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修　士　論　文

Mobility Based Environmental Justice: Understanding Inequity in Transit-Oriented Development (TOD) Station Usage and Artificial Light at Night (ALAN) Exposure

モビリティベースの環境正義：公共交通指向型開発（TOD）ステーションの使用と夜間の人工照明（ALAN）曝露における不公平の理解

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TABLE OF CONTENT

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Abstract

The purpose of environmental justice (EJ) is to protect all people, regardless of age, gender, income, etc., from disproportionate environmental harm. Previous EJ studies have been residence-based, assuming that people's environmental exposures only occur in the residential environment. The current challenge for EJ research is how to measure the environmental resources and exposures that people are actually exposed to during their daily travel and activities. A possible solution is to use mobility data to conduct mobility-based EJ studies. This thesis outlines my efforts in mobility-based EJ research.

In chapter 2, I propose a method for user attribute inference on trajectory data using a small number of known labels and non-sensitive government statistics. By matching the user's home location with the demographic statistics of the block where it located in, we determine the marginal probability distribution matrix of each user's social labels. Using multivariate statistics published by the government, we build a Bayesian network for all social labels. After generating a set of initial labels for each user with sampling based on probability matrix, the Bayesian network is used to resample each social attribute and update the labels by rotating the axes. Finally, I obtained the exact inference of social information labels for individual users.

In chapter 3, I provide a framework for TOD age inequity research applicable to high-density and public-transport-oriented cities. This chapter uses big mobile phone positioning data to extract the age information of TOD (Transit-Oriented Development) station users and uses geographic information and survey data to quantify the TOD service level. Then, I used the Gini coefficient, correlation coefficient analysis, and cluster analysis to explore the differences in TOD resource allocation across age groups on the JR Yamanote Line and part of the JR Chuo line in Tokyo. The results show that inequity indeed exists at the TOD service level in terms of user age, and there is a negative correlation between the average age of users and most indicators of TOD. In the clustering results, three unique TOD groups are formed: a) Residence-oriented aging TOD, b) Livable middle-age TOD, and c) Commuter-oriented young TOD. Based on the research results, I made three suggestions for building an age-friendly TOD: a) More diverse land use, b) Better connectivity between transit nodes and multimodal transportation, and c) Affordable housing cost.

In chapter 4, based on mobile phone positioning big data and night-light satellite imagery, I conducted an empirical study on the inequity of ALAN exposure in Tokyo, Japan. I quantified the intensity of ALAN on the grid of mobile phone positioning data. Then I used the Gini coefficient and population-weighted mean exposure to evaluate the inequity of ALAN exposure among individuals and between different population groups. As a result, I found evidence of the inequity of ALAN exposure in Tokyo. For age inequity, younger people suffer higher exposure to light pollution at night, but children are an exception. For gender inequity, there is almost no inequity between men and women. For residence inequity, the average ALAN exposure of non-residents can reach up to about twice that of residents. At time and space nodes where there are more travel behaviors, such as central Tokyo during 18:00-24:00, I have detected higher exposure and stronger inequity, indicating that ignoring personal mobility will cause underestimation.

1. Introduction

1.1. Background

Environmental justice (EJ) has been an important issue for over a century (CUTTER, 1995). Certain environmental injustices will become prominent under certain spatial and temporal contexts. For example, in transit-oriented cities, gentrification of transit-oriented development (TOD) may reduce livable opportunities for disadvantaged groups (Appleyard et al., 2019; He et al., 2021); the popularity of light-emitting diode (LED) has made artificial light at night (ALAN) an emerging environmental pollution that has been shown to be relevant to human health (Xiao et al., 2020; Zhong et al., 2020). To formulate relevant and equitable social policies, it is necessary to examine how environmental inequities are assumed among social groups.

Human's residential neighborhoods are often considered as the main unit of EJ research. Numerous studies have shown that disadvantaged groups such as ethnic minorities and people with low socioeconomic status are more likely to live in areas with scarce environmental resources and serious environmental pollution (Badland & Pearce, 2019; Hajat et al., 2015; Mitchell & Dorling, 2016). Therefore, the residence-based EJ study may just be a coincidence of the residents' own attribute disadvantage and residential neighborhoods disadvantage. This can make interpretation of EJ problems challenging. In particular, the static residential neighborhood fails to capture the entire background of the EJ population, as most people leave their residential area for daily travels or activities (Helbich, 2018; Kwan, 2012). In contrast, mobility-based EJ research takes into account people's mobility characteristics and thus can fully consider situations relevant to people's daily lives. In today's era of abundant sources of mobility data available, mobility-based EJ research will be a new breakthrough.

Using Tokyo as a case study, this thesis explores two mobility-based EJ research subtopics using mobile phone location data: 1) 2. Understanding inequity in transit-oriented development (TOD) station usage. 2) Understanding inequity in artificial light at night (ALAN) exposure.

1.2. Literature Review

1.2.1. Environmental Justice: From residence-based to mobility-based

Environmental justice (EJ) means that no one, regardless of race, nationality, income, age, or gender, should suffer a disproportionate share of the negative environmental consequences (US Environmental Protection Agency, 2020). Since the concept of EJ was proposed in the 1980s, scholars have conducted a lot of EJ research and expanded its content. The initial research focused on the unequal exposure of ethnic minorities and people with low socioeconomic status to toxic pollution (Aksaker et al., 2020; BROWN, 1995; Brulle & Pellow, 2006; Nadybal et al., 2020). Then the field was extended to other types of pollution and environmental disasters, including air pollution (Ard, 2015; Chakraborty, 2021; T W Collins et al., 2015; Grineski et al., 2007; Maantay, 2007), noise exposure (Lagonigro et al., 2018) and flooding (Timothy W. Collins et al., 2019). In the past ten years, researchers have expanded the scope of environmental justice by exploring the convenience of access to environmental resources and the social injustices exposed to a wider range of environmental disasters. In terms of environmental convenience, the researchers analyzed the social inequity of the accessibility of green spaces and beaches (Dahmann et al., 2010; Montgomery et al., 2015). In terms of environmental disasters, research has found that ethnic minorities and people with low socioeconomic status are related to higher urban high-temperature exposure (Harlan et al., 2007; Voelkel et al., 2018).

Much of the EJ literature argues that disadvantaged groups suffer more environmental hazards, rooted in the fact that they are in disadvantaged residential areas. In some European countries, for example, there is a strong geographic correlation between air pollution and poor communities (Brunt et al., n.d.; Chaix et al., n.d.; Pearce & Kingham, 2008). A key question facing EJ research is how to measure the environmental resources and risks that people are actually exposed to during their daily travel and activities. For example, light pollution, previous studies have assumed that environmental exposures of different groups occur in residential environments (Nadybal et al., 2020). However, there is a growing consensus that environmental exposures do not only occur in residential areas, but also extend to people's daily travel and activities (Sheller & Urry, 2006). Considering the mobility of human, the results of the EJ study may vary widely because of differences in the mobility characteristics of different groups. For example, studies have found that people with low socioeconomic status are often limited to the periphery of their residential areas due to the limitations of available travel modes. On the other hand, the spatiotemporal dynamics of environmental elements can also affect the results of EJ studies. Specifically, mobility reduces environmental inequity when people's environmental exposures associated with their daily lives are described as greater environmental benefits or less environmental risks than the environment in which they live, and vice versa.

1.2.2. TOD: Gentrification and Typology

Transit-oriented development (TOD) is an urban development strategy that aims at developing multiple land use functions such as residential, working, and space for daily activities within the catchment area of public transit(Z. Yu et al., 2022). The proponent of the TOD concept, Calthorpe, emphasizes the concept of "community". His main focus is to build a sustainable urban community around public transit. In such a community, “mix residential, retail, office, open space, and public uses in a walkable environment, making it convenient for residents and employees to travel by transit, bicycle, foot, or car”(Calthorpe, 1993; Carlton, 2009). Therefore, typical TOD models include two characteristics, namely, efficient and accessible transportation services and the potential for users to obtain various land functions.

However, in recent years, some studies have found that TOD can lead to an unequal phenomenon called “gentrification” that is often overlooked. Low-income families and minority families living in the surrounding areas of TOD often face high rents, which makes life extremely difficult (Baker & Lee, 2017; Clagett, 2014; H. Dong, 2017; Sandoval & Herrera, 2015; Sandoval & Gerardo, 2016). The problem that scholars worry about is that although TOD can indeed improve the accessibility of public transportation, reduce transportation costs, improve the environment of community facilities, etc., these benefits may not have a major effect on those who rely on public transportation (Bostic et al., 2018; Chapple et al., 2017). Thus, understanding the built environment differences of different TOD stations and their relationship with users is crucial for environmental justice research.

TOD typology is a method for exploring TOD heterogeneity by classifying morphologically and functionally similar site regions. The node-place model (Figure 1) is the most popular method in the worldwide study of TOD typology (L. Bertolini, 1999). The model provides an analytical framework to evaluate the development of transfer stations (nodes) and their surrounding areas (places). The basic idea is the feedback loop between transportation supply and land use: (1) Improving transportation services and supply is beneficial to the diversification and intensification of surrounding land use. (2) Diversification and intensification of land use provide favorable conditions for the further development of transportation infrastructure (Luca Bertolini, 2005). Node-place model distinguishes five types of TOD (L. Bertolini, 1999, see Figure 1). The first type is the "balanced" form: the coordinated development of transportation and land use provides the most favorable conditions for each other. The second category is the situation of "dependence": transportation and land use are both underdeveloped, making a TOD difficult to generate the driving force for independent development. Conversely, the third category is the "stress" form: both transportation and land use are highly developed; their competition for space is intense and tensions are likely to arise. The last category is the "unbalanced" form: "unbalanced nodes" (where transportation far outweighs land use development) and "unbalanced places" (land use far outweighs transportation development).

