109 (0.102)	0.098 (0.083)
Tue.		0.205 (0.267)	0.165 (0.227)	0.138 (0.227)	0.163 (0.207)	0.101 (0.096)	0.076 (0.077)
Wed.			0.173 (0.248)	0.153 (0.219)	0.169 (0.197)	0.109 (0.097)	0.091 (0.078)
Thu.				0.188 (0.244)	0.163 (0.207)	0.105 (0.098)	0.089 (0.075)
Fri.					0.211 (0.218)	0.142 (0.098)	0.119 (0.075)
Sat.						0.181 (0.146)	0.122 (0.094)
Sun.							0.137 (0.126)

References

Akiyama, T., Kim, J.K., 2005. Transportation policies for the elderly and disabled in Japan. *Int. J. Urban Sci.* 9, 87–98. https://doi.org/10.1080/12265934.2005.9693575.

Alsnih, R., Hensher, D.A., 2003. The mobility and accessibility expectations of seniors in an aging population. *Transp. Res. A* 37, 903–916. https://doi.org/10.1016/S0965-8564(03)00073-9.

Arentze, T., Timmermans, H., Jorritsma, P., Olde Kalter, M.J., Schoemakers, A., 2008. More gray hair-but for whom? Scenario-based simulations of elderly activity travel patterns in 2020. *Transportation* 35, 613–627. https://doi.org/10.1007/s11116-008-9170-z.

Arthur, D., Vassilvitskii, S., 2007. K-means++: The advantages of careful seeding. *Proc. Annu. ACM-SIAM Symp. Discret. Algorithms,* 07–09-Janu, 1027–1035.

Baker, S., & White, P., 2010. Impacts of free concessionary travel: Case study of an English rural region. *Transp. Policy*, *17*(1), 20-26. https://doi.org/10.1016/j.tranpol.2009.09.002

Bloom, D.E., Luca, D.L., 2016. The Global Demography of Aging: Facts, Explanations, Furture, 1st ed., Handbook of the Economics of Population Aging. Elsevier B.V. https://doi.org/10.1016/bs.hespa.2016.06.002.

Boschmann, E.E., Brady, S.A., 2013. Travel behaviors, sustainable mobility, and transit-oriented developments: A travel counts analysis of older adults in the Denver, Colorado metropolitan area. *J. Transp. Geogr. 33*, 1–11. https://doi.org/10.1016/j.jtrangeo.2013.09.001.

Burkhardt, J.E., 2003. Better transportation services for older persons. *Transp. Res. Rec.* 1843, 105–112. https://doi.org/10.3141/1843-13.

Chandraratna, S., Stamatiadis, N., 2003. Problem driving maneuvers of elderly drivers. *Transp. Res. Rec.* 1843, 89–95. https://doi.org/10.3141/1843-11.

Chihuri, S., Mielenz, T.J., Dimaggio, C.J., Betz, M.E., Diguiseppi, C., Jones, V.C., Li, G., 2016. Driving cessation and health outcomes in older adults. *J. Am. Geriatr. Soc.* 64, 332–341. https://doi.org/10.1111/jgs.13931.

Choi, J., Do Lee, W.D., Park, W.H., Kim, C., Choi, K., Joh, C.H., 2014. Analyzing changes in travel behavior in time and space using household travel surveys in Seoul Metropolitan Area over eight years. *Travel Behav. Soc.* 1, 3–14. https://doi.org/10.1016/j.tbs.2013.10.003.

Chu, K.K.A., Chapleau, R., 2010. Augmenting transit trip characterization and travel behavior comprehension:

Multiday location-stamped smart card transactions. *Transp. Res. Rec.* 2183, 29–40. https://doi.org/10.3141/2183-04.

Collia, D.V., Sharp, J., Giesbrecht, L., 2003. The 2001 National Household Travel Survey: A look into the travel patterns of older Americans. J. Saf. Res. 34, 461–470. https://doi.org/10.1016/j.jsr.2003.10.001.

Cui, J., Loo, B.P.Y., Lin, D., 2017. Travel behaviour and mobility needs of older adults in an ageing and car-dependent society. *Int. J. Urban Sci.* 21, 109–128. https://doi.org/10.1080/12265934.2016.1262785.

Currie, G., Delbosc, A., 2010. Exploring public transport usage trends in an ageing population. *Transportation* 37, 151–164. https://doi.org/10.1007/s11116-009-9224-x.

Deschaintres, E., Morency, C., Trépanier, M., 2019. Analyzing transit user behavior with 51 weeks of smart card data. *Transp. Res. Rec.* 2673, 33–45. https://doi.org/10.1177/0361198119834917.

