Revealing transport inequality from an activity space perspective: A study based on human mobility data

Abstract: Closing mobility and accessibility gaps between public transit riders and private car users is key to tackling social exclusion and achieving sustainable development goals (SDGs). However, place-based potential accessibility methods do not accurately measure real gaps in the uptake of activity opportunities because people usually have limited activity spaces. This study introduces people-based activity space approaches to measure activity disparities between the two modal groups. To overcome difficulties in obtaining large-scale individual activity data, this study used vehicle plate recognition data and public transit smart card data to anonymously identify activities. Individual activity spaces were characterised by six primary activity features from different dimensions. The analysis confirmed that, relative to transit riders, people who use cars on average accessed more activities within a larger activity space and enjoyed overall higher travel efficiency. A comprehensive indicator was further derived from the primary activity features to quantify activity disparities at the zone level. Zones with the highest risk of social exclusion were observed in the outskirts. In contrast, the city centre and inner suburbs exhibited significant equality of the two transport modes in fulfilling mobility needs for engagement in activities. Activity disparities between the two modalities were determined per area in specific activity dimensions, namely activity extensity, activity diversity, and travel efficiency. Finally, statistical models provided evidence that public transport facilities (especially rail transit) and location factors (distance to the city centre) are essential in determining modality-associated gaps in access to urban activity opportunities. Socioeconomic status and land use diversity also partially contributed to the inequality in specific dimensions of the activity space. This people-centred approach is critical for tackling transport inequality and achieving SDGs while “leaving no one behind”.

Keywords: transport inequality; social exclusion; activity space; human mobility; private car; public transit

1. Introduction

Tackling social inequality is one of the key goals of achieving the sustainable development of cities. Social exclusion occurs when people are prevented from participating in activity opportunities required to participate fully in society (Burchardt, Le Grand, & Piachaud, 1999; Church, Frost, & Sullivan, 2000). In particular, transport-related social exclusion refers to a lack of participation as a result of limited mobility and reduced accessibility to activities, services and opportunities (Kenyon, Lyons, & Rafferty, 2002). Inadequate public transport services are disadvantaged in meeting mobility needs for engagement in activities, which puts people who rely on public transit at a higher risk of social exclusion (Benenson, Martens, & Rofé, 2010; Bradshaw, Kemp, Baldwin, & Rowe, 2004). Indeed, non-car-owning households have been considered transport disadvantaged due to the difficulty in accessing opportunities such as employment, education resources, and social activities (Currie & Delbosc, 2011; Social Exclusion Unit, 2003; Shay et al., 2016). To achieve global goals of sustainable development and improve social inclusion in society, it is essential to develop an improved understanding of the inequality between transport modalities in terms of fulfilling the need for access to opportunities and services (Kanbur & Venables, 2005).

It is expected that a higher level of accessibility is related to more participation in activities. However, place-based accessibility may not accurately measure social exclusion in terms of actual participation in activities (Burchardt, Le Grand, & Piachaud, 2002). People usually have limited activity spaces and undertake a small number of activities; thus, the range of potential opportunities may not match the actual access of individuals under various socioeconomic and spatio-temporal constraints. Moreover, disadvantaged groups may access few urban services even in transit-rich areas because other significant barriers may limit their engagement in opportunities (Bradshaw et al., 2004). Distinct from place-based accessibility measures, activity space reflects the activity opportunities that are reached to some extent over a certain period, including all places frequently visited by individuals and the travels undertaken between and around those points (Li & Tong, 2016; Schönfelder & Axhausen, 2003). By using a multidimensional measurement of activity space, variation in the ability to access urban opportunities can be quantified (Wang, Kwan, & Hu, 2020). In this regard, people-based activity space methods can provide a more accurate evaluation of the inequality between different social groups (Church, Frost, & Sullivan, 2000; Kamruzzaman, Yigitcanlar, Yang, & Mohamed, 2016).

The collection of activity space data is supported by surveys and activity-travel diaries (Buliung et al., 2008; Kamruzzaman & Hine, 2012). When collecting through surveys and interviews, respondents are asked to recall the locations and visiting times of their daily or regular activities and whether they had difficulty accessing activities due to a lack of transport (Currie et al., 2010). These self-reported measurements are usually costly and time-consuming to collect and are biased because self-reported experiences of transport disadvantage do not necessarily match the actual trips (Currie, 2010). Hence, it is challenging to examine activity space-based social exclusion across an entire city robustly in terms of the representativeness of the study sample. In recent years, studies of mobility and activity behaviours have been extended through various human mobility data that capture the whereabouts of large populations in space and time (Xu, Xue, Park, & Yue, 2021). In particular, these "big" datasets capture variations in access to activity opportunities across social groups through extracting various mobility indicators (Järv, Müürisepp, Ahas, Derudder, & Witlox, 2015). However, despite the increasing adoption of such data for studying human activities, there remains a paucity of research investigating the disparities between transit riders and car users. This is partly because prior studies have relied on single-source mobility data, which is insufficient for the task of distinguishing social groups by transport mode.

To fill the abovementioned gaps, this study proposed a framework for quantifying transport inequality between public transit riders and private car users from an activity space perspective based on two kinds of human mobility data. The main contributions of this study are four-fold: 1) This study documents transport inequality using people-based activity spaces instead of place-based accessibility, which enables the measurement of realised activity participation from multiple views. 2) In addition to an overall city-wide comparison of car users and transit riders, inter-group activity disparity at the zone level is measured to highlight potential areas of social exclusion. 3) Given that social exclusion may be reflected in the characteristics of activity space, different types of areas are identified based on the dimensions that determine the observed disparities. 4) This study explores the factors responsible for the activity disparities between the two groups and the spatial heterogeneity. The proposed analytical framework extends to the traditional methodology of measuring transport-related social exclusion and provides deeper insights to reduce modality-associated transport inequality and promote sustainable city development in the Chinese context.

2. Related work

2.1 Transport-related social exclusion

Since the mid-1990s, a growing interest in social exclusion and its theories and methodologies has been witnessed within the social science and policy disciplines. Social exclusion is a key theoretical concept in combating inequality with multiple connotations in different contexts and for different purposes (Silver, 1994). A number of research developed various theoretical perspectives and methodological approaches to understanding social exclusion and social consequences (Agulnik, 2002; Cass, Shove, & Urry, 2005). The basic notion of social exclusion tends to be understood as a lack of access to key activities and opportunities (e.g., employment, education, health and social network) that are required to participate fully in society, with being both a cause and an outcome (Kenyon, Lyons, & Rafferty, 2002; Stanley & Vella-Brodrick, 2009). As suggested, social exclusion reaches beyond poverty and involves multiple dimensions of deprivation that reduce the capability of individuals and communities to participate in key aspects of society (Sen, 2000). It is characterised as multi-dimensional, relational (disadvantaged in comparison with other individuals or groups, dynamic (changes over time) and experienced by both individuals and communities (Church, Frost, & Sullivan, 2000; Lucas, 2011; Luz & Portugal, 2021).

Research and urban policymakers are particularly concerned about the relationship between transport and social exclusion because transport provides mobility ability for individuals and communities to participate in key life-enhancing opportunities (Preston & Rajé, 2007; Stanley & Vella-Brodrick, 2009). In the early 2000s, a range of concerns in relation to transport and accessibility needs had been recognised in the UK context and the theme of social exclusion had been put on the transport policy agenda (Lucas, Grosvenor, & Simpson, 2001; Social Exclusion Unit, 2003). Subsequently, a growing number of studies have theorised and exemplified the role of transport in the lives of disadvantaged groups and communities (Lucas, 2011; Martens, 2016). For example, the concept of social capital has been widely used to look into the linkages between social exclusion and transport disadvantage (Schwanen et at., 2015; Lucas, 2012). Transport-related social exclusion highlights the mobility and accessibility dimensions, namely the social outcomes of reduced accessibility to opportunities, services and social networks, due to insufficient mobility (Cass, Shove, & Urry, 2005; Ureta, 2008; Kenyon, Lyons, & Rafferty, 2002). It was recognised that differential access to cars potentially contributed to the social exclusion of certain social groups and communities. Non-car owners tend to make fewer trips and travel shorter distances with the consequence that many low-income people experience social exclusion due to these transport inequalities (Social Exclusion Unit, 2003). Another case study in San Francisco Bay Area shows that all neighbourhoods suffer from substantial gaps in accessibility between car and public transport (Golub & Martens, 2014). The links between transport disadvantages and social exclusion have an important influence on transport policy due to the requirement to understand the performance of transport investment in addressing the travel needs of socially disadvantaged groups and communities.

To date, most of the theoretical debates have been within the western and South African contexts, and few have looked at the conceptualisation of transport inequality in the Chinese context (Lucas, 2012). In the Chinese context, social equity concerns are more about the differences in the living conditions between the privileged groups and themselves (Liu et al., 2019). In this case, people who can't afford cars think that driving cars may be a kind of privilege because the usage of cars makes it more convenient access to jobs, goods and services. Consequently, policies that make car ownership and use unaffordable for low-income groups without providing them with alternative transport options are inequitable and unjust. Drawing on the notion of social exclusion, the inter-modal comparison is helpful to identify if people experience social inequality with some people getting more benefits because of differential access to cars. As the Chinese researchers' growing contributions to the transport inequalities by using western-based theorisations, more empirical evidence will offer policy implications and practical recommendations to develop more inclusive transport towards sustainability (Liu et al., 2022).