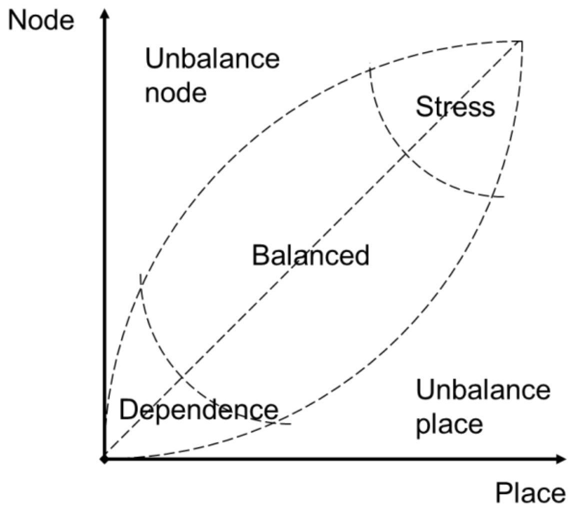


Figure 1. Five TOD types for node-place models
Source: Bertolini, 1999

The node-location model has been applied in many regions since its inception (L. Bertolini, 1999; Chorus & Bertolini, 2011; Z. Li et al., 2019; Lyu et al., 2016; Vale, 2015; Z. Yu et al., 2022). Furthermore, with the help of cluster analysis or principal component analysis, these metro station areas are classified into different types with similar node and place characteristics (Atkinson-Palombo & Kuby, 2011; Chorus & Bertolini, 2011; Kamruzzaman et al., 2014; Nasri & Zhang, 2014; Reusser et al., 2008; Schlossberg & Brown, 2004; Zemp et al., 2011). With the development of TOD research, the node-place model has been further expanded to meet different research purposes. For example, to assess the interrelationship between transit stations and surrounding areas, one possible enhancement is to add an "oriented" dimension in the node-place model. Vale (2015)conducted a pioneering study along this line by introducing pedestrian accessibility into the node-place model to assess and classify station areas in Lisbon. Lyu et al. (2016) extended the node-place model by dividing 94 indicators into transit, oriented, and development dimensions. Li et al. (2019) proposed 8 TOD types using the "node-tie-place" model. However, the TOD indicators selected in existing research are basically about the built environment, and rarely about the users of TOD - humans and human activities.

Among the indicators involving humans, the existing TOD literature often reports the number of residents in the catchment area(Chorus & Bertolini, 2011; Lyu et al., 2016). But residents cannot be equated with users, because visitors from other places are not included. Aware of this, some scholars use questionnaires to collect information on TOD users(Sandoval & Gerardo, 2016). Although questionnaires can provide detailed descriptions of users, the data collection process is time-consuming and labor-intensive. With the maturity of information and communication technologies (ICT) and the popularization of mobile phones, a large amount of personal data with spatiotemporal information is used for research on urban transportation (Z. Wang et al., 2018), such as traffic demand forecasting (Q. Yu et al., 2020; H. Zhang et al., 2018) and urban traffic emission measurement (Chen et al., 2020; X. Song et al., 2020; Sui et al., 2020). Compared to the high cost and workload of traditional data survey methods, location data is currently being generated at an unprecedented scale in terms of volume, variety, and speed (C. Wang & Hess, 2020). The emergence of such data allows researchers to grasp the actual population movement within a certain space and time (Batran et al., 2018; P. Li et al., 2022; W. Li et al., 2022a). In TOD research, some scholars have used trajectory data to calculate the real demand of transit nodes (Liao & Scheuer, 2022; van Wee, 2016).

To sum up, this literature review found that the current research lacks user characteristic information, and mobile phone location data provides the possibility to collect user information on a large scale. Chapter 4 attempts to address some of the deficiencies identified in existing research. First, based on mobile phone location data with user personal attributes and spatiotemporal location, this study calculates the average age of users in the TOD catchment area within a certain period to make up for the neglected user information in previous studies. In addition, this study introduces the "user" dimension into the "node-place" model to more intuitively capture the relationship between users and the TOD built environment.

1.2.3. ALAN: An Emergent Environmental Health Hazard

Excessive artificial light at night (ALAN) is one of the fastest-growing and most common hazards (Chepesiuk, 2009; Kyba et al., 2017). A study of satellite imagery by Falchi et al. (2016) shows that 83% of the world's population lives under light-polluted skies. Several recent studies at the individual and group levels have revealed a statistical association between some human diseases and ALAN exposure. Most of these studies have used the Defense Meteorological Satellite Program (DMSP) imagery or the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night band (DNB) imagery to measure ALAN. James et al. (2017) and Portnov et al. (2016) (using DMSP imagery) found that women exposed to higher levels of ALAN had an increased risk of breast cancer. Tang et al. (2022) (using VIIRS imagery) found that exposure to ALAN during adolescence may contribute to a higher risk of atopic diseases in young adulthood through a study of Chinese college students. Other studies have also revealed associations between ALAN and non-Hodgkin lymphoma

(Zhong et al., 2020), sleep disturbances (Xiao et al., 2020), depression (Min & Min, 2018), and obesity (Koo et al., 2016). Notably, this association may not be linear. Lan et al.(2022) found that when air pollution was taken into account, the significant association between ALAN and mental health was not observed anymore.

Despite the evidence that ALAN may be harmful to human health, there are few studies on the inequity of ALAN exposure in the field of EJ so far. Until 2020, Nadybal et al. (2020) conducted the first EJ study of unequal exposure to night light pollution in the United States using VIIRS imagery and census data. They found that the population-weighted average light pollution exposure rate in Asian, Hispanic, or black communities was approximately twice that of whites (Nadybal et al., 2020). However, using census data may ignore the mobility of people due to the lack of information on travel behavior (B. Dong et al., 2021; Kang et al., 2021; P. Li et al., 2022; W. Li et al., 2022b; Y. Song et al., 2018; H. Zhang, Chen, et al., 2022; H. Zhang, Li, et al., 2022). Studies have shown that due to the spatial heterogeneity of some pollution, exposure may be incorrectly estimated without considering population mobility (Fallah-Shorshani et al., 2018b; Shekarrizfard et al., 2017b, 2017a; Y. Song et al., 2019). Recently, Fallah-Shorshani et al. (2018a) used GPS data to estimate the exposure of 5,452 people in Montreal, Canada to NO_2, $PM_{2.5}$, and UFPs at home and on the move. By tracking an individual's daily trajectory and calculating multiple activity locations, misclassifications can be avoided (Fallah-Shorshani et al., 2018b; Perchoux et al., 2013; Setton et al., 2011; Steinle et al., 2013). In the context of evidence that personal mobility may affect exposure estimates, no studies have been conducted on ALAN exposure and its inequity using trajectory data.

1.3. Contribution

1) The methodology of environmental justice research is further explored from the perspective of human mobility.
2) Provided a mobility-based TOD inequity analysis framework applicable to transit-oriented development, high population density cities.
3) Conducted the first mobility-based ALAN exposure environmental justice study.

1.4. Organization

The remaining four sections of this thesis will be organized as follow: Chapter 2 will describe the data used in this thesis and the method in data preprocessing. Chapter 3 will introduce research on the inequity in the usage of TOD stations of different age groups. Chapter 4 will introduce research on the inequity in the exposure in ALAN of different demographic groups. Chapter 4 will be a summary and reflection on the whole research topic. Finally, Chapter 5 is an acknowledgment to those who contributed to the completion of this thesis.

2. Data Preparation

2.1. Data Description

To conduct mobility-based environmental justice research, this paper mainly uses mobile phone location data as human mobility data. In the preprocessing part of the flow data, I also used administrative boundary data, social information data and prior data. In Chapter 3, open geospatial data is used to construct TOD built environment indicators. Chapter 4 uses satellite nighttime remote sensing imagery to measure ALAN intensity.

1) Mobile phone positioning big data

I mainly use Mobaku data coming from Mobaku Inc. The Mobaku data is a dynamic population grid data estimated from location data covering 80 million of the 126 million mobile phone users in Japan (NTT DOCOMO, 2018c), which is obtained after the location data of mobile phone users goes through three processing procedures of De-identification, aggregation, and concealment (NTT DOCOMO, 2018b). In addition to hourly population distribution across Japan, Mobaku data also includes demographic information such as age, gender, and place of residence (NTT DOCOMO, 2018a). This chapter selects Mobaku data of Tokyo from 2019/12/01 to 2019/12/07 (7 days of data for December 2019) for research. As shown in *Figure 2*, each grid (500m*500m) contains population of different demographic groups: male/female with age falling into 8 groups (>0-15, >15-20, >20-30, >30-40, >40- 50, >50-60, >60-70, >70-80) and place of residence (district level). For ALAN exposure analysis, I filtered the data from 6 pm to 6 am. To explore how travel behavior affects estimates of ALAN exposure and its inequity, I split Mobaku data into two groups by time. The period of the first group is from 18:00 to 24:00, during which time people still travel normally. The second group is from 0:00 to 6:00, during which time most people are resting, and it can be approximately considered that there is no travel behavior.

2) Administrative boundary dataset

The preprocessing of mobility data employed the polygon shapefile of the Tokyo metropolis in chome (translated as block) level. This data is published in 2018 and recorded the name of the block for each polygon. In chapter 4 I also use district level administrative boundary dataset. This dataset comes from the open geographic data of the Ministry of Land, Infrastructure, Transport, and Tourism. The administrative area data of Tokyo collected in 2021 is used in this chapter. The raw data uses JGD2011 (EPSG: 6668) as the coordinate reference system, and each polygon contains the code attribute of the administration in which it is located. Since the mobile phone positioning data contains the administrative code of the user's registered residence, it can be combined with the administrative area data to classify residents and non-residents.

3) Social information dataset

I used a dataset named “chomonicx” from Zenrin Marketing Solutions Co., Ltd. Chomonicx is geodemographic data that classifies blocks all over Japan from the viewpoint of lifestyle, by combining various statistical data such as census, estimation of the number of households by annual income class, and official land price. 219055 blocks are classified into 38 clusters, and the social information characteristics of each category is counted, including family structure, household income and occupation etc. This social information is recorded in the form of probabilistic proportions (eg. 49% for men and 51% for women).

4) Prior dataset

To construct a Bayesian network to calculate conditional probabilities involving all variables, I collected a large amount of prior data from government statistics websites. These data contain joint statistics of two or more variables, and after transformation I obtain conditional distribution probabilities between variables with dependencies.

5) Open geospatial data

The railway station data describes the spatial information of the railway line and its stations, including passenger flow, number of lines, etc., which can be obtained from the website of the subway operator. The measurement data describes information about the area around the station, such as land use, points of interest (POI), residential population, commuting population, and so on. These are publicly accessible data that can be downloaded from the Open Street Map (OSM), the Ministry of Land, Infrastructure, Transport and Tourism (MLIT), and the Portal Site of Statistics of Japan (e-Stat).