Dickerson, A.E., Molnar, L.J., Eby, D.W., Adler, G., Bédard, M., Berg-Weger, M., Classen, S., Foley, D., Horowitz, A., Kerschner, H., Page, O., Silverstein, N.M., Staplin, L., Trujillo, L., 2007. Transportation and aging: A research agenda for advancing safe mobility. *Gerontologist* 47, 578–590. https://doi.org/10.1093/geront/47.5.578.

Egu, O., Bonnel, P., 2020. Investigating day-to-day variability of transit usage on a multimonth scale with smart card data. A case study in Lyon. *Travel Behav. Soc*. 19, 112–123. https://doi.org/10.1016/j.tbs.2019.12.003.

Engels, B., Liu, G.J., 2011. Social exclusion, location and transport disadvantage amongst non-driving seniors in a Melbourne municipality, Australia. *J. Transp. Geogr.* 19, 984–996. https://doi.org/10.1016/j.jtrangeo.2011.03.007.

Föbker, S., Grotz, R., 2006. Everyday mobility of elderly people in different urban settings: The example of the city of Bonn, Germany. Urban Stud. 43, 99–118. https://doi.org/10.1080/00420980500409292.

Goulet-Langlois, G., Koutsopoulos, H.N., Zhao, J., 2016. Inferring patterns in the multi-week activity sequences of public transport users. *Transp. Res. C* 64, 1–16. https://doi.org/10.1016/j.trc.2015.12.012.

He, S.Y., Cheung, Y.H.Y., Tao, S., 2018. Travel mobility and social participation among older people in a transit metropolis: A socio-spatial-temporal perspective. *Transp. Res. A* 118, 608–626. https://doi.org/10.1016/j.tra.2018.09.006.

Hjorthol, R.J., Levin, L., Sirén, A., 2010. Mobility in different generations of older persons. *J. Transp. Geogr.* 18, 624–633. https://doi.org/10.1016/j.jtrangeo.2010.03.011.

Ipingbemi, O., 2010. Travel characteristics and mobility constraints of the elderly in Ibadan, Nigeria. *J. Transp. Geogr.* 18, 285–291. https://doi.org/10.1016/j.jtrangeo.2009.05.011.

Japan Statistical Yearbook 2020. Statistics Bureau, Ministry of Internal Affairs and Communications, Japan, 2020. https://www.stat.go.jp/english/data/nenkan/69nenkan/index.html

Kim, J., Schmöcker, J.D., Nakamura, T., Uno, N., Iwamoto, T., 2020. Integrated impacts of public transport travel and travel satisfaction on quality of life of older people. *Transp. Res. A* 138, 15–27. https://doi.org/10.1016/j.tra.2020.04.019.

Kim, S., Ulfarsson, G.F., 2004. Travel mode choice of the elderly: Effects of personal, household, neighborhood, and trip characteristics. *Transp. Res. Rec.* 1894, 117–126. https://doi.org/10.3141/1894-13.

Liu, S., Yamamoto, T., Yao, E., Nakamura, T., 2021. Exploring travel pattern variability of public transport users through smart card data: Role of Gender and Age. *IEEE Trans. Intell. Transport. Syst.,* https://doi.org/10.1109/TITS.2020.3043021.

Metz, D., 2003. Transport policy for an ageing population. *Transp. Rev.* 23, 375–386. https://doi.org/10.1080/0144164032000048573.

Miranda-Moreno, L.F., Lee-Gosselin, M., 2008. A week in the life of baby boomers: How do they see the spatial–temporal organization of their activities and travel? *Transportation* 35, 629–653. https://doi.org/10.1007/s11116-008-9171-y.

Moniruzzaman, M., Páez, A., Nurul Habib, K.M., Morency, C., 2013. Mode use and trip length of seniors in

Montreal. *J. Transp. Geogr.* 30, 89–99. https://doi.org/10.1016/j.jtrangeo.2013.03.007.

Morency, C., Trépanier, M., Agard, B., 2007. Measuring transit use variability with smart-card data. *Transp. Policy* 14, 193–203. https://doi.org/10.1016/j.tranpol.2007.01.001.

Morris, J.A., Gardner, M.J., 1988. Calculating confidence intervals for relative risks (odds ratios) and standardised ratios and rates. *Br. Med. J. (Clin. Res. Ed.)* 296, 1313–1316. https://doi.org/10.1136/bmj.296.6632.1313.

Muramatsu, N., Akiyama, H., 2011. Japan: Super-aging society preparing for the future. *Gerontologist* 51, 425–432. https://doi.org/10.1093/geront/gnr067.

Musselwhite, C., Holland, C., Walker, I., 2015. The role of transport and mobility in the health of older people. *J. Transp. Heal.* 2, 1–4. https://doi.org/10.1016/j.jth.2015.02.001.