2.2 Place-based accessibility measurement

Identifying transport disadvantages and capturing variation in access to urban opportunities among different social groups serves as the first step to tackling the social exclusion (Pyrialakou, Gkritza, & Fricker, 2016). Due to the great importance of transport mode in determining access to activities, one of the most straightforward approaches is to quantify accessibility gaps between private cars and public transit based on counting accessible opportunities within a certain travel distance or time (Benenson et al., 2010; Kawabata & Shen, 2006). Accordingly, a considerable body of literature has documented such accessibility gaps (Benenson, Martens, Rofé, & Kwartler, 2011; Salonen & Toivonen, 2013). In most developed Western cities, private cars provide better accessibility to urban services and opportunities than public transport (Kawabata, 2003; Golub & Martens, 2014). However, findings in some urban contexts contrast to some degree. For example, in some high-density cities where public transit is highly developed (e.g., Hong Kong), it has been reported that inter-zone accessibility by public transport is better than that by car (Kwok & Yeh, 2004). These studies mainly focused on job accessibility and commuting differences because working is the most critical activity in daily life and demonstrated that people without cars often face reduced accessibility to job opportunities (Kawabata & Shen, 2006; Kawabata & Shen, 2007). Although significant efforts have been made in inter-modal comparative analysis of job accessibility, the field lacks a comprehensive view of all the activities carried out by individuals (Al-Ayyash & Abou-Zeid, 2019).

Traditional methods of measuring accessibility gaps in transport focus on the spatial relationships between places rather than people. Such place-based accessibility measures are helpful in measuring differences in potential opportunities within the bounds of a certain travel cost. These methods consider the same level of accessibility for people in the same zones while ignoring the complex travel behaviour and space-time constraints of individuals. Meanwhile, they provide little information concerning the realised participation of people in activities (Stanley & Vella-Brodrick, 2009). It is still unknown whether disadvantaged groups in areas with high-level accessibility (i.e., transit-rich areas) enjoy urban services and activities to the same extent as advantaged groups in the same place. Not owning a car may not be a problem if public transport services are available and within reach (Lucas, 2012), but other significant barriers may exist that limit engagement in opportunities by residents (Church et al., 2000). Meanwhile, a residential location with sparse opportunities may constrain access to activities and services even for a person with a high level of mobility (e.g., a car user). With this in mind, measurements of transport-related social exclusion could be extended from people-focused and outcome-based perspectives (Kamruzzaman et al., 2016).

2.3 People-based activity space measurement

People-based activity space-based approaches are better capable of capturing disparities in accessibility for different social and demographic groups given that activity participation is an individual-level behaviour. An individual activity space can be defined as the set of locations that an individual frequently travels to regularly for work, leisure, and other typical activities; in aggregate, these spaces portray a more accurate and realistic picture of the ability of a population to engage in activities (Buliung, Roorda, & Remmel, 2008; Chen & Yeh, 2020; Schnell & Yoav, 2001). In actuality, most people engage in only a limited number of activities and small activity spaces. An increasing number of studies have shown that activity space-based methods provide a more comprehensive view of the actual usage of urban opportunities and that they present great potential to shed light on aspects of socio-spatial equality such as segregation and social exclusion (Wang & Li, 2016; Wang, Li, & Chai, 2012; Wong & Shaw, 2011). Therefore, measurements of transport-based social exclusion could be complemented and enhanced by the people-based methods that capture individual realised activity-travel patterns.

In time geography, an individual's movements are characterised by space-time prisms representing space-time allocations for pre-planned trips and delimit the space-time paths of activities (Newsome, Walcott, & Smith, 1998). Space-time paths reveal activity locations, time durations, and the efficiency of a given travel mode (i.e., the path slope) (Miller, 2005). The interior of a prism is the potential path space, and its projection to geographic space is called the potential path area (Lenntorp, 1976), which depicts the spatial extent within which an individual could potentially engage in activities given their time constraints (Miller, 1991). This space-time prism method is appropriate for visualisation but challenging to implement, especially when comparing large-scale collections.

The delineation of activity space can be extended with a focus on summary metrics, which provide appropriate representations for quantification and comparison among different social groups. Such metrics include the number of activities/trips, spatial locations (e.g., mean centre), average/maximum travel distance, and the areas and shapes of activity spaces (e.g., minimum convex polygon and standard deviational ellipse) (Järv, Müürisepp, Ahas, Derudder, & Witlox, 2015; Wu et al., 2019). Some features are referred to as mobility indicators in the literature on human mobility and travel behaviour, such as the radius of gyration and travel distance (trip length/displacement) (Farber, Páez, & Morency, 2012; Xu et al., 2016). Other indicators are more activity-oriented, for example, activity number, type, and visiting frequency. Given the inseparable relationship between activities and travel, some literature has summarised them as activity-travel behaviour (Buliung et al., 2008; Kwan, Dijst, & Schwanen, 2007; Manoj & Verma, 2015; Wang & Lin, 2013). Activity space is likewise a broader concept that includes both elements and is employed as the theoretical framework for conceptualising individual activity and travel patterns.

Activity space is based on observed behaviour and thus could be more explicitly described as an observed or actual activity space (Zhang, Wang, Kwan, & Chai, 2019). Theoretically, an observed activity space may represent the area over which one is likely to regularly engage in activities (Newsome et al., 1998). It also suggests the ability of a traveller to participate in activities given location constraints and limited individual choices. Through analysing summary metrics derived from observed activity spaces, it should be possible to extend our understanding of gaps in access to activity opportunities among different groups. In particular, due to encompassing indicators of distance travelled and the number of activity sites visited, activity space-based approaches reveal more about the intensity, duration, and frequency of individuals' participation in different activities, which are important perspectives in the social exclusion (Farber & Páez, 2009; Schönfelder & Axhausen, 2003). For example, some studies have indicated that disadvantaged groups tend to experience high levels of social exclusion in a variety of dimensions, particularly the extensiveness and diversity of the activity space (Tao, He, Kwan, & Luo, 2020). Based on household travel survey data, one study concluded that vulnerable groups tend to make fewer trips and have smaller activity spaces than the average population (Páez, Ruben, Faber, Morency, & Roorda, 2009). In addition, people without a car tend to less frequently undertake shopping and social trips such as visits to friends and family (Lucas, 2012). Taken together, these findings suggest that these groups are disadvantaged in terms of mobility and the capability to explore activity opportunities.

A critical issue of these methods is how activity space characteristics actually interpret social exclusion. For example, smaller activity spaces are generally considered to reflect a high degree of social exclusion based on evidence that disadvantaged groups usually have smaller activity spaces (McCray & Brais, 2007; Schönfelder & Axhausen, 2003). In contrast, large activity spaces and more out-of-home locations visited may indicate better facility accessibility (Wang, Kwan, & Hu, 2020). However, this is not always true. Some disadvantaged people need extended travel for employment and other services, leading to large activity spaces (Huang & Wong, 2016). In such a situation, large activity spaces do not necessarily imply a transport advantage. Meanwhile, individuals living in an area with high availability of goods and services may present smaller activity spaces while still being able to participate in their required activities (Kamruzzaman & Hine, 2012). Due to the dual implications of these observations, when evaluating social exclusion, indicators should be carefully interpreted. Combining indicators with other dimensions (e.g., activity diversity) and paying attention to spatial context (e.g., availability of transportation and services) allows for avoiding ambiguity and making a relatively accurate assessment of the extent to which one can travel and access activity opportunities over a given space.

3. Study area and data

3.1 Study area

The focus area of this study is Shenzhen, a city in the Guangdong-Hong Kong-Macau Greater Bay Area in China. Shenzhen is also one of the most rapidly urbanising cities in the world (Wang, Tong, Gao, & Chen, 2019). Shenzhen's permanent population was 0.31 million before it became China's first Special Economic Zone in the 1980s; as of 2017, the population had increased to 12.53 million (Shenzhen Statistical Yearbook 2018). With the city occupying 1997.47 km^2, Shenzhen's built-up area encompassed 925.20 km^2 by 2017, making it an ideal representation of Chinese cities undergoing rapid urbanisation (China Urban-Rural Development Statistical Yearbook 2017).

As shown in **Fig. 1**, Shenzhen consists of ten districts, including nine administrative districts and one functional district (Dapeng). Overall, it is a polycentric city with a circular spatial structure. Nanshan, Futian, and Luohu Districts are commonly referred to as the inner city, while areas outside those three districts are separated into the inner suburbs and the outskirts. Two main employment centres located in the inner city provide the majority of job opportunities and urban facilities. However, several sub-centres have been and are being developed in suburban areas. Public transit in the inner city is well-developed and features an intensive rail transit system, whereas the suburbs, especially the outskirts, are transit-poor areas with sparse rail stations. The Shenzhen transport authority has spatially partitioned the city into 491 traffic analysis zones (TAZs), which are used as the spatial units in this study.

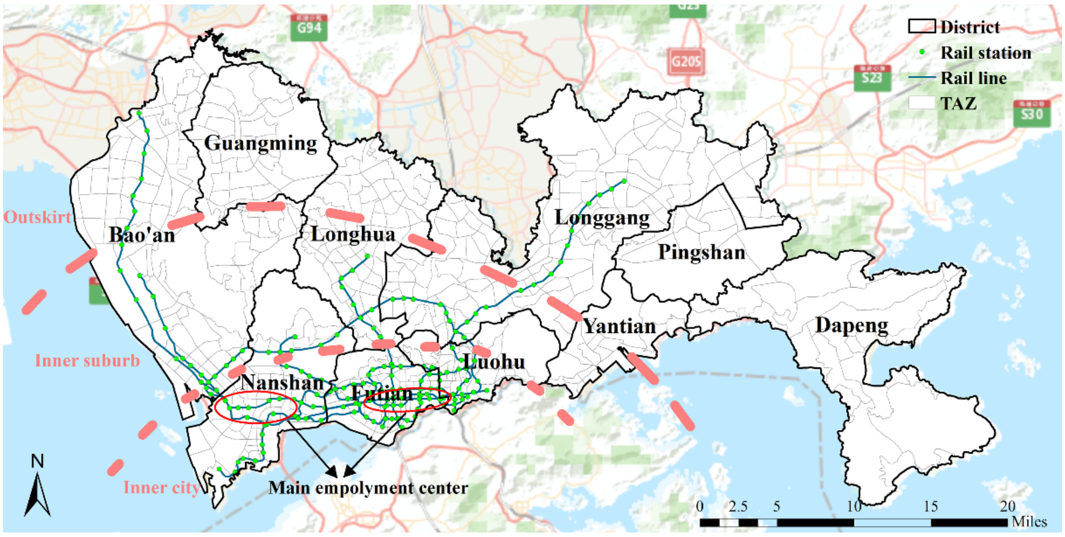

Fig. 1. Study area: Shenzhen, China.