6) Satellite nighttime remote sensing imagery

The Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite launched in 2011 uses the day-night band (DNB) of the airborne Visible Infrared Imaging Radiometer Suite (VIIRS) for night imaging technology. Compared with its predecessor Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS), DNB has made great progress in radiation accuracy, spatial resolution, and geometric quality (Jing et al., 2016; P. Li et al., 2020). The NPP/VIIRS DNB cloud-free composite night light imagery released by NOAA (National Oceanic and Atmospheric Administration) is the most commonly used data type for NPP/VIIRS. These imageries are monthly composite data that have been post-processed to remove clouds and correct for stray light, with a spatial resolution of 15 arc seconds, which is approximately 462.5 m (NOAA, 2017). Each pixel of the satellite imagery records its night-time light (NTL) value of it in nW/cm²/sr. In this chapter, I used the first version of VIIRS Day/Night Band Nighttime Lights of October 2013 as the data source for ALAN.

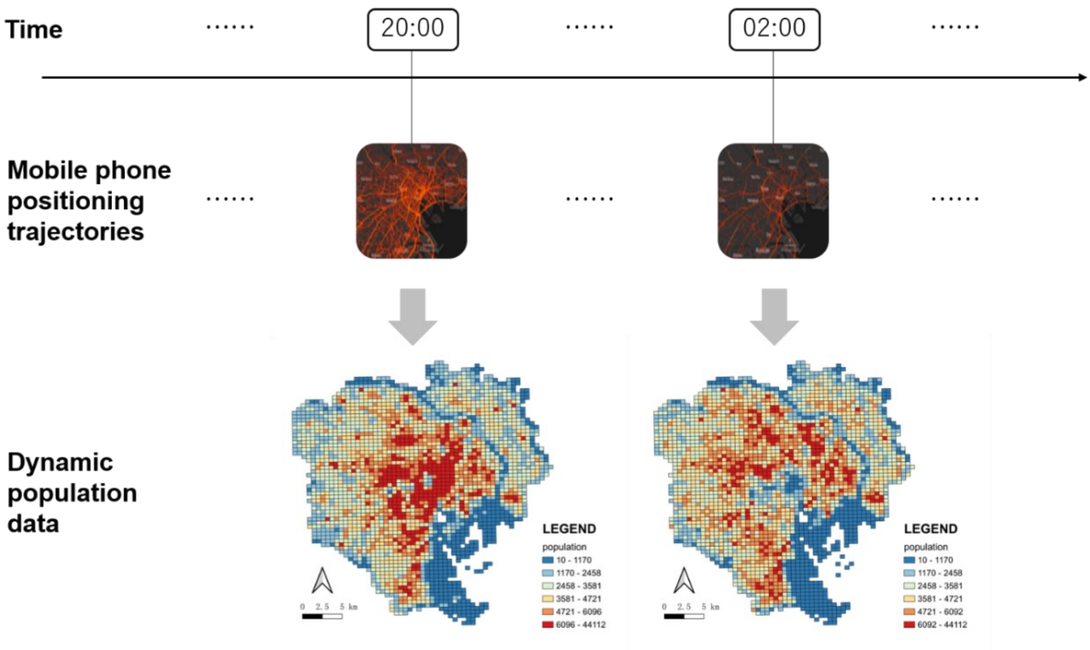


Figure 2. Illustration of mobile phone positioning big data (mobile phone enables instant fine-

scale population tracking)

2.2. Data Preprocessing: Social Information Labelling for Individual Trajectory

Since the human mobility data only contains information of gender and age, it is not enough to support intersected inequity research, so it is necessary to add more labels of social characteristics (such as occupation, income, etc.). In the previous work of other members in our lab (P. Li et al., 2022; W. Li et al., 2022), we generated trajectories from mobility data and used those trajectories for life-pattern clustering and demographic information tracking, annotating users' home location (longitude and latitude) and age-gender (probability table) information. In this chapter, we selected users whose home location is within the Tokyo metropolis.

2.2.1. Framework

Taking users living in the Tokyo metropolis as case study, I propose the research framework as Figure 3. First, I matched the social information with every user according to their home location to obtained the marginal probability matrix. Then I constructed a Bayesian network using the prior dataset of conditional probabilities. In the labeling section, I generate a set of initial labels for each user, and update the label by sampling with rotating variables. Finally, I can obtain individual-level social information labels, and demographic dynamics with social information through further integration.

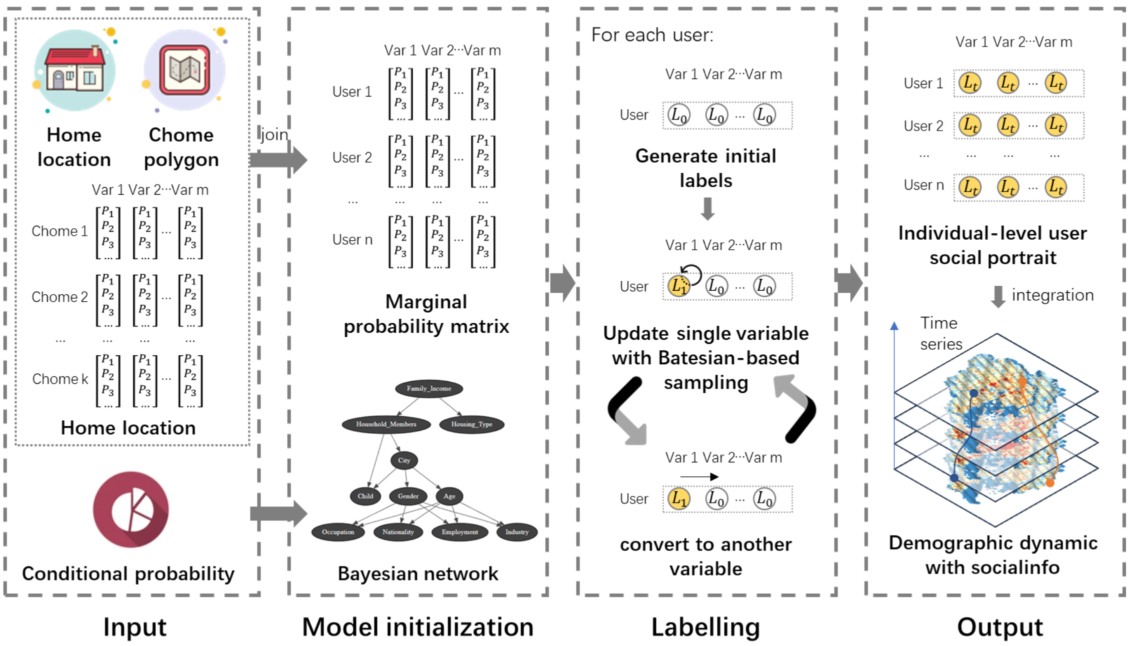


Figure 3. The framework of social information labelling

2.2.2. Methodology

1) Social information matching

I overlayed the home location point layer and administrative border data, and use the "join attributes by location" function of QGIS to obtain the name of the block where the user lives. Using block names as the key, I then use the "join" function to match the marginal distribution (MD) of social information corresponding to blocks in the chomonicx data with each individual user.

2) Bayesian network construction

A Bayesian network is composed of random variables (nodes) and their conditional dependencies (arcs) which, together, form a directed acyclic graph (DAG) (Renjith Raj et al., 2015). They are used to express the conditional dependencies relationship between various factors. Every arc is directed. If event B is conditionally dependent on A, A is called the parent node B, and the direction of the arc is from A to B. If there is no connection between events A and B, they are considered independent of each other. In Bayesian networks, each variable represents a node, and each node corresponds to a conditional probability table $P(X \,|\, Parent(X))$. The set of conditional probabilities of a Bayesian network shows the uncertainty of the correlation between the target event and the condition variable event (Renjith Raj et al., 2015). The current popular method is to build a Bayesian network model from real data. Subject to chomonicx data, we adjusted the number of labels for each variable in the government survey data. Then we applied the package "pyAgrum" in python, inputting nodes, arcs and conditional probability distributions (CPD) to create a Bayesian network (Figure 4). There are a total of eleven variables in this network, where home location (City) is the observed variable, variable “Gender” and “Age” use probabilities inferred from our previous work, and other variables use government statistics.

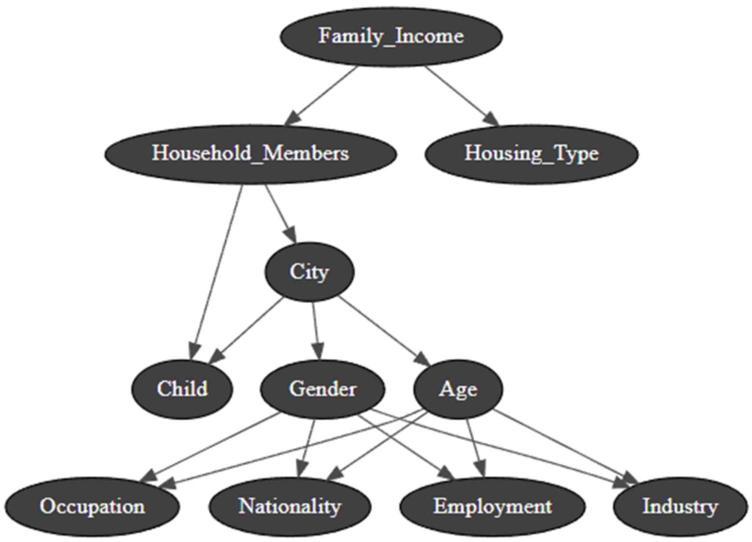


Figure 4. The Bayesian network

3) Sampling

Input: The set of probability distribution function for all individual variables $P = \left(p(x_1), p(x_2), \dots, p(x_k)\right)$, the number of samples drawn each time m, the number of cycle times n.

Step 1: Fix observations (home location) and initialize other variables according to marginal distributions P to obtain an initial label set $x^{(0)}$.

$$x^{(0)} = \left(x_1^{(0)}, x_2^{(0)}, \dots, x_k^{(0)}\right)$$

Step 2: For $i = 1$ to n and $j = 1$ to k, Choose non-evidence variable and draw m samples according to its probability distribution function $p(x_j)$ to obtain sample set X_j .

$$X_j = (x_{j,1}, x_{j,2}, \dots, x_{j,m})$$

Step 3: Resample the non-evidence variable x_j from its conditional probability

$P\left(x_j \middle| x_1^{(i)}, x_2^{(i)}, \dots, x_{j-1}^{(i)}, x_{j+1}^{(i-1)}, \dots, x_k^{(i-1)}\right)$ in the Bayesian network. If this sample is belonged to X_j, it can be assigned to $x_j^{(i)}$.