Olawole, M.O., Aloba, O., 2014. Mobility characteristics of the elderly and their associated level of satisfaction with transport services in Osogbo, Southwestern Nigeria. *Transp. Policy* 35, 105–116. https://doi.org/10.1016/j.tranpol.2014.05.018.

Ranković Plazinić, B., Jović, J., 2018. Mobility and transport potential of elderly in differently accessible rural areas. *J. Transp. Geogr.* 68, 169–180. https://doi.org/10.1016/j.jtrangeo.2018.03.016.

Ritter, A.S., Straight, A., Evans, E., 2002. Understanding Senior Transportation: Report and Analysis of a Survey of Consumers Age 50+. AARP, Public Policy Institute.

Rosenbloom, S., 2001. Sustainability and automobility among the elderly: An international assessment. *Transportation* 28, 375–408. https://doi.org/10.1023/A:1011802707259.

Schwanen, T., Páez, A., 2010. The mobility of older people – An introduction. *J. Transp. Geogr.* 18, 591–595. https://doi.org/10.1016/j.jtrangeo.2010.06.001.

Shao, F., Sui, Y., Yu, X., Sun, R., 2019. Spatio-temporal travel patterns of elderly people – A comparative study based on buses usage in Qingdao, China. *J. Transp. Geogr.* 76, 178–190. https://doi.org/10.1016/j.jtrangeo.2019.04.001.

Shoval, N., Auslander, G., Cohen-Shalom, K., Isaacson, M., Landau, R., Heinik, J., 2010. What can we learn about the mobility of the elderly in the GPS era? *J. Transp. Geogr.* 18, 603–612. https://doi.org/10.1016/j.jtrangeo.2010.03.012.

Siren, A., Haustein, S., 2013. Baby boomers' mobility patterns and preferences: What are the implications for future transport? *Transp. Policy* 29, 136–144. https://doi.org/10.1016/j.tranpol.2013.05.001.

Song, C., Qu, Z., Blumm, N., Barabási, A.L., 2010. Limits of Predictability in human mobility. *Science* 327, 1018–1021. https://doi.org/10.1126/science.1177170.

Szeto, W.Y., Yang, L., Wong, R.C.P., Li, Y.C., Wong, S.C., 2017. Spatio-temporal travel characteristics of the elderly in an ageing society. *Travel Behav. Soc.* 9, 10–20. https://doi.org/10.1016/j.tbs.2017.07.005.

Truong, L.T., Somenahalli, S.V.C., 2015. Exploring frequency of public transport use among older adults: A study in Adelaide, Australia. *Travel Behav. Soc.* 2, 148–155. https://doi.org/10.1016/j.tbs.2014.12.004.

United Nations Department of Economic and Social Affairs, Population Division, 2017. World Population aging 2017 – Highlights (ST/ESA/SER.A/397).

van den Berg, P., Arentze, T., Timmermans, H., 2011. Estimating social travel demand of senior citizens in the Netherlands. *J. Transp. Geogr.* 19, 323–331. https://doi.org/10.1016/j.jtrangeo.2010.03.018.

Whelan, M., Langford, J., Oxley, J., Koppel, S., Charlton, J., 2006. The Elderly and Mobility: A Review of the Literature, Monash University Accident Research Center.

Wong, R.C.P., Szeto, W.Y., Yang, L., Li, Y.C., Wong, S.C., 2017. Elderly users' level of satisfaction with public transport services in a high-density and transit-oriented city. *J. Transp. Heal.* 7, 209–217. https://doi.org/10.1016/j.jth.2017.10.004.

Wong, R.C.P., Szeto, W.Y., Yang, L., Li, Y.C., Wong, S.C., 2018. Public transport policy measures for improving elderly mobility. *Transp. Policy* 63, 73–79. https://doi.org/10.1016/j.tranpol.2017.12.015.

Yamamoto, T., Liu, S., Nakamura, T., 2021. Variability of passenger travel patterns observed using smart card data in Japan, in: Mulley, C., Nelson, J., Ison, S. Eds. Routledge Companion of Public Transport, 1st ed. Routledge, Abingdon, Oxfordshire, UK.

Zhang, Y., Yao, E., Zhang, R., & Xu, H., 2019. Analysis of elderly people's travel behaviours during the morning peak hours in the context of the free bus programme in Beijing, China. *J. Transp. Geogr. 76*, 191-199. https://doi.org/10.1016/j.jtrangeo.2019.04.002.

Zhao, J., Qu, Q., Zhang, F., Xu, C., Liu, S., 2017. Spatio-temporal analysis of passenger travel patterns in massive smart card data. *IEEE Trans. Intell. Transport. Syst.* 18, 3135–3146. https://doi.org/10.1109/TITS.2017.2679179.