3.2 Human mobility data

Information and communication technology allows fine-grained depictions of human activity and travel behaviours, which can complement place-based analysis by providing a people-based, large-scale view of activity engagement (Scholz & Lu, 2014; Silm & Ahas, 2014). Some research has employed mobile phone and social media data to achieve a fine-grained investigation of the activity space (Hu, Li, & Ye, 2020; Järv, Müürisepp, Ahas, Derudder, & Witlox, 2015) and highlighted significant variation in activity spaces across socioeconomic groups. To portray the two groups of interest (i.e., public transit riders and private car users) and their activity spaces, the present study relied on two types of human mobility data, public transit smart card data (SCD) and vehicle plate recognition data (PRD). SCD captures public transit riders' travel trajectories by recording the unique anonymised card number, transaction time, and boarding and alighting stations. Meanwhile, PRD stores the movement tracks of vehicles by arranging a series of trajectory points in chronological order, which are captured by cameras on roads or in parking lots. The activity places derived from smart card data were accordingly spatially joined to transit stations, while those extracted from vehicle plate recognition data were linked to monitoring cameras. By the end of 2016, Shenzhen possessed more than 1,800 bus lines with over 6,000 unique bus stations and 8 rail transit lines (including 199 metro stations), along with a total of 8,137 monitoring cameras, of which 5,528 were installed in parking lots.

The collection period for SCD was 22nd-28th November 2016. A total of 1,381,876 transit riders with complete travel trajectories were identified, with an average of 2.17 trips per day. The collection period for PRD was very close to that for SCD, encompassing 7th-13th November 2016; a total of 389,024 car users were observed, with each vehicle generating on average 6.84 track points per day. As neither of the two datasets is inclusive of public holidays, it is reasonable to assume that activity patterns are similar across both collection periods for a given data type (i.e., SCD or PRD), which ensures a valid comparison of the two datasets.

One of the limitations of this study is the lack of consideration of the users who travel by both transport modes, such as car owners who prefer to realise certain trips by public transport. People were anonymised in both the public transit smart card data and private car trajectory data due to privacy issues, making it impossible to identify people who use both transport modes for daily travel. However, those multi-mode users only account for a small proportion of the total population. According to the Shenzhen household travel survey during the same study period, only 2% of survey people used multiple transport modes. Therefore, we expect that the influence of using multiple transport modes on activity spaces of public transit and private car users is limited.

To better understand the socioeconomic characteristics of the two groups, the household annual income of car-owning households and non-car-owning households are presented. According to the Shenzhen household travel survey in 2016, household car ownership is around 25%. Household annual income was divided into five levels. Level 1(less than 100,000 CNY) means the lowest household annual income and level 5 (greater than 500,000 CNY) represents the highest. As shown in **Fig. 2**, nearly 50 % of non-car-owning households had the lowest level of annual income, and 90% were no more than level 2 (100,000-200,000 CNY). In contrast, only about 10 % of car-owning households had the lowest level of annual income, and over 40 % had an annual income greater than level 2. For each TAZ, the income difference between the car-owning group and the non-car-owning group was calculated. In 96 % of TAZs, the average household income level of car owners was higher than that of households without a car. In summary, car-owning households on average have higher incomes than those without a car. Car ownership is very low in the lowest-income households, only accounting for 7.7% (level 1).

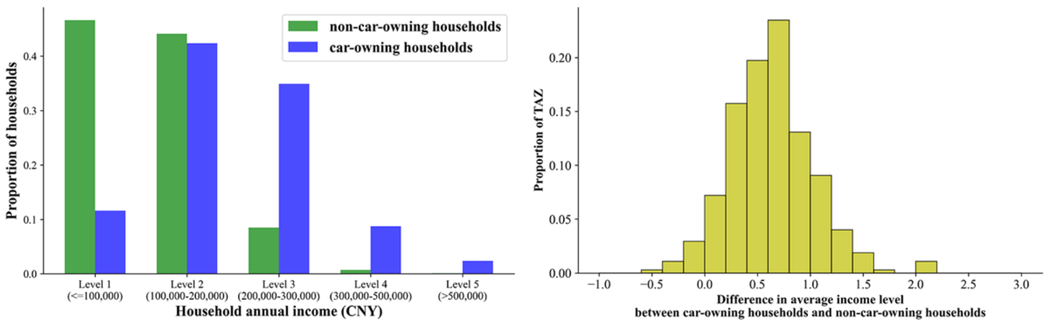

Fig. 2. The distribution of household annual income of the car-owning group and non-car group (left) and the difference in average income level between the two groups in each TAZ (value > 0 means the average household income level of car owners was higher than that of households without a car)

4. Methodology

Concerning evaluating social exclusion from the perspective of activity space, a general framework does not yet exist to follow. This study proposed a methodology framework based on human mobility data. As illustrated in **Fig. 3**, the framework consists of three steps. (1) Portraying individual activity spaces. First, individual activity features characterising activity spaces need to be extracted from mobility data. Then, overall disparities between groups can be obtained by statistically comparing activity spaces. (2) Measuring zone-level activity disparity. In addition to the overall evaluation, the scope of this work includes a comparison of the activity-travel characteristics of different groups in different locations. Identification of spatial heterogeneity can facilitate policy implementation by highlighting areas of social exclusion to be targeted. (3) Identifying factors influencing activity disparity. This work examines factors driving inter-group differences in activity-travel behaviours, particularly whether and to what extent the availability and convenience of public transit determine gaps in activity engagement. The proposed framework is applicable to other human mobility data, can be used to compare any two socioeconomic and demographic groups, and can be easily extended by introducing other activity dimensions and potential factors of interest.

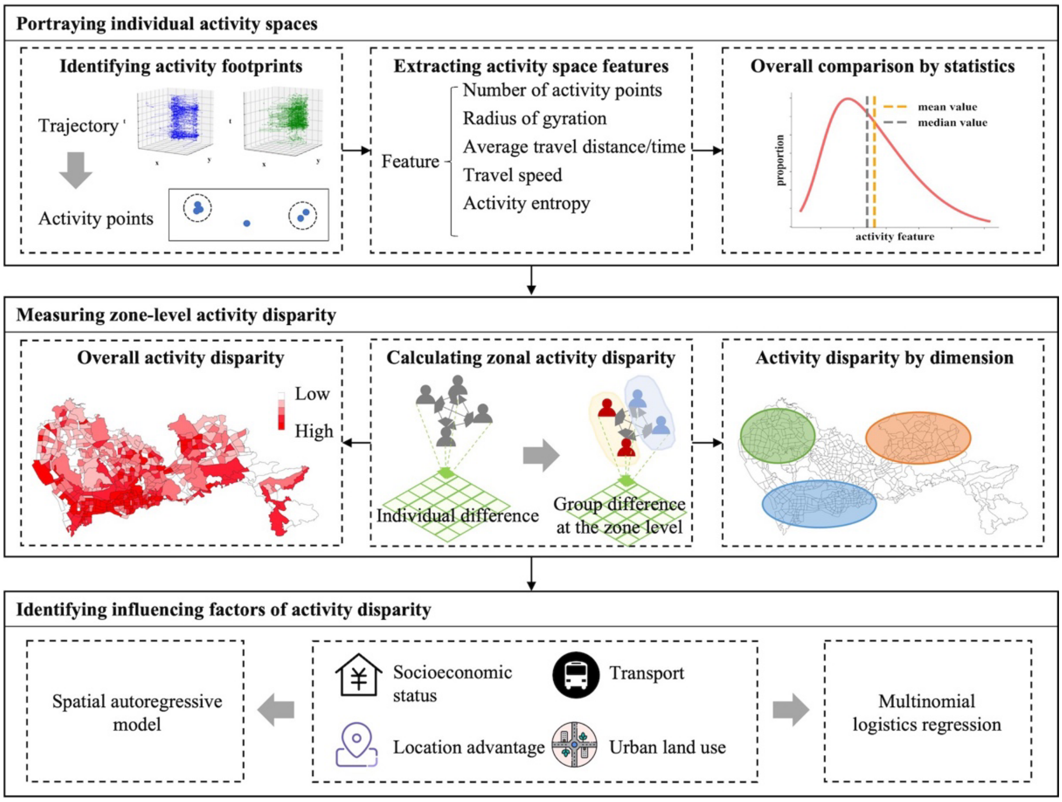

Fig. 3. The methodology flowchart for examining activity space-based social exclusion.

4.1 Portraying individual activity spaces

Activity spaces include the locations people regularly travel to for activities. Activity locations can be inferred from travel trajectories based on spatial and temporal regularities across multiple days. Here, stay points were firstly extracted from two kinds of travel trajectories. If two sequential points are in the same place (less than 500 meters) and the time difference is greater than half an hour, that place is considered a stay point. Temporal stays of less than half an hour were filtered out for the following reasons. First, modal transfer behaviour (e.g., bus to rail transit) will influence the value of one-way travel time and distance, and transfer stations are not meaningful activity places; hence we considered a stay of less than half an hour in the vicinity of a station (within 500 meters) as a transfer behaviour. We merged the trips before and after that stay into one complete journey. Such trips accounted for only a small proportion of the total. Second, given that employment, leisure, and socialised activities generally last for a few hours, short-time stays are likely to be interference or noise (e.g., refuelling or traffic congestion), thus have been filtered out in similar studies by setting thresholds of 10 minutes, 30 minutes, or one hour (Jiang et al., 2013; Tu et al., 2017; Yu, Li, Yang, & Zhang, 2020).

We classified daily activities into in-home and non-home activities. Following the study (Gao, et al., 2021), the first daytime point of the daily trajectory (after 6:00 am) was considered as an in-home candidate point because people usually travel from their homes in the morning. Then, the DBSCAN method was applied to a set of in-home points and stay points derived from one-week trajectories to estimate the average locations of activities. We set the minimum number of points required to form a cluster as *minPts* = 2 and the neighbourhood radius as *eps* = 500 m, which means that an activity place must have been visited at least twice during the week and any two locations ascribed to that place must be within 500 meters. As activity spaces are usually represented by frequently-visited places, those places that were only visited once a week were considered random activities and filtered out.