Step 4: Record the final sample as the label set of the user.

$$x^{(n)} = \left(x_1^{(n)}, x_2^{(n)}, \dots, x_k^{(n)}\right)$$

4) Evaluation Metrics

For all users, we computed marginal distributions for each variable based on the inferred labels and compared the results with government statistics. We use the sum of the squares of the marginal probability differences of the same label as the metric to evaluate the performance of the model.

$$bias = \sum_i (GMP_i - SMP_i)^2$$

Since the ground truth joint probability distribution for all labels is not available, we qualify the results by comparing the average joint probability of users in different parameter combinations.

$$P_{joint} = \frac{1}{K} * \sum_k^K P_k(a, b, c, d \dots)$$

2.2.3. Result

I have tried six parameter combinations for n and m ((1, 10), (1, 5), (1, 15), (2, 10), (2, 5), (2, 15)). Among them, the parameter combination (1, 15) performs the best on the first metrics (Table 1), and the parameter combinations (2, 10) and (2, 15) perform the best on the second metrics. According to the preference of the target, the corresponding parameter combination can be selected. Here I choose parameter combination 6 as the best resolution.

Table 1. Evaluation for parameter combinations

	n	m	$bias$	P_{joint}
parameter combination 1	1	10	0.072	0.000011
parameter combination 2	1	5	0.134	0.000009
parameter combination 3	1	15	0.046	0.000011
parameter combination 4	2	10	0.095	0.000013
parameter combination 5	2	5	0.181	0.000011
parameter combination 6	2	15	0.060	0.000013

I counted the proportion of all inferred labels among users. Figure 5 shows the comparison of ground truth and inference statistics for each variable when the parameter combination is (2, 15). It can be seen that the inferred statistics are close to the real data on most variables. The errors in the age and gender variables are mainly due to the sample bias of the mobile phone location data. Finally, I re-aggregate these trajectories into the grid to get mobility data with social information.

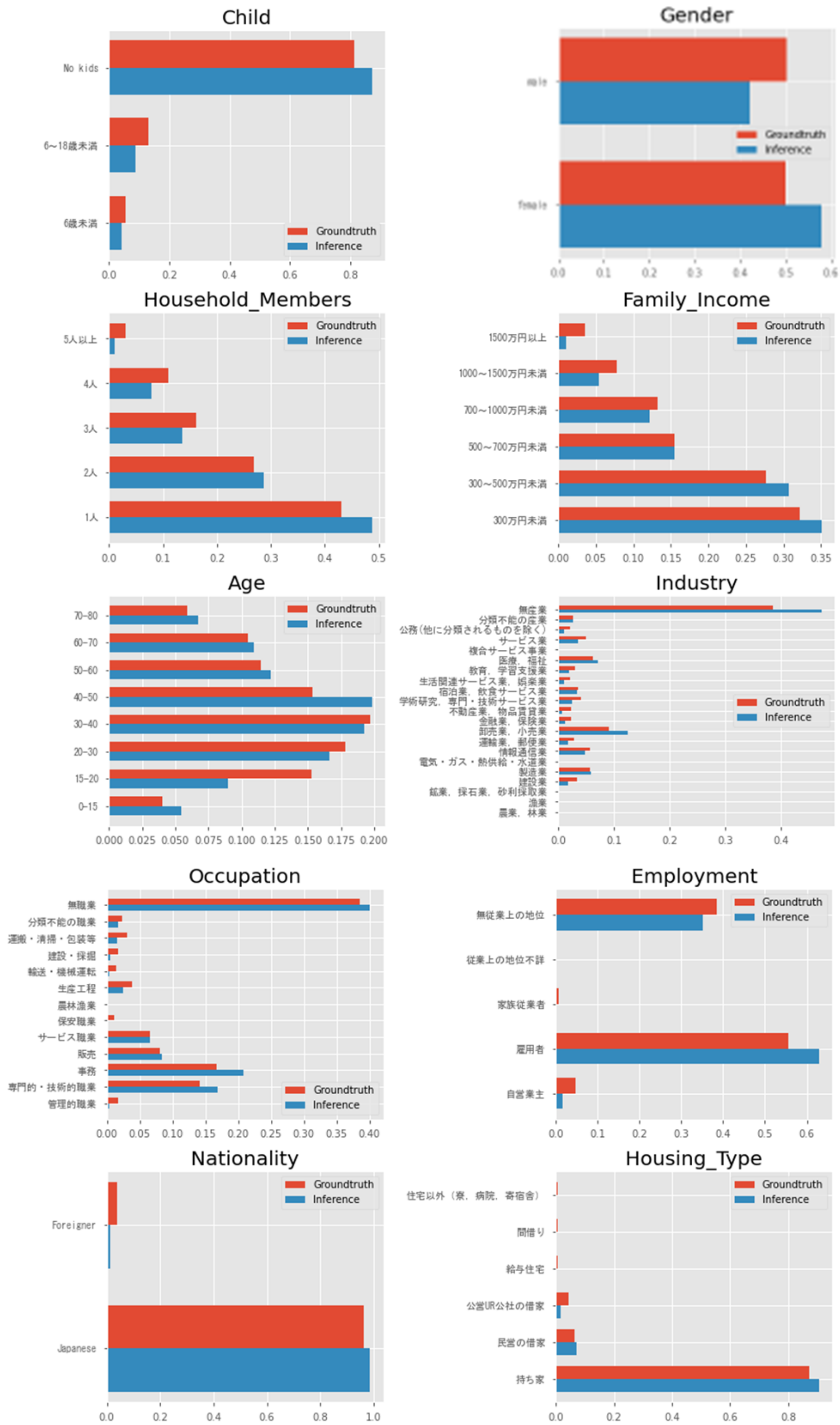


Figure 5. The ground-truth and inference statistics of each variable

3. Understanding Inequity in Transit-Oriented Development (TOD) Station Usage: A Case Study in Tokyo

3.1. Introduction

Population aging is the 21st century's dominant demographic phenomenon (Bloom & Luca, 2016). According to United Nations (2019), one in eleven people was an older person (aged 65 and above). In 2015, Japan ranked first in the world in the proportion of people aged 65 or over (28.4 %) (United Nations, 2019), and it is estimated that the proportion of the elderly will reach 38.4% in 2064 (National Institute of Population and Social Security Research, 2017). With the intensification of the aging population, the travel behavior of the elderly has attracted more attention. For older adults, mobility is important for independence and ensuring good health and life quality (Whelan et al., 2006; Wong et al., 2018). Impaired mobility may limit older adults from participating in social events, leading to depression and loneliness (Musselwhite et al., 2015). Therefore, it is important to ensure the mobility of the elderly to ensure their social participation, and it is also beneficial to their physical and mental health (Dickerson et al., 2007; He et al., 2018).

Older people in different countries have different travel mode preferences. There are three main modes of travel: private car travel, active travel (walking and cycling), and public transport travel. In most western countries,, cars are still the main mode of transportation (Whelan et al., 2006). In Denver, Colorado, USA, despite the presence of paratransit (Bezyak et al., 2017), only 2.9% of trips are completed by public transport and the proportion of trips using private cars has reached 88.6%. (Boschmann & Brady, 2013). In sharp contrast, transportation-oriented cities (such as Hong Kong, Tokyo, and Shanghai) have established dense and advanced public transportation networks, and have achieved high efficiency and reliability in public transportation services, as well as extensive spatial and temporal coverage (Wong et al., 2018). The travel mode of the elderly in these cities is dominated by public transportation. For example, over 92% of people use public transport in Hong Kong, making it the most common travel mode across all age groups (Szeto et al., 2017). However, how the transportation system should respond to an aging population is often overlooked by city planners. It can even be said that the elderly have never been included in the mainstream of thinking, planning and policies (Buffel & Phillipson, 2016).

Tokyo is one of the cities which most reliant on public transportation (Newman & Kenworthy, 1989). Although TOD was first proposed and implemented in the United States and European countries, Japan began to advocate the development of a combination of public transportation systems and land use (Ke et al., 2021). After years of development, Tokyo has been regarded as a leading city for TOD practice (Thomas & Bertolini, 2020). In a super-aging society such as Tokyo, whether the elderly as an EJ population can obtain equal transportation and livable opportunities as other population is an issue that cannot be ignored. In addition, some recent studies have found that the intersection between inequities of social characteristics (such as gender, race and socioeconomic status) may exacerbate the inequities experienced by individuals (Holman & Walker, 2021).

In this chapter, I proposed a research framework that correlates TOD performance evaluation and user attributes for evaluating TOD inequity in traffic-oriented, high-density metropolises. This chapter attempts to address two questions: 1) Is the transportation and land use development of TOD stations unequal to the elderly? 2) Does the aging user group experience other unequal intersections in the use of TOD stations?

3.2. Framework and Case Study

3.2.1. Framework

Shown as *Figure 6*. This chapter first selected and collected the TOD indicators within the defined station catchment area. Then I proposed an inequity analysis of the node and place value of TOD and explored the correlation between the social characteristics of users and other indicators. Finally, in the "node-place-user" three-dimensional model, this chapter uses the Kmeans clustering method to classify TOD and compares the indicator scores of all categories to validate the inequity in TOD usage among population groups.

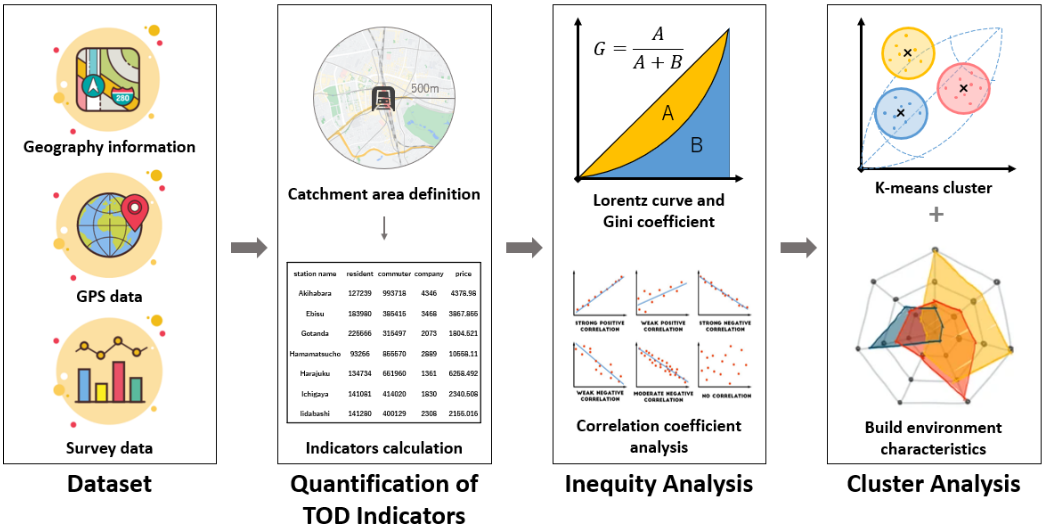


Figure 6. The framework of this chapter

3.2.2. Case Study

Tokyo is the first city in Asia to open a subway. It opened the subway line from Ginza to Sensoji in 1927. So far by 2019, the Tokyo Metro system has 13 lines, more than 220 stations, and a total length of 312.6 kilometers. The Tokyo Metro has an average daily passenger flow of 11 million passengers, making it the largest subway system in the world. As one of the busiest and most important lines in Tokyo, the JR Yamanote Line operates in a loop line, connecting the city center (Tokyo Station) with major transportation hubs and business districts. Since the government does not allow private railway operators to expand lines within the JR Yamanote Line, private rail operators must build terminals along the JR Yamanote Line, where millions of commuters have to transfer. As a result, the JR Yamanote Line has become an important transportation corridor and, together with the JR Chuo-Sobu Line running through central Tokyo, constitutes Tokyo's two major metropolitan commuter railways. This chapter will examine 36 subway stations and their surrounding area on the JR Yamanote Line and part of the JR Chuo line (*Figure 7*).

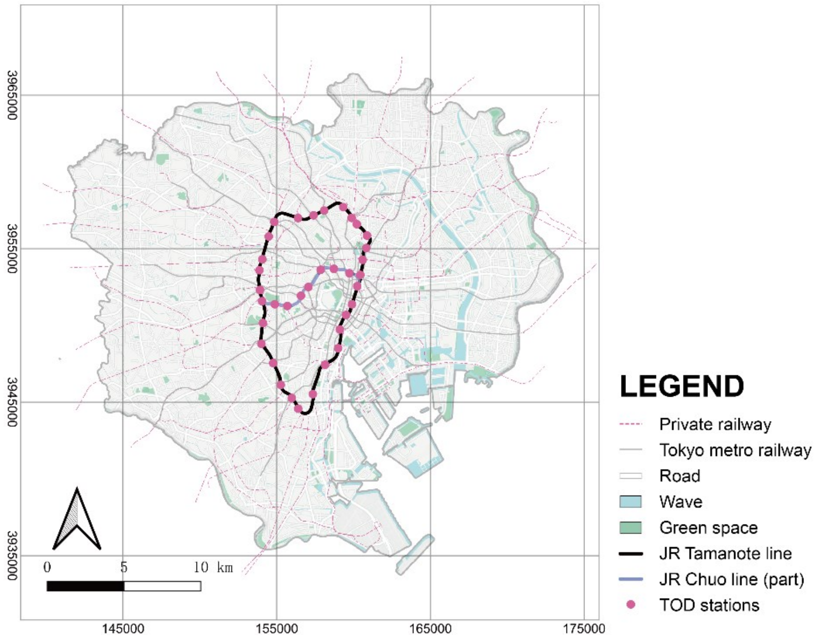


Figure 7. The study area

3.3. Methodology

3.3.1. Identification of TOD indicators

Before selecting and collecting TOD indicators, I need to define the station catchment area. Previous research has extensively discussed the radius of the station catchment area and has shown that a walkable range of 400 to 600 meters is suitable (Lyu et al., 2016; Vale, 2015). Whereas the study by Z. Yu et al. (2022) showed that a catchment at a distance of 400 m produced relatively limited coverage, while a catchment at a distance of 600 m showed too much overlap. In addition, Guo et al. (2018) found that the radius of a single catchment area is close to 1500 m if more than 90% of the passengers are to be covered. Therefore, this chapter uses 500 m as the radius of the station catchment area and expands the collection radius of passenger-related indicators (resident population, commuter population, users' age) to 1500 m to cover more comprehensive information.

In the selection of indicators, this chapter mainly refers to the research of Z. Li et al. (2019) and Rodríguez & Kang (2020). Based on the node-place model, I introduced "user" as the third dimension and designed the indicators system (Table 2).

1) Node indicators

Most of the previous studies are divided into two categories: railway service capacity and node accessibility. The selection of node indicators should reflect not only the operational capacity of the station but also the connectivity of multimodal transport. In this chapter, passenger traffic and transfer lines are selected to represent the operational capacity of the station. The number of bicycle parking lots, the number of bus stops, the number of intersections, etc. represent the connectivity of multimodal transport.

2) Place indicators

Place indicators often reflect the density and diversity of land use in the area surrounding a transit node. I, therefore, choose demographic data (number of residents, commuters) and various POI data to represent density and to represent diversity by calculating land use entropy within the catchment area. In addition, to examine the cost of living in the TOD catchment, I also included the average land price and rent.

$$\text{Land use diversity} = 1 - \sum_{i=1}^{n} (a_i/A)^2$$

where a_i represents the area of a certain type of land in the station catchment area, and A is the total area of all types of land in the buffer zone. In this chapter, referring to the Japanese urban land classification, 12 types of land use were considered.

3) User indicators

I use the average age of users to represent the age structure of the station user group. In the mobile phone positioning data, I selected the grid within 1500 m of the center point from the station as the coverage area. And the average age of all users who have passed the coverage within a week is calculated with the number of staying hours as the weight.

Table 2. The indicators of TOD

Dimension	Component	Indicator	Scope	Source
Node	Metro station operational capability	N_1 - passenger load	station	Homepage of JR station
		N_2 - number of transfer lines	station	Homepage of JR station
	Connectivity with multimodal transportation	N_3 - Length of footway and cycleway	500m	OSM
		N_4 - Walkability index	--	Real Estate Homepage
		N_5 - Intersection density	500m	OSM
		N_6 - Number of bus stops	500m	OSM
		N_7 - Number of bicycle parking lots	500m	OSM
Place	Employment density	P_1 - Number of commuters	1500m	e-Stat
	Residential density	P_2 - Number of residents	1500m	e-Stat
	POI density	P_3 - Number of hospitals	500m	MLIT
		P_4 - Number of welfare facilities	500m	MLIT
		P_5 - Number of parks	500m	MLIT
		P_6 - Number of entertainment facilities	500m	OSM
		P_7 - Number of restaurants	500m	OSM
		P_8 - Number of shopping malls	500m	OSM
	Price	P_9 - Average land price	1500m	MLIT
		P_{10} - Average housing price	--	Real Estate Homepage
	Diversity	P_{11} - Land use diversity	1500m	MLIT
User	average age	U_1 - Average age of TOD users	1500m	NTT DOCOMO

After calculating all the indicators, the indicators need to be aggregated into node and place values. Because the numerical difference between different indicators may be very large, I normalized all indicators from 0 to 1 before aggregation. Finally, calculate the average value of each indicator in each dimension as the node and place value.

$$X\ value = (X - Min(X))/(Max(X) - Min(X))$$

Where $X\ value$ refers to the standardized value of indicator X, $Max(X)$ is the maximum value of indicator X, and $Min(X)$ is the minimum value of indicator X.

3.3.2. Inequity analysis: Gini coefficient and correlation coefficient analysis

First, to check whether node and place values are unfair among users, we used the Lorentz curve and Gini coefficient. In the field of economics, the Lorenz curve is usually used to reflect the equity of economic resource allocation or property distribution, and it is now often used in equity research in many fields. In this chapter, the node value or place value percentages owned by different users are sorted in an ascending sort, and the percentages of the population corresponding to them are accumulated separately. In a two-dimensional coordinate system, the horizontal axis represents the cumulative proportion of the population, and the vertical axis represents the cumulative proportion of node value or place value. By connecting the points, I can obtain the Lorentz curve. Among them, the 45° diagonal is the absolute equity line. The closer the Lorentz curve is to the absolute equity line, the fairer the resource allocation of TOD.

The Gini coefficient is calculated using the following formula based on the Lorentz curve and is equal to the ratio of the area A enclosed by the absolute fair line and the Lorentz curve to the area of the right triangle under the absolute fair line $(A + B)$ (Figure 2). The value range of the Gini coefficient is between 0 and 1. The closer to 1, the more concentrated the resources and the more unfair the distribution. Internationally, 0.4 is usually used as a warning line for distribution differences, and more than this value may cause social unrest.

$$Gini\ coefficient = \frac{A}{A + B}$$

Then, to examine whether inequity is related to user's age, I examined the correlation between user average age and other metrics. Here I use Pearson's correlation coefficient to express the relationship between variables. The value range of Pearson's correlation coefficient is between -1 and 1. If the correlation coefficient is positive, there is a positive correlation between the variables, and if the correlation coefficient is negative, there is a negative correlation. The larger the absolute value, the stronger the correlation.

$$\mathrm{r}(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var[X]Var[Y]}}$$

where $Cov(X, Y)$ is the covariance of X and Y, $Var[X]$ is the variance of X, and $Var[Y]$ is the variance of Y

3.3.3. Validation of inequity: Cluster analysis

To further explore the relationship between the built environment difference of TOD and the average age of users, I implemented Kmeans clustering on 36 stations with node, place, and user as three dimensions. Kmeans is one of the simplest algorithms for solving clustering problems, it can be used to classify point cloud data and quickly obtain compact and independent clusters (Y. Li & Wu, 2012). Before clustering, I first determined the optimal number of clusters using the elbow method. The core of the elbow method is SSE (Sum of Squared Errors). As the number of clusters k increases, the sample division will be more refined, and the degree of aggregation of each cluster will gradually increase, so the error squared sum SSE will gradually become smaller. When k is less than the true number of clusters, the SSE will decrease greatly since the increase of k will greatly increase the degree of aggregation of each cluster. When k reaches the number of true clusters, the return obtained from the aggregation level will decrease rapidly as k increases. So, the decline of SSE will decrease sharply, and then it will flatten out as the value of k continues to increase. That is to say, the relationship between SSE and k is in the shape of an elbow, and the k value corresponds to this elbow is the true number of clusters of the data. After getting the clustering results, I counted the averages of the different indicators in each category and visualized them on a radar chart.