According to related research, activity-travel behaviour can be effectively quantified using elementary characteristics of activity space such as the number of activity locations, activity radius, travel distance, travel time, and the frequency of travel to each activity location. Taken together, these features allow a relatively comprehensive assessment of the extent to which one can travel and enjoy different activity opportunities across a given space. Notably, human mobility data often lacks information regarding activity type. Although some fixed activities (e.g., home and work) can be inferred from data collected over a longer period, random activities like recreation and socialisation are hard to identify, thus, studies using human mobility data often exclude varied activity types. In this study, we mainly focused on gaps in access to activity opportunities from a spatial perspective. The specific activity features used to characterise activity patterns are as follows:

- **The number of unique activity points:** Num.
- **Activity radius of gyration:** $Radius = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((x_i - \overline{x})^2 + (y_i - \overline{y})^2)}$ (1)
- **Average travel distance:** $Dis = \frac{1}{N^t}\sum_{i=1}^{N^t}\sqrt{(x_{iD} - x_{iO})^2 + (y_{iD} - y_{iO})^2}$ (2)
- **Average travel time:** $Time = \frac{1}{N^t}\sum_{i=1}^{N^t}(t_{iD} - t_{iO})$ (3)
- **Average travel speed:** $Speed = \frac{Dis}{Time}$ (4)
- **Activity entropy:** $Entropy = -\sum_{i=1}^{N} p_i * \log(p_i),\ \sum_{i=1}^{N} p_i = 1$ (5)

where (x_i, y_i) denotes the geographic location of activity point i, N^t is the number of travel trips in a week, (x_{iO}, y_{iO}) and (x_{iD}, y_{iD}) are the OD locations of activity trip i, and p_i represents the frequency of visits to activity location i.

4.2 Measuring zone-level activity disparity

Large differences in activity spaces represent great inequality in engagement in daily activities. However, the ability of people to engage in activities varies from place to place within a city. To identify areas in which the two transport modes exhibit the greatest gaps in meeting daily mobility needs and access to activity opportunities, we measured activity disparity at the zone level based on individual activity spaces.

We first mapped individuals to TAZs by their home locations, and then measured the dissimilarity between groups for each TAZ by calculating the Euclidean distances between basic activity features. Because the various activity features differ in magnitude, it was necessary first to perform normalisation to facilitate their comparison.

Assuming that the activity features of individuals i and j are respectively defined as $\{x_i^1, x_i^2, \dots, x_i^k\}$ and $\{x_j^1, x_j^2, \dots, x_j^k\}$, k represents the total number of activity features. The dissimilarity between any two users is calculated as equation (6), after which we can derive a distance matrix that represents their dissimilarity. The distance matrix vector is expressed as D, which consists of k distances for k activity features:

$$\mathrm{D} = [D_1, D_2, .., D_k]$$

$$D_k = \begin{bmatrix} d_{1,1}^k & d_{1,2}^k & \dots & d_{1,p}^k \\ d_{2,1}^k & d_{2,2}^k & \dots & d_{2,p}^k \\ \vdots & \vdots & \ddots & \vdots \\ d_{\mathrm{p},1}^k & d_{\mathrm{p},2}^k & \dots & d_{p,\mathrm{p}}^k \end{bmatrix}, \mathrm{d}_{i,i}^k = 0, \mathrm{d}_{i,j}^k = \mathrm{d}_{j,i}^k, \mathrm{d}_{i,j}^k = |x_i^k - x_j^k| \tag{6}$$

where, $\mathrm{d}_{i,j}^k$ is the distance between user i and user j in the k^{th} activity feature. Assuming that there are p_{m1} individuals in the public transit group G_{m1} and p_{m2} individuals in the private car group G_{m2}, a total of p_m individuals are included in the spatial unit m. Based on the similarity matrix, inter-group dissimilarity at the zone level can be derived and expressed as the matrix $AveD$:

$$AveD = \begin{bmatrix} Aved_1^1 & Aved_1^2 & \dots & Aved_1^k \\ Aved_2^1 & Aved_2^2 & \dots & Aved_2^k \\ \vdots & \vdots & \ddots & \vdots \\ Aved_m^1 & Aved_m^2 & \dots & Aved_m^k \end{bmatrix}, Aved_m^k = \frac{\sum_{i \in G_{m1}, j \in G_{m2}}^k \mathrm{d}_{i,j}^k}{p_{m1} * p_{m2}} \tag{7}$$

Since the applicable range of values varies widely between activity features, we scale the values of matrix $AveD$ to between 0 and 1 using the max-min normalization method, ensuring that each feature contributes approximately proportionately to the final distance. The value $(Aved_m^k)'$ in the scaled matrix $AveD'$ is calculated as follows:

$$(Aved_m^k)' = \frac{Aved_m^k - \min(Aved^k)}{\max(Aved^k) - \min(Aved^k)}, Aved^k = \{Aved_1^k, Aved_2^k, \dots, Aved_m^k\} \tag{8}$$

To construct a comprehensive indicator reflecting activity disparity between the two groups at the zone level, we perform exploratory factor analysis (EFA) on the scaled matrix $AveD'$. If n principal components are extracted, and the corresponding component scores are expressed as $C_1, C_2, \dots, C_n$, the comprehensive index CI can be calculated as follows:

$$\mathrm{CI} = \sum_{t=1}^{n} \lambda_t C_t \tag{9}$$

where λ_t denotes the eigenvalue corresponding to the t^{th} principal component.

By applying spatial statistical methods to the comprehensive index, those areas having the greatest equalities and gaps in activity participation can be identified. Furthermore, based on the extracted principal components, spatial heterogeneity in transport inequality can be revealed by exploring which activity space characteristics determine the respective activity disparity for each TAZ.

4.3 Identifying influencing factors of activity disparity

To identify potential factors driving transport inequality, spatial statistical models are adopted at the zone level. In response to the citywide spatial variance in activity disparity, this study carries out spatial autoregression analysis on the comprehensive indicator. Spatial regression typically incorporates two categories of autocorrelation, namely spatial lag (equation 10) and spatial error (equation 11), with the form (error or lag) being specified by the robust Lagrange multiplier (Anselin, Syabri, & Kho, 2006). The spatial matrix is constructed using the inverse distance matrix.

$$Y = \alpha + \beta X + \lambda W_Y + \varepsilon \quad (10)$$

$$Y = \alpha + \beta X + e, e = \lambda W_e + u \quad (11)$$

where X and Y are the exploratory and dependent variables, respectively; β is the coefficient of the exploratory variable; W_Y and W_e denote the spatial matrix for the dependent variable and its error term; λ is the spatial autoregressive coefficient; e represents the error term; and α and u are scalar variables.

With respect to spatial heterogeneity, in which different areas are characterised by different activity dimensions, multinomial logistics regression is introduced to unveil which factors determine the main dimension of activity disparity. Assuming that spatial units are classified into K clusters based on multiple activity dimensions, the multinomial logistics regression model is as follows.

$$P(Y = k|X) = \frac{\exp(\alpha_k + \beta_k X)}{1 + \sum_{k=1}^{K-1} \exp(\alpha_k + \beta_k X)}, \ k = 1, 2, \ldots., K - 1 \quad (12)$$

$$P(Y = K|X) = \frac{1}{1 + \sum_{k=1}^{K-1} \exp(\alpha_k + \beta_k X)} \quad (13)$$

where X is the exploratory variables; Y denotes the dependent variable with the set of values $\{1, 2, \ldots, K\}$; $P(Y = k|X)$ is the probability of the cluster k; β_k represents the weight coefficient of the exploratory variable, and α_k is the intercept for the cluster k.

Transport facilities, especially the accessibility of public transit, play a vital role in the engagement of public transit users with activities. Apart from the lack of available transport, transport-related social exclusion is also attributed to the inappropriate spatial distribution of activity opportunities (Lucas, 2011). Moreover, activity participation might be determined by advantages in socioeconomic status and geographic location (Gwilliam, 2003). Therefore, we incorporated four types of factors into statistical models and examined their influence on activity disparity. In specific, transport facilities are measured by the density of bus stops (den_{bus}), distance to the nearest metro station (dis_{metro}), and density of the road network (den_{road}); Migrant ratio ($ratio_{migrant}$) is used as a proxy for socioeconomic differences between the groups; location advantage is expressed as the distance to the city centre (dis_{centre}); and land use diversity (div_{land}) as calculated by Shannon's entropy method is used to measure urban function in terms of four categories: residential space, commercial space, public service, and business.

5. Analysis and findings

5.1 Comparison of activity spaces

We identified all activity points visited within the study period and examined their statistical properties in terms of the six basic activity features. The results are summarised in **Table 1**. T-statistics was employed to test the significance of differences in means between the two groups, and all differences were statistically significant at the 0.01 level. The main findings are as follows: 1) Regarding unique activity points, public transit riders had an average of 2.1 activity points within a week. In comparison, private car users exhibited a more diverse activity pattern with on average 2.7 activity points. 2) Examining activity space coverage revealed that car users, on average had a larger activity radius, suggesting that they formed a more dispersed activity space compared to transit riders. 3) Disregarding the impact of total activity locations on activity space, a considerably larger average travel distance was observed for car users. 4) For both groups, the average travel time was around 30 minutes; while car users on average travelled a little longer than bus users, the difference was not as significant as that for travel distance. 5) The average travel speed of private cars was 30.7 km/h, far higher than that of public transit at 22.2 km/h. This difference in overall travel speed directly highlights the gap in the mobility ability between the two transport modes. 6) Our analysis yielded high mean activity entropy values for both transit riders and car users, but transit riders had a relatively higher activity entropy; specifically, the proportion of transit riders with activity entropy between 0.95 and 1 was significantly greater than for car users. This means that the activity behaviours of public transit riders were more predictable. One potential explanation is that, across both groups, the proportion of people with two fixed activities is very high. These two activities are likely to be residence and workplace/school; thus, the high regularity of mandatory activities determines the high activity entropy. From the previous analysis, car users, on average engaged in more activities; however, the frequency of their visits to other places was significantly lower than that of visits to home and workplace, leading to a smaller activity entropy for the car-owning group.