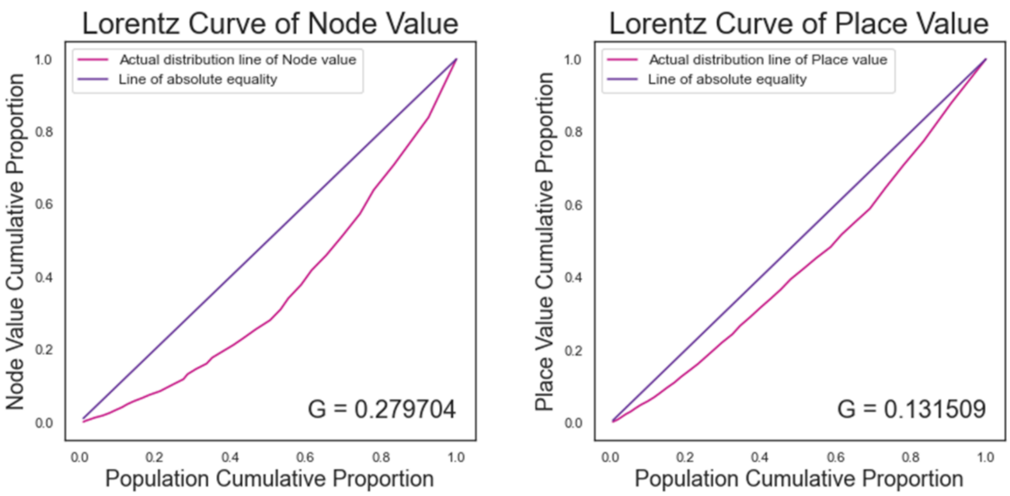
3.3.4. Intersection of Inequity

To explore whether older users experience inequity in addition to age inequity in the use of TOD stations, I examined the correlation between gender ratio and average family income among older users and TOD indicators. I first filtered out all elderly users (over 60 years old), and calculated the proportion of males and average household income of elderly users at each TOD station, weighted by the number of hours of stay. Then, the correlation coefficient analysis method in 3.3.2 and cluster method in 3.3.3 were used to examine the correlation between these two user social characteristics and TOD built environment indicators.

3.4. Result and Discussion

3.4.1. Equity analysis based on Lorentz curve and Gini coefficient

From the Lorentz curve in the two dimensions of node and place, we can know that the inequity of TOD resource allocation is universal, and the inequity of nodes is greater than that of places (*Figure 8 a), b)*). From the perspective of places, the Gini coefficient of place value is around 0.13, indicating that it is basically reasonable, and resource allocation still needs to be optimized. From the point of view of the node, the Gini coefficient of the node value is close to 0.28, and there is a large gap in resource allocation, which requires attention.



a) b)

Figure 8. a) Lorentz curve and Gini coefficient of Node value

b) Lorentz curve and Gini coefficient of Place value

3.4.2. Correlation coefficient analysis

Figure 9 shows the correlation analysis of the average age of users and other indicators. It can be seen that apart from the "number of parks" variable, there is a clear correlation between the average age of users and other indicators. Among them, the average age of users is positively correlated with "number of welfare facilities" and "number of residents", and negatively correlated with other variables. This suggests that TOD stations with a higher average age of users may have a lower level of development.

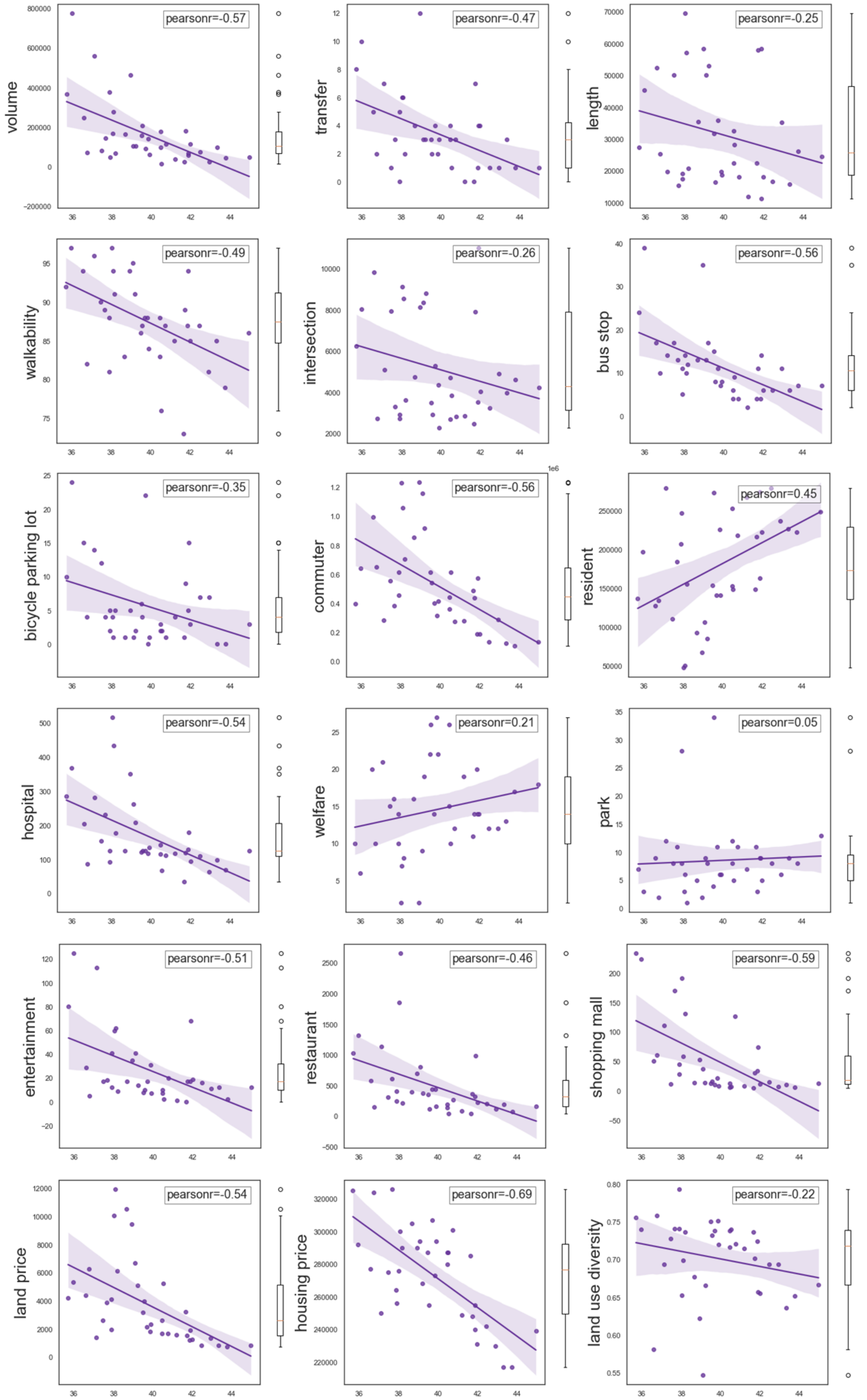


Figure 9. The correlation coefficient between the average age of users and other indicators

3.4.3. Clusters of TODs

Using the elbow method, I find that the distortion improvement is greatest when the number of clusters k = 3 (*Figure 10*). I, therefore, choose to cluster the stations into three categories.

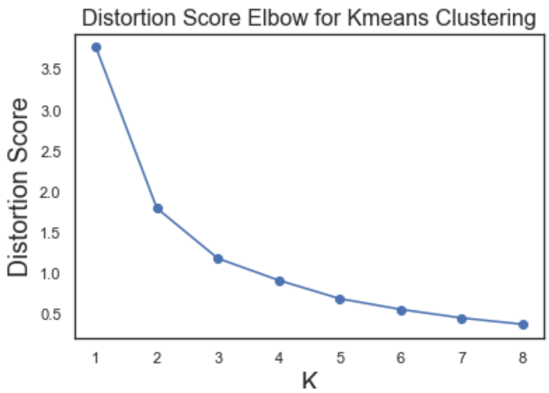


Figure 10. The elbow results

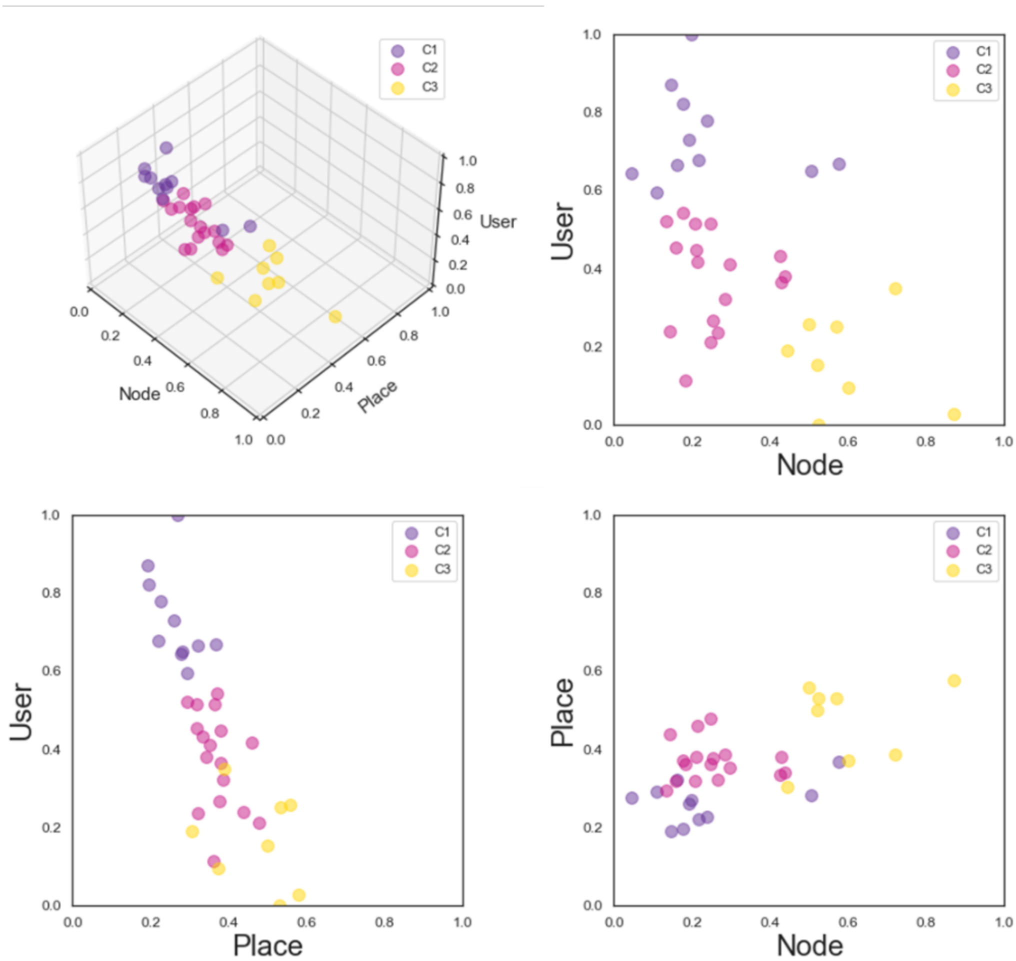


Figure 11. Scatter plot of all station areas and the three clusters in the extended node-place model, representing the indexes for the 'Node', 'Place', and 'User' dimensions from both a synthetic and three paired perspectives.

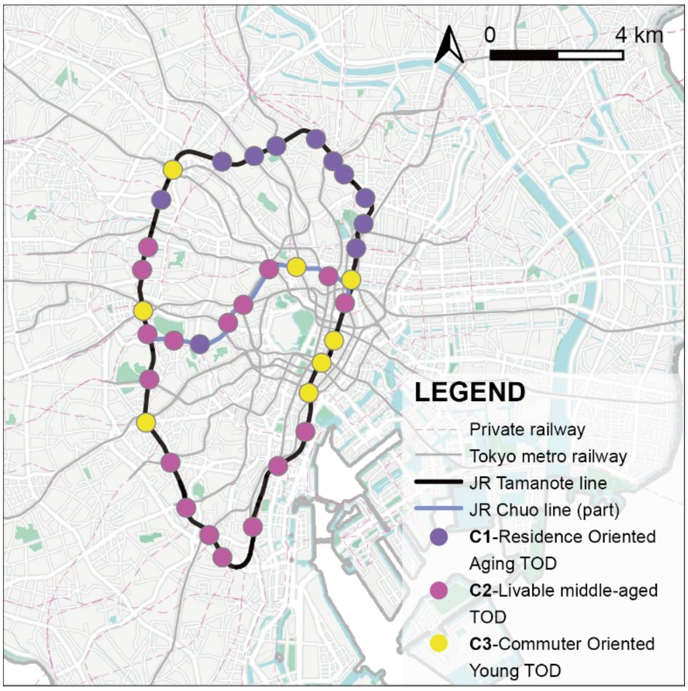


Figure 12. Geographic visualization of clustering results

Kmeans generates three clusters (Figure 11), Figure 12 shows the geographic distribution of the three types of TOD stations, and Table 3 shows the corresponding numerical distribution. To compare the differences between clusters more intuitively, I visualized all the indicators and summarized the characteristics of each cluster (Figure 13).

- **C1 (N=11) - Residence Oriented Aging TOD**: Stations in cluster 1 are mainly located in the northern part of the Yamanote Line, with the lowest score for both "Node" and "Place", and the highest score for "User". TOD users in this cluster were older on average (U_1), or had a higher proportion of older people among them. The level of operation (N_1) and the connectivity with multimodal transport (N_2) of such stations are relatively poor. In terms of land use, the number of residents (P_2) scored the highest among the three clusters, indicating that these station catchment areas are dominated by residential functions. Correspondingly, this also leads to a lower score in land use diversity (P_{11}). Therefore, these stations are identified as "residential oriented aging TOD"

- **C2 (N=17) - Livable middle-aged TOD**: Compared with cluster 1, cluster 2 has no significant difference in the "Node" dimension, but gets a higher score in the "Place" dimension and a lower score in the "User" dimension. The average age of users (U_1) of such stations is moderate.

The scores for the number of residents (P_2) and the number of commuters (P_1) are close to each other, indicating a better job-housing balance. The mix of land functions also gave this cluster the highest score for land use diversity (P_{11}). In addition, cluster 2 is also the most advantageous in terms of the number of welfare facilities (P_4) and parks (P_5). Based on these characteristics, I identify this cluster as “livable middle-aged TOD”. However, having the highest housing prices (P_{10}) in the three clusters may make it less "livable" for disadvantaged groups.

- **C3 (N=8) – Commuter Oriented Young TOD**: The stations in cluster 3 are basically located in several commercial centers of Tokyo, such as Akihabara, Shinjuku, Shibuya, Ikebukuro, etc. They get the lowest average user age score (U_1) indicating the youngest user group. Among the various indicators of the node dimension (N_1~N_7), cluster 3 has an overwhelming advantage. In the indicators of the location dimension, the number of various commercial POIs (P_6~P_8) is the largest among the three clusters. Likewise, the number of commuters (P_1) also scored the highest among the three clusters, so such stations were identified as "commuter-oriented young TOD". However, as in cluster 1, the monotonic functions make the land use around the station less diverse (P_{11}). On the other hand, higher land prices (P_9) and housing prices (P_{10}) have also caused a certain exclusion of disadvantaged groups.

Table 3. Cluster description and summary means on rescaled TOD indicators

Indicators	**C1(N=11)**	**C2(N=17)**	**C3(N=8)**	**All**
N_1	0.072505	0.145328	**0.462301**	0.193515
N_2	0.174242	0.230392	**0.572917**	0.289352
N_3	0.272046	0.271279	**0.621405**	0.349319
N_4	0.484848	0.553922	**0.885417**	0.606481
N_5	0.287431	0.207021	**0.63992**	0.327791
N_6	0.137592	0.209857	**0.52027**	0.256757
N_7	0.204545	0.159314	**0.442708**	0.236111
P_1	0.14182	0.41102	**0.613051**	0.37366
P_2	**0.77864**	0.536807	0.342918	0.567614
P_3	0.142399	0.2165	**0.600363**	0.279161
P_4	0.516364	**0.569412**	0.335	0.501111
P_5	0.212121	**0.270945**	0.159091	0.228114
P_6	0.127273	0.126588	**0.521**	0.214444
P_7	0.080001	0.10434	**0.441775**	0.171889
P_8	0.063914	0.164141	**0.489083**	0.205725
P_9	0.056539	0.297092	**0.483601**	0.265036

P_{10}	0.221852	**0.652455**	0.629587	0.5158
P_{11}	0.55955	**0.709034**	0.556469	0.629455
U_1	**0.736655**	0.37565	0.16572	0.439306
Node	0.233316	0.253873	**0.592134**	0.322761
Place	0.263679	0.368939	**0.470176**	0.359274
User	**0.736655**	0.37565	0.16572	0.439306

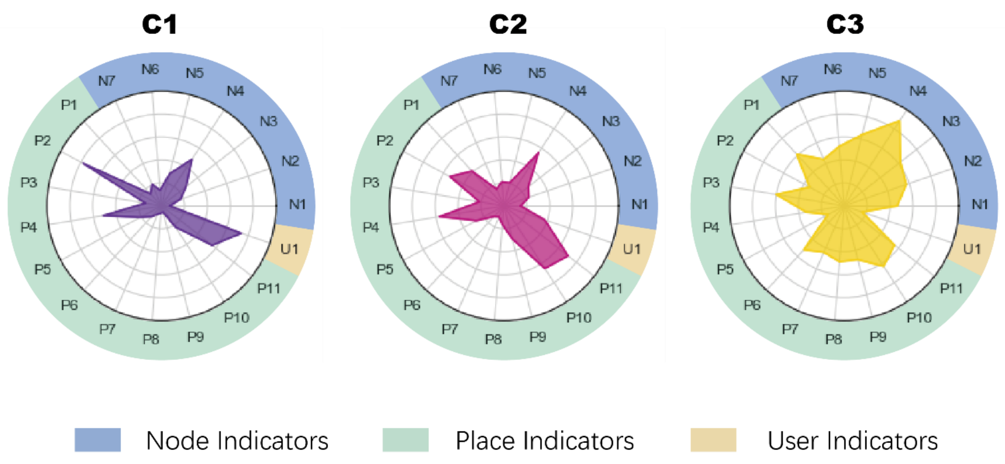


Figure 13. Indicator visualization results for each cluster

3.4.4. Intersection of Inequity

Figure 14 illustrates that most TOD built environment indicators are positively correlated with the proportion of males among older users, especially the “Node” related indicators. This shows that in the usage of TOD stations, the intersection of age inequity and gender inequity does exist, and older female suffer more inequity. Figure 15 shows the cluster results of 36 TOD stations in the "Node-Place-User" model. Kmeans generates three clusters, and the summary of indicators for each cluster and its visualization are given in Figure 16, respectively. Based on the results, we summarize the characteristics of each cluster. Station in C1 has the lowest proportion of males among older users. Lower scores for both node- and location-related indicators imply worse levels of transportation and land-use development. Stations in C2 are mainly dominated male elderly user and have better accessibility than C1. It is worth noting that the land prices and housing prices around such stations are the highest among the three clusters. This means that there may also be economic inequities between different genders of older users. The gender ratio of C3's elderly users is relatively balanced, and it has an absolute advantage in the level of transportation development and land use.