Overall, the above results provide a general picture of the differences in access to activity opportunities between the two groups over the whole city. It can be inferred that car users have good travel ability, which enables them to travel long distances and undertake more activities. Thus, car ownership represents a kind of transport advantage, whereas the no-car-owning group is more likely to face the risk of social exclusion, which may hinder their well-being and access to opportunities.

Table 1. Statistical properties of activity features.

Activity feature	**Mean value**			**Median value**	
Feature name	**Transit users**	**Car owners**	**Diff. P-value**	**Transit users**	**Car owners**
Num	2.11	2.66	0.000***	2.00	2.00
Radius (km)	4.02	6.13	0.000***	3.23	5.22
Dis (km)	11.71	13.64	0.000***	9.63	11.57
Time (minute)	29.72	31.32	0.000***	26.62	27.07
Speed (km/h)	22.16	30.65	0.000***	22.46	26.80
Entropy	0.97	0.96	0.000***	0.99	0.97

Note: ***p<=0.01; **p<=0.05; *p<=0.1.

5.2 Activity disparity at the zone level

Based on equations (6, 7), we derived the activity disparity between the car and transit groups in each TAZ. Since this involves calculating differences between the two groups, TAZs not having both groups were filtered out, leaving 269 TAZs for the analysis. After normalising activity features at the TAZ scale, EFA was carried out to derive a comprehensive indicator for quantifying overall activity disparity. The EFA analysis results are presented in **Appendix A2**.

Three generalised dimensions of activity extensity, activity diversity and travel efficiency were extracted from the six original variables. According to this criterion, the first component mainly consists of three features: activity radius, average travel distance, and average travel time. Since all these features represent the coverage of activity space, the first component can be generalised as activity extensity. The second component is characterised by the number of unique activity points and entropy, which quantify activity diversity in terms of activity types and corresponding preferences. The third component has average travel speed as its primary contributor, representing travel efficiency.

The component scores and the comprehensive index (CI) were calculated from the eigenvalues and the rotated component loading matrix. Global Moran's I analysis was applied to the CI to reveal spatial heterogeneity and detect whether activity disparity presented a spatial association pattern at the city level. This yielded a Global Moran's I value of 0.30, indicating spatial aggregation with a significant positive spatial correlation. The Getis-Ord Gi* statistic was further determined to identify spatial clusters of CI, including both high-value and low-value clusters. As illustrated in **Fig. 4**, TAZs in urban centres and sub-centres exhibited small activity disparities (blue colour), while those in the outskirts exhibited great activity disparities (red colour), particularly in the northwest and northeast areas of the city. This means that within the study area, the outskirts (low-value clustering areas) had more considerable activity inequality between transit riders and car users. Residents without cars there suffered a higher risk of social exclusion.

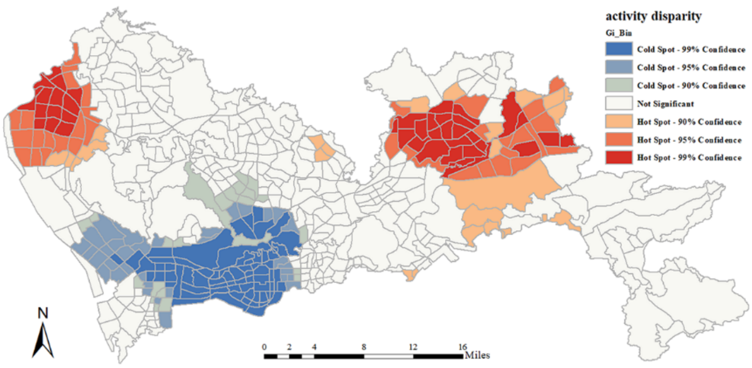

Fig. 4. Spatial cluster analysis using the Getis-Ord Gi* statistic.

Importantly, the manifestations of social exclusion may vary in areas having different socio-spatial contexts. While the comprehensive index reveals the overall spatial heterogeneity in activity disparity, it could not illuminate the features contributing to that heterogeneity. To capture the main dimension in which activity disparity occurred for each TAZ, we adopted k-means clustering on the three components and categorised the TAZs into types. Silhouette coefficients and the Calinski-Harabaz index were calculated to identify the optimal number of clusters (Caliński & Harabasz, 1974; Rousseeuw, 1987); for both indicators, a higher score suggests a more appropriate clustering. As illustrated in **Fig. 5**, both indices yielded their highest scores when the number of clusters was 4. Thus we classified TAZs into four types.

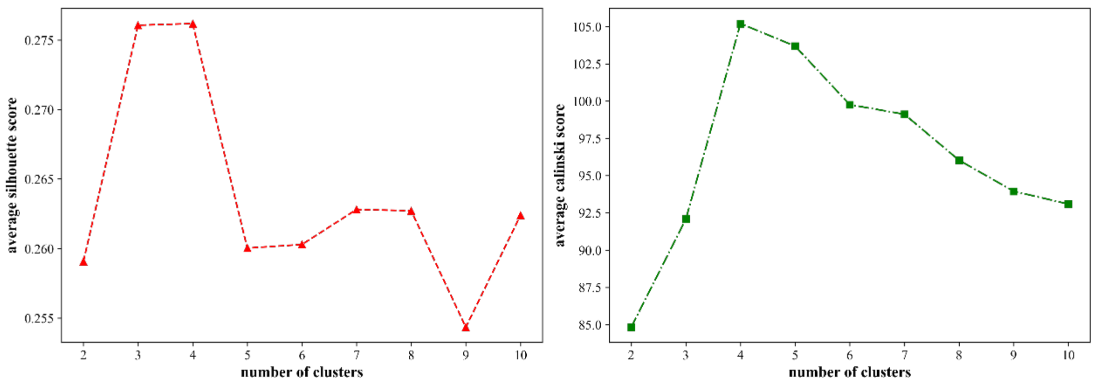

Fig. 5. Silhouette coefficients and Calinski-Harabaz index for different numbers of clusters.

Fig. 6 depicts the spatial distribution of the four clusters, which presents a clear core-periphery pattern. TAZs in Cluster 1 and Cluster 2 mainly concentrate in the inner city and inner suburbs, whereas Cluster 0 and 3 are mainly located in the outskirts. Cluster 2 accounts for the largest proportion of TAZs, followed by Cluster 1, Cluster 0 and Cluster 3. The number of transit users is greater than car owners in each cluster (**Appendix A4)**. From the policy implication perspective, the greater number of transit users justifies the significance of focusing on the roles of public transport in improving the likelihood of engagement in activity opportunities. From the methodology perspective, the inter-group comparison is meaningful despite the difference in population size because the cross-group difference is represented by the average difference between any two individuals within the two groups instead of the total difference.

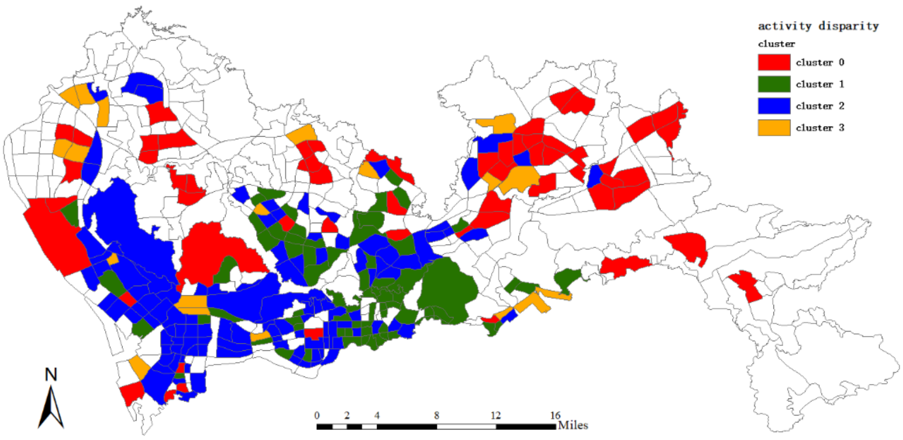

Fig. 6. Spatial distribution of the four TAZ clusters identified by the k-means method.

According to the distribution of each cluster in each activity dimension (see **Appendix A3**), the four clusters were summarised as follows.

- **Cluster 0**: **HLL** (**High** disparity in extensity, **Low** disparity in diversity, and **Low** disparity in efficiency)

Cluster 0 contains those TAZs where the largest gaps in activity extensity were observed. Zones belonging to this cluster were mainly distributed around the outskirts of Shenzhen.

- **Cluster 1**: **LHL** (**Low** disparity in extensity, **High** disparity in diversity, and **Low** disparity in efficiency)

TAZs belonging to Cluster 1 were characterised as having the highest disparity in activity diversity. These zones were mainly located in suburban areas in the middle of the city and the southern part of the city centre.

- **Cluster 2**: **LLL** (**Low** disparity in extensity, **Low** disparity in diversity, and **Low** disparity in efficiency)

Most TAZs belonging to Cluster 2 were located in the city centre and along metro lines in suburban areas. Within these areas, activity patterns of public transit riders exhibited the highest similarity to those of private car users.

- **Cluster 3**: **LLH** (**Low** disparity in extensity, **Low** disparity in diversity, and **High** disparity in efficiency)

Cluster 3 consists of those TAZs in which the two groups exhibited considerable travel efficiency differences. These zones were mainly found in outer suburbs and the Yan-tian District (refer to **Fig. 1**).

Although areas having the greatest disparities in each activity component were identified, what the disparity between private car drivers and public transit users looks like (i.e., which group has a higher value in each activity feature) for each cluster remained unclear. Hence, we further examined differences in certain activity features for each cluster. Since the two groups in Cluster 2 exhibited the most similar activity space characteristics across all components, we treated Cluster 2 as the baseline. The high similarity in activity patterns characteristic of this cluster is likely attributable to the well-developed transit system and proximity to the abundant facilities and resources in the city centre. In contrast to other parts of the city, these zones provide an environment that facilitates the two groups to develop the same level of activity participation.

For the areas in Cluster 0, we measured group-level differences in the features delineating activity extensity (i.e., the radius of gyration, travel distance and travel time). As depicted in **Fig. 7(a)-(c)**, the y values are greater than zero. It means that public transit riders, on average, had smaller activity spaces and travelled much shorter distances and times than private car users. The differences between groups in this cluster were pronounced in comparison to the baseline (Cluster 2).

With respect to the zones in Cluster 1, we examined differences in the number of activities and in entropy, which quantify activity diversity. According to the y values, public transit riders, on average, had fewer activity points and higher activity regularity, as observed in **Fig. 7(d)-(e)**. TAZs in Cluster 1 exhibited a more significant difference between groups in terms of activity diversity compared with baseline Cluster 2.

Regarding the areas in Cluster 3, the most significant disparity was observed for travel speed, representing the travel efficiency of a given transport mode. As shown in **Fig. 7(f)**, private cars provided residents with higher mobility ability than public transit (y values are greater than zero). Meanwhile, the TAZs in Cluster 3 presented larger differences in travel efficiency than the zones in the baseline Cluster 2.

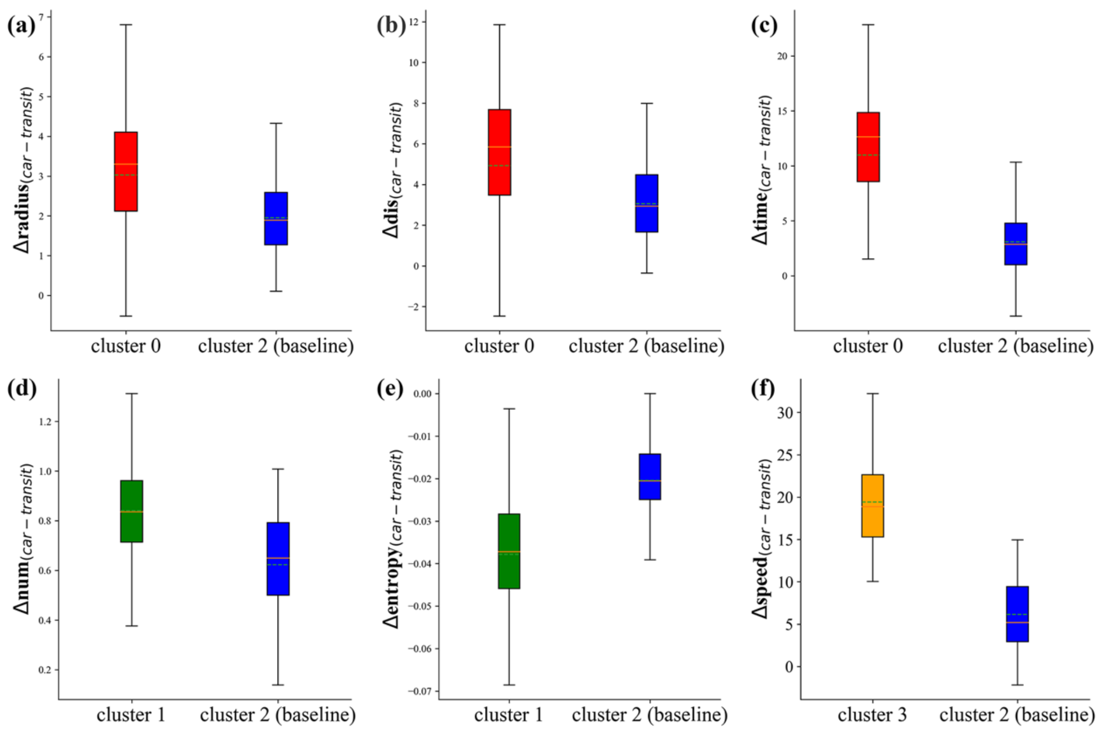

Fig. 7. Differences in activity features between private car users and public transit riders for the different zone clusters: (a) radius of gyration (km); (b) travel distance (km); (c) travel time (minute); (d) number of activity points; (e) activity entropy; (f) travel speed (km/h). If the y value

is greater than zero, it means that the car users have a larger value in the activity feature than the transit users in the same cluster.

5.3 Factors driving activity disparity

Spatial differentiation in access to activity opportunities was evident in Shenzhen. To identify the driving forces underlying the citywide spatial variance in activity disparity, this study first carried out a spatial regression analysis on the comprehensive indicator. According to **Table 1**, the average travel radius for both groups was about 5 km, which means that people tend to partake in activity opportunities within areas that are less than 5 km from home. Accordingly, we created a 5-km buffer for each TAZ and calculated the land use entropy within it. As shown in **Fig. 8**, urban resources were unevenly distributed across the city at the time of data collection. Generally, the central urban area presented a high degree of mixed land use, whereas, in the suburbs and outskirts, the urban functional diversity was low. We expected that diverse land use within reachable areas can fulfil the needs of engaging in various activities for both modal groups.

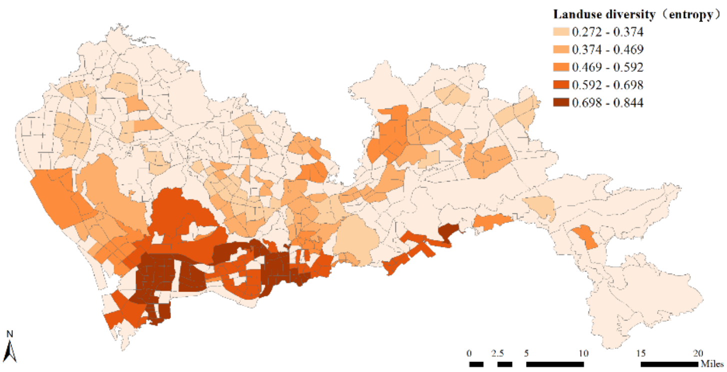

Fig. 8. Land use diversity in Shenzhen.

Before performing the regression, we normalised all variables. We first adopted an ordinary least squares (OLS) model to estimate the impact of each variable on activity variability. The OLS regression results are provided in **Appendix A5**. The multicollinearity of independent variables was tested using the variance inflation factor, for which all values were less than 2, indicating that no variable had a significant collinear relationship with any other. The OLS model featured an R-squared value of 0.16 and an adjusted R-squared of 0.14. According to spatial dependence diagnostics, the LM error model was significant while LM lag was not; thus, the spatial error model was utilised in further analysis.

The spatial regression results are shown in **Table 2**. The R-squared was 0.26, indicating a considerable improvement in model fitting over the OLS model. The lag coefficient (lambda) was 0.65, implying significant spatial autocorrelation and hence the suitability of the data for a spatial regression model. Significant associations with CI were observed for bus stop density, distance to the city centre, and distance to the nearest metro station. In particular, bus stop density was negatively related to CI, suggesting that increasing the density of bus stops in a zone would decrease activity disparity between the two groups. In contrast, distance to the city centre and distance to the nearest metro station both presented positive associations with CI. These findings imply that developing the public transport system, especially rail transit, can reduce activity inequality between users of the two transport modes. Moreover, beyond poor public transport facilities (i.e., low bus density and no rail transit), greater distance to the city centre can decrease the willingness of transit riders to travel long distances for activities, thus increasing activity disparity relative to private car users. Land use diversity was found to have no significant impact on the overall activity disparity. The result was unexpected in light of our assumption. One possible reason is that the local activity facilities cannot be completely accessible for one or both groups in some diverse zones. For example, the activity opportunities may not match the needs of some individuals (e.g., high-cost activities for poor people or low-end opportunities for high-skill people). They have to travel out of local spaces to access activity opportunities, leading to the difference in certain activity features between the two groups. Hence, despite diverse land use, some people still cannot participate in required activities within the reachable areas (5 km distance from residential zones in this study). Secondly, in some low-mixed land use areas, it is possible that both groups need to travel out of local spaces to access activities, resulting in small differences in certain activity features (e.g., travel distance). This suggests that there existed some areas in which the activity opportunity needs of car users and transit users couldn't be fulfilled simultaneously by the current land use pattern.

Table 2. Results of the spatial regression model for CI.

Variable	Coefficient	Std. Error	Z-value	Probability
constant	-3.347	1.329	-2.519	0.012**
$\boldsymbol{dis_{centre}}$	5.312	2.002	2.653	0.008***
$\boldsymbol{den_{bus}}$	-2.451	1.066	-2.300	0.021**
$\boldsymbol{dis_{metro}}$	4.611	2.459	1.876	0.061*
$\boldsymbol{den_{road}}$	0.816	1.086	0.752	0.452
$\boldsymbol{div_{land}}$	1.621	1.199	1.352	0.176
$\boldsymbol{ratio_{migrant}}$	-0.051	0.784	-0.065	0.948
Lambda	0.649	0.095	6.818	0.000***
R-squared	0.258			

Note: ***p<=0.01; **p<=0.05; *p<=0.1.

Regarding the four clusters identified, we set Cluster 2 as the reference group because it presented the smallest inequalities between the two groups. As **Table 3** shows, compared with the zones with the lowest levels of activity disparity, the increased distance to the city centre and rail facilities will increase the possibility of inequality in activity extensity. In contrast, increasing the density of the road networks would reduce the likelihood of gaps in travel coverage and efficiency. It means disadvantaged groups face high risks of limited activity space and low travel efficiency in the outskirt zones with poor transport accessibility. In addition, the proportion of migrants, which is a proxy for socioeconomic inequality, significantly impacts the manifestation of differences in activity extensity. The finding suggests that the zones with a larger proportion of migrants are more likely to suffer inequality in the extensity of activity space. In the zones near the city centre, rail transit accessibility and land use diversity contributed to the access to diverse activity opportunities. It means that more convenient transport, more mixed land use patterns and matched urban functions would decrease inter-group difference in activity diversity. The negative influence of distance to the city centre in Cluster 1 model is mainly attributed to the shorter average distance to the city centre of TAZs in Cluster 1 in comparison with TAZs in Cluster 2.

Table 3. Multinomial logistics regression results

Reference group: Cluster 2 (LLL)	Cluster 0 (HLL)		Cluster 1 (LHL)		Cluster 3 (LLH)	
Variable	**Coefficient**	**Exp.**	**Coefficient**	**Exp.**	**Coefficient**	**Exp.**

$intercept$	-2.565	-	1.224	-	-1.053	-
dis_{centre}	3.949***	51.859	-6.150***	0.002	4.659***	105.542
den_{bus}	-0.685	0.504	-0.078	0.925	1.050	2.858
dis_{metro}	4.963***	142.968	6.717***	826.313	0.856	2.354
den_{road}	-3.197**	0.041	-0.379	0.684	-5.125**	0.006
div_{land}	-1.285	0.277	-1.384*	0.251	-1.347	0.260
$ratio_{migrant}$	1.900*	6.687	1.008	2.740	-1.318	0.268
Pseudo R-squared	0.477					

Note: ***p<0.01; **p<0.05; *p<0.1.

6. Discussion and implications

Although social exclusion can be quantified in multiple ways, it centres upon access to activity opportunities and mobility (Cass, Shove, & Urry, 2005). It is considered that opportunities within a person's routine activity spaces are more accessible than outside since observed activity space is the outcome of individual preferences, socioeconomic and spatio-temporal constraints, and geographical environments (Wang, Kwan, & Hu, 2020). In this regard, people-based activity space can better measure the accessibility to opportunities compared to place-based approaches. Besides, activity space methods are able to capture spatial variances by aggregating individuals into spatial units, which can facilitate spatial planning for improving transport and opportunities in socially excluded areas. Recently, activity space methods have presented great potential for measuring socio-spatial inequalities benefiting from the growing accessibility to various human mobility big data (Comber, Park, & Arribas-Bel, 2022; Gao et al., 2021). Drawing on the activity space notion, this study used the extensity of activity space, the diversity of activities and travel efficiency to quantify the access to opportunities, extending the measurement of social exclusion.

This study observed that car users travelled further, engaged in more activities and had higher travel efficiency than transit users. The finding is consistent with other small-scale studies based on surveys that the high mobility afforded by a private car enables a user to travel at their convenience and access more facilities and resources with a more extensive activity space (Ta, Kwan, Lin, & Zhu, 2020). In contrast, transit riders are more likely to be restricted by the reach of the public transit system. This study provides additional evidence for the established acknowledgement that car owners are the least constrained across all social groups and enjoy higher levels of access to activity opportunities (Lucas, 2019). On the contrary, individuals without cars may face barriers and inequalities in carrying out economic and social activities, suffering a high risk of social exclusion (Benenson et al., 2010; Kawabata & Shen, 2007).

As observed in this study, the activity disparity between the two groups varies in location. Larger between-group gaps in activity engagement occur in the outer suburban areas of the city, which are less developed relative to the central areas. The finding echoes the studies using place-based accessibility measures, which demonstrated that the modal differences are smaller in the city centre than in the suburban areas (Kawabata, 2003). Given the fact of poor transport accessibility (e.g., low density of bus stations and no subways) in the urban periphery, the people who rely on public transit for daily travels, options are fewer but restricted to smaller areas and reliant on nearby limited resources, whereas car users can travel further for more job opportunities and urban facilities. It means that the non-car-owning group in outer suburban areas faces higher social exclusion risks than those in the city centre. A similar spatial pattern of social exclusion has been observed in other cities with sparse services and facilities (Currie et al., 2010). Since the locational disadvantage is intertwined with transport, it has become a non-negligible aspect of transport-related social exclusion, namely geographical exclusion (Church, Frost, & Sullivan, 2000; Engels & Liu, 2011). It occurs when people are prevented from accessing activity opportunities because of the lack of transport connections between their residences and services (Luz & Portugal, 2021).

Activity disparities in different locations were found to be determined by different dimensions. The detailed analysis of the clusters allows us to understand the unequal access to opportunities between the two groups across different locations. The places with the largest differences in activity extensity and travel efficiency lie in the outer suburbs. Understandably, car owners can easily travel long distances for opportunities in city centres, while transit riders are hindered by the long distances separating their residences from employment and entertainment centres, leading to the greatest disparities in extensity. Meanwhile, transport systems in the outer suburbs are not as well-developed as in the inner city. Thus, public transit users experience much lower travel efficiency for access to services compared with people who own cars. The places with the largest differences in activity diversity are distributed in the city centre and inner suburbs. The gaps in activity extensity and travel efficiency are smaller between the two groups than those in the outskirts due to the proximity of opportunities and dense transport networks. However, some transit users living in city centres are still at risk of social exclusion with less access to diverse activity opportunities.

The analysis of potential driving factors informs urban policymakers on tackling social exclusion. The findings suggest that proximity to transport and activity opportunities, socioeconomic status, and land use patterns jointly determine the risk of social exclusion of disadvantaged people in terms of activity space characteristics, with different areas exhibiting different risks. The significance of location disadvantage (i.e., distance to the city centre) implies an inequitable distribution of urban resources across the city. The city centres encompassed the majority of urban opportunities and transport facilities and presented a high degree of mixing of urban functions. To reduce gaps in activity uptake, there is a need to create more skill-matched opportunities, diverse land use, and efficient public transport for areas at a high risk of social exclusion. The socially excluded zones identified in this study provide targets for future transport development. The significance of the proportion of migrants in a zone implies that the non-car-owning individuals who are migrants have lower access to activity facilities than local residents living in the same zone. This finding is in line with evidence from similar urban contexts that migrants are often located on the urban fringe and have constrained activity spaces (Ta, Kwan, Lin, & Zhu, 2020). Another empirical study of Shenzhen observed that transit users were continually relocated to urban suburbs, which may reduce the relocators' chances of engaging in activities (Gao et al., 2018). Therefore, efforts should be made to improve the transport system, create diverse and appropriate activity opportunities, and devote attention to migrants without cars.

Although this study demonstrated the advantages of cars in facilitating activity participation, providing private vehicles for the people living in socially excluded areas is not encouraged. Overusing private cars might worsen social exclusion by contributing to the decline in public transport and widening the mobility gap (Luz & Portugal, 2021). An empirical analysis of Shenzhen documented that people living or working in the suburbs are more likely to drive a car than those living in the city centre (Song, Chen, & Pan, 2012). Although Shenzhen is not a car-dependent city, there are still some people in the lowest income group who rely on cars to access opportunities. Car dependence may aggravate poverty for these poor households in outer and fringe areas and reduce the chances of participating in other non-mandatory activities. The “forced car ownership” issue has been observed in many megacities and metropolitan regions (Carroll, Benevenuto, & Caulfield, 2021; Currie et al., 2010; Mattioli, 2017). While considering the non-car groups, we must also be vigilant about the financial stress of car ownership imposed upon these low-income households with cars. To maintain the usage of vehicles, they might reduce other expenditures and restrict their activity spaces, ultimately leading to social exclusion (Mattioli, Wadud, & Lucas, 2018).

7. Conclusion

An improved understanding of transport inequality is important for the promotion of sustainable development and social equity. Existing studies have mainly measured transport inequality between travel modes in terms of place-based accessibility and so lacked a view of the actual gaps in access to activity opportunities, which is an essential component of social exclusion. This study attempts to extend transport inequality research by unveiling disparities from the perspective of people-centred activity space. To overcome the insufficient sample sizes typical of conventional survey-based studies, this study takes advantage of two types of large-scale individual mobility data that enable the investigation of activity disparity and its potential driving forces at a finer spatial scale.

The preliminary comparative analysis confirmed our understanding that in comparison to people who rely on public transit, those who own private cars can access more activity opportunities across a larger coverage area by travelling longer distances and enjoying higher travel efficiency. Furthermore, a comprehensive indicator of activity disparity demonstrated those areas having the highest risk of social exclusion and identified four categories of urban areas associated with distinct disparity patterns. The results yielded two critical findings. First, in Shenzhen, with its circular urban structure, the two groups in the city centre and inner suburbs exhibited more similar activity patterns than those in the outer suburban areas. Second, disparities within different urban areas were determined by different activity dimensions. In the outer suburbs, activity differentiation was mainly rooted in activity extensity and travel efficiency, while in the inner suburbs, diversity was the primary dimension in which activity disparity occurred. These revelations add to our understanding of the mobility and accessibility gaps between private cars and public transit. By highlighting significantly unequal areas for targeted implementation of urban planning policies, it becomes more likely that the potential social exclusion of disadvantaged groups can be successfully reduced.

This work explored the potential driving forces underlying activity disparity and its spatial heterogeneity using statistical models. The results indicate that public transport facilities, especially rail transit, and location factors represented by distance to the city centre play essential roles in determining between-group gaps in access to urban facilities. In addition, socioeconomic gaps and land use patterns also partially contribute to some dimensions of access. These findings provide important insights for guiding transport and land use planning to facilitate sustainable development. For example, public transport and especially rail transit should be strengthened to facilitate greater convenience for people in the outskirts undertaking activities by public transit. Besides, attention should also be paid to disadvantaged social groups (e.g., migrants) and other factors that impede activity participation, such as less diverse urban functions.

Through a case study, we illustrate that people-based activity space methods and big data could help us develop a more accurate and comprehensive evaluation of transport inequality and its spatial patterns. More broadly, examinations of transport inequality are relatively scarce in developing countries. Different from developed cities with very high car ownership, most megacities in developing countries adopt sustainable transport strategies and prioritise public transit development. On the other hand, public transit networks are not extensive enough to provide people with alternative mobility ability to easily access opportunities across the urban space, increasing the risks of social exclusion for people who don't own cars and have lower access to public transit. Therefore, identifying possible inequality across social groups using different transport modes serves as the first step toward developing effective interventions to reduce potential social exclusion in these urban contexts. The study contributes to discussions on transport-related social exclusion by highlighting modality-associated differences in activity participation in a typical megacity in a developing country. This study also helps create a globally generalised understanding of the effects of potential factors on transport equality.

There are several limitations and opportunities for future studies. First, this study mainly focuses on activity features from spatial dimensions and lacks concerns about temporal dimensions and activity type due to data limitations. However, the study does not attempt to illustrate all activity features that could be compared. We believe several representative aspects are helpful in highlighting the disparities between subgroups. Another limitation is the lack of any estimation of activities accessed through soft modes of travel (e.g., walking and bicycling), which may be more effective in certain areas and for short-distance travels. Although this study mainly unveiled differences in fulfilment of mobility needs between users of public transit and private cars, access to activity opportunities around residences is also an important consideration when evaluating social exclusion. Moreover, the present study did not identify mixed-mode users, such as car owners who prefer to realise certain trips by public transport or transit users who may take taxis for certain activities. However, people were anonymised in both the public transit smart card data and private car trajectory data due to privacy issues, and taxi data related to individuals are unavailable; as such, it was impossible to identify people who use more than one transport mode for daily travels. These limitations will be addressed in future studies when related data is available.

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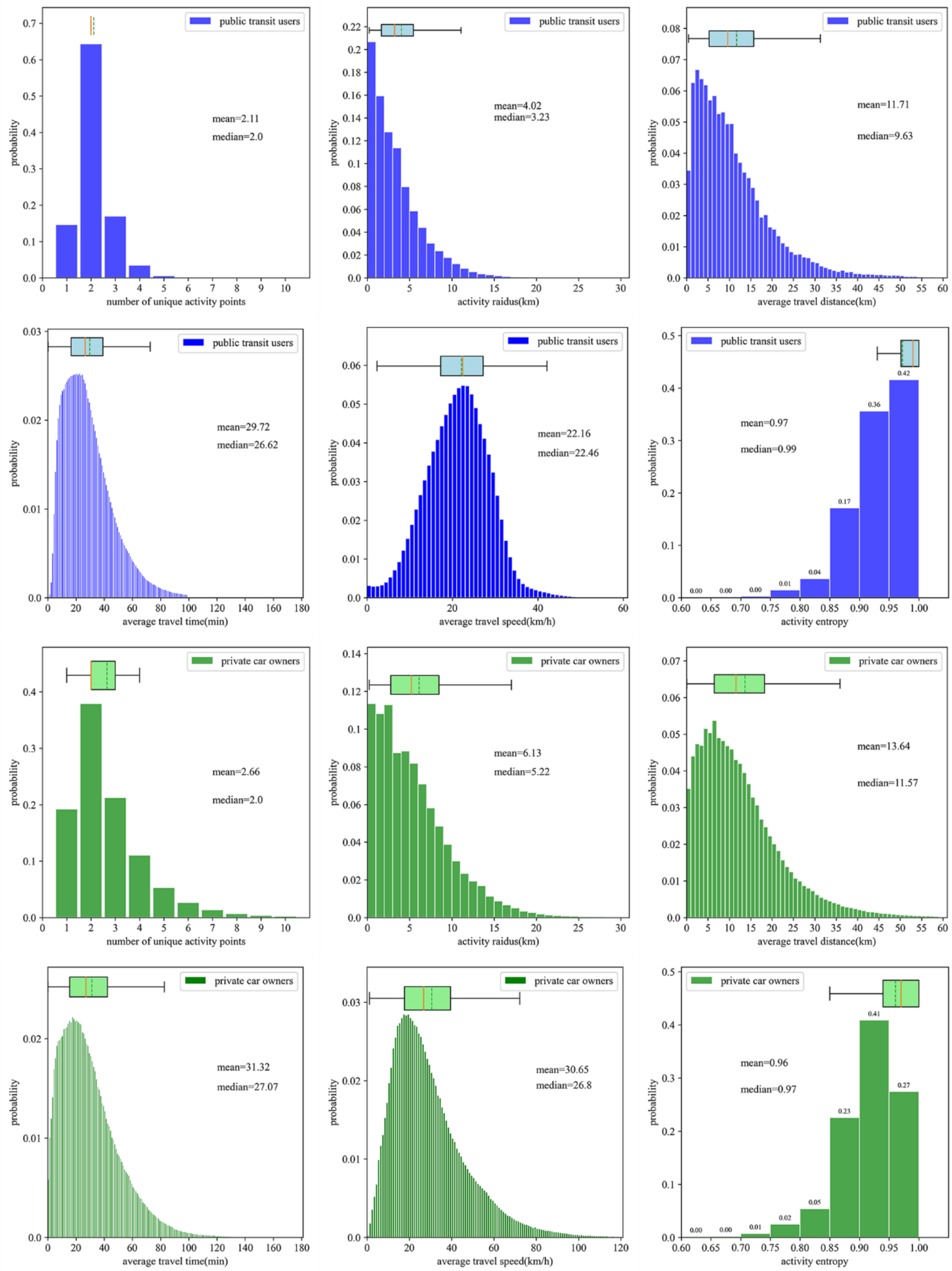
Appendix A1. Histogram of activity features of public transit riders and private car users.



Appendix A2. The EFA analysis results.

Table. Eigenvalues and explained variance for each component.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.898	48.300	48.300	2.898	48.300	48.300	2.399	39.976	39.976
2	1.251	20.846	69.146	1.251	20.846	69.146	1.428	23.808	63.784
3	0.989	16.490	85.636	0.989	16.490	85.636	1.311	21.852	85.636
4	0.639	10.649	96.285						
5	0.183	3.046	99.331						
6	0.040	0.669	100.000						

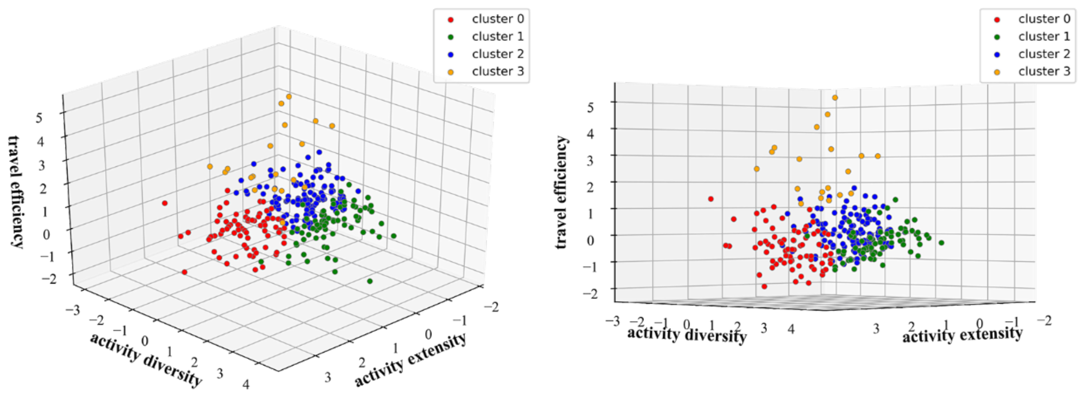
Extraction Method: Principal Component Analysis

Table. The rotated component (loading) matrix.

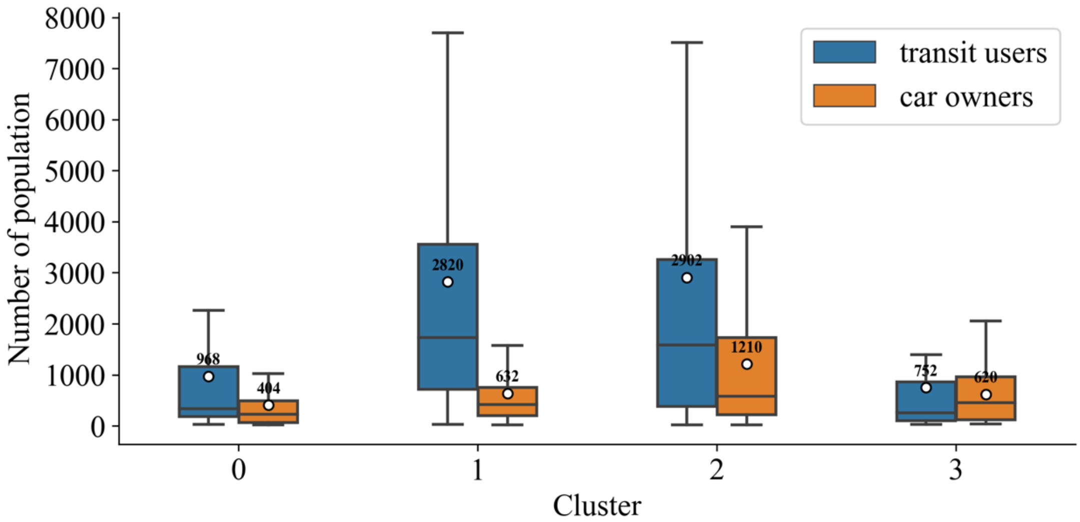
Variable	Component 1 Activity extensity	Component 2 Activity diversity	Component 3 Travel efficiency
num	-0.043	0.842	-0.063
radius	0.868	-0.107	0.394
distance	0.885	-0.123	0.400
time	0.904	-0.115	-0.278
speed	0.139	-0.148	0.950
entropy	-0.156	0.811	-0.111

Rotation method: Varimax with Kaiser Normalization

Appendix A3. The four TAZ clusters identified by the k-means method.



Appendix A4. The distribution of the number of transit users and car owners within TAZ for each cluster.



Appendix A5. Results of the multiple linear regression model for the activity disparity.

Variable	Coefficient	Std.Error	Sig.	VIF
constant	-2.06	0.936	0.029**	
$\boldsymbol{dis_{centre}}$	3.244	0.921	0.001***	1.746
$\boldsymbol{den_{bus}}$	-1.707	0.933	0.087*	1.227
$\boldsymbol{dis_{metro}}$	3.971	1.432	0.006***	1.340
$\boldsymbol{den_{road}}$	1.255	1.114	0.261	1.384
$\boldsymbol{div_{land}}$	-0.729	0.880	0.408	1.896
$\boldsymbol{ratio_{migrant}}$	0.548	0.809	0.498	1.268
R-squared	0.144			

Note: ***p<=0.01; **p<=0.05; *p<=0.1.