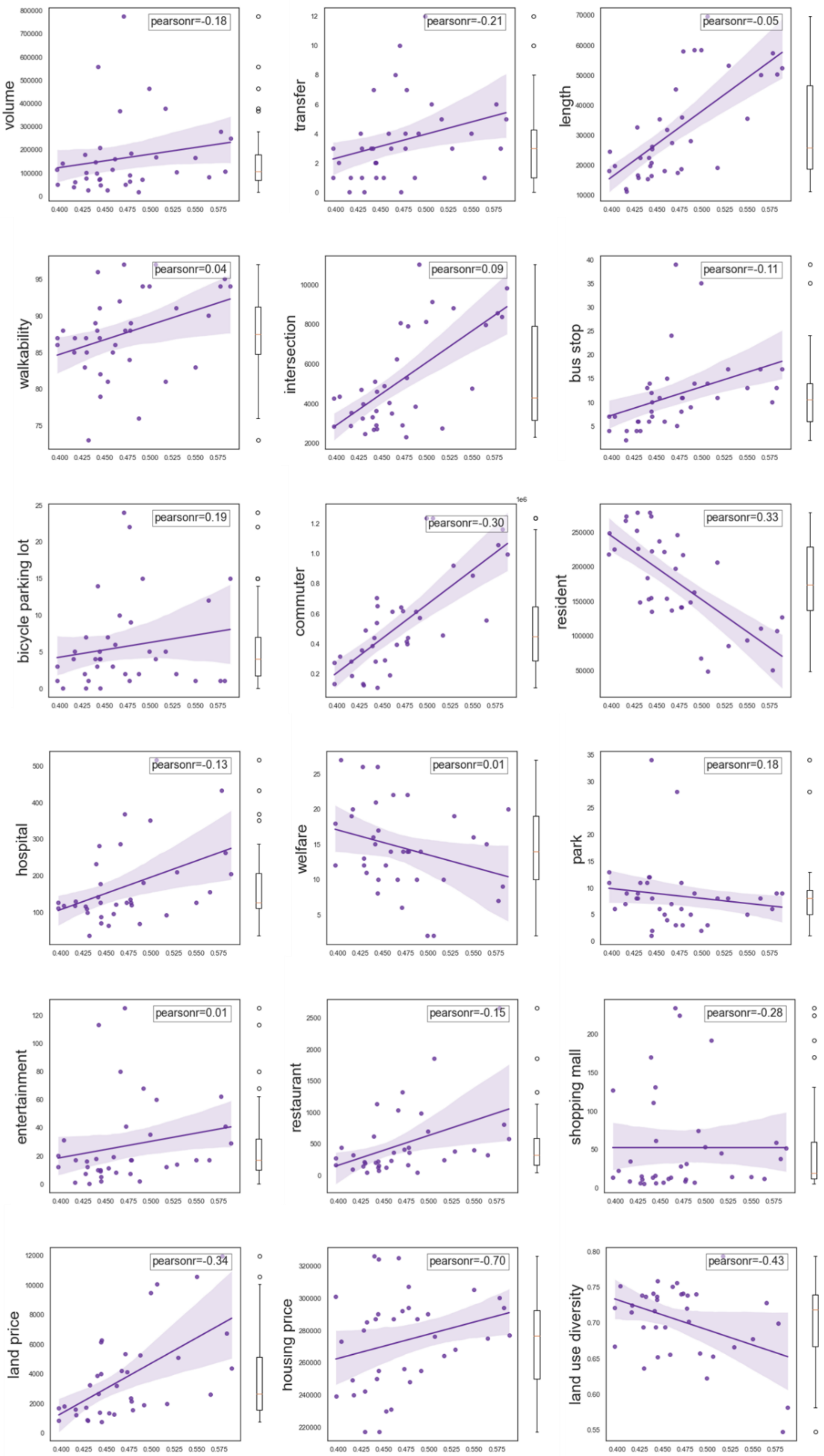


Figure 14. The correlation coefficient between the male proportion of older users and other indicators

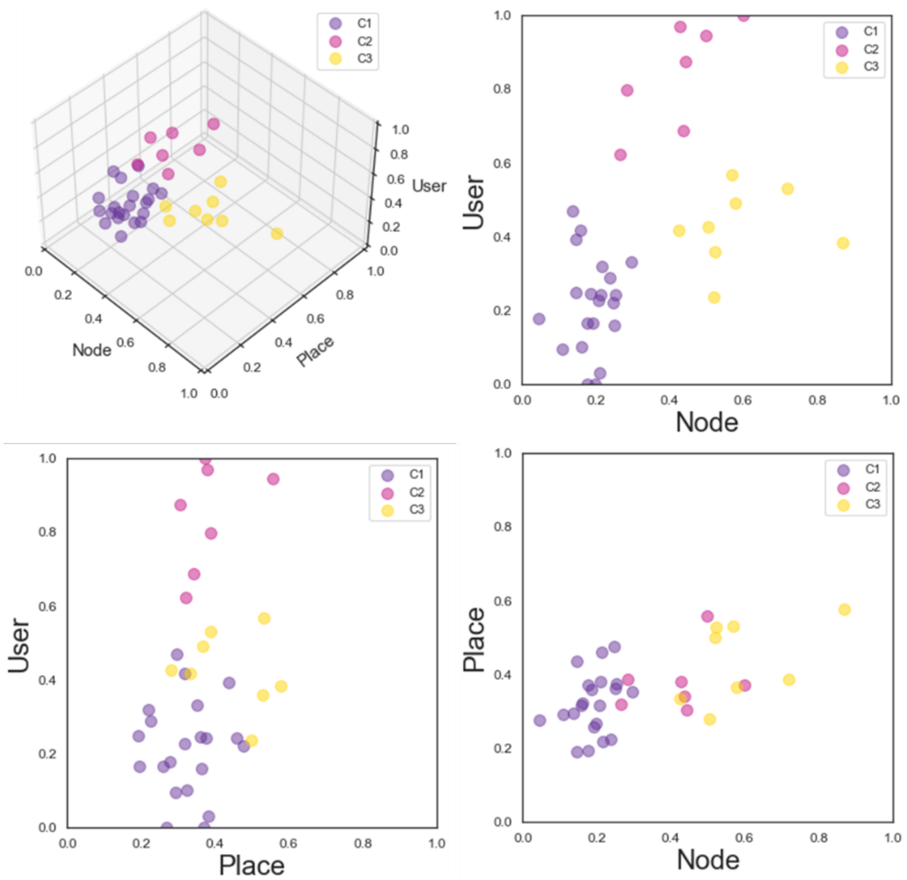


Figure 15. Scatter plot of all station areas and the three clusters in the extended node-place model, representing the indexes for the 'Node', 'Place', and 'User' dimensions from both a synthetic and three paired perspectives.

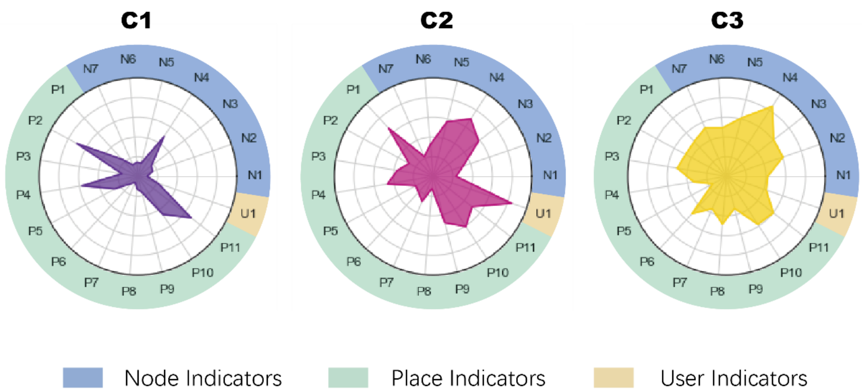


Figure 16. Indicator visualization results for each cluster

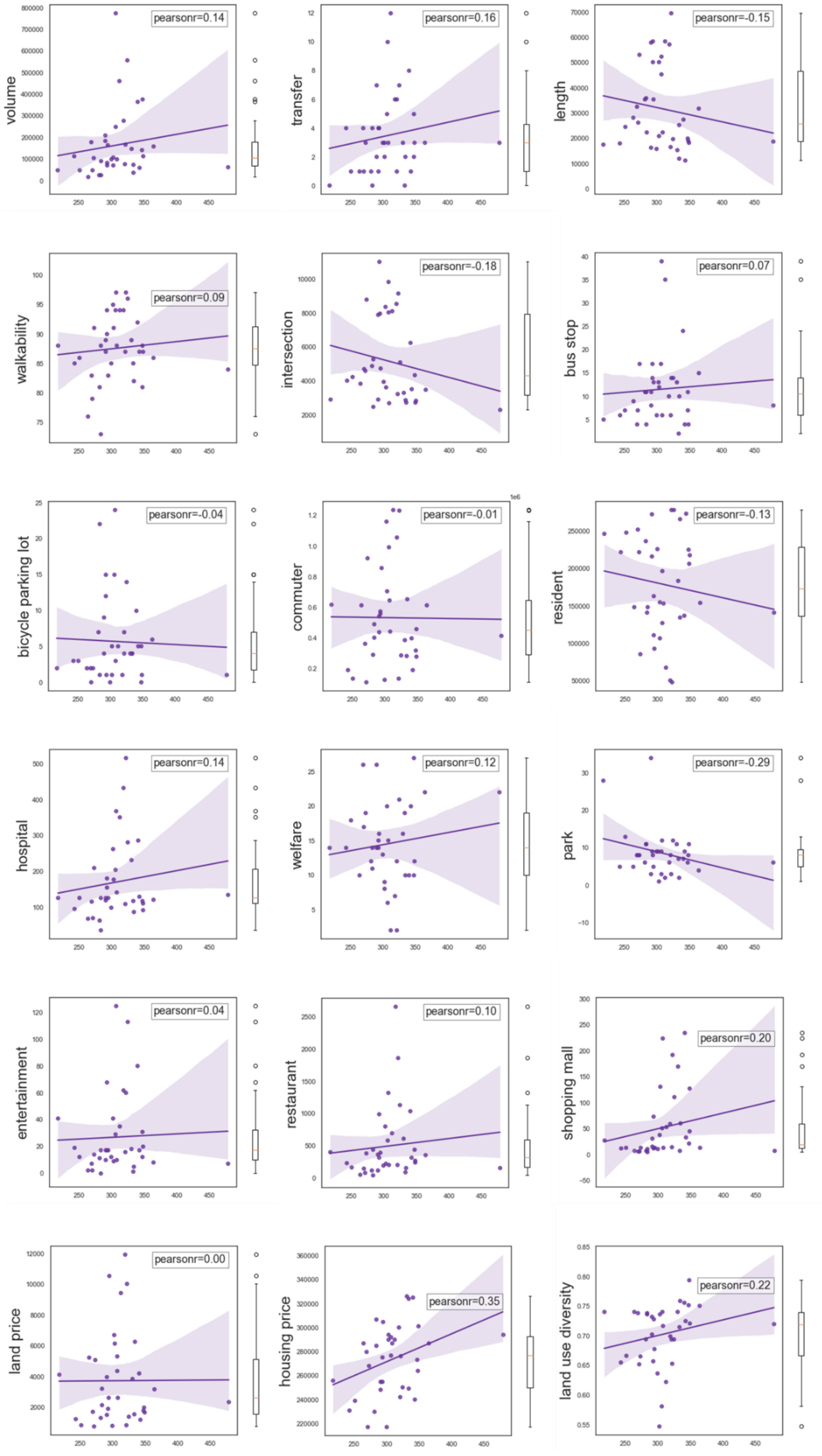


Figure 17. The correlation coefficient between the average family income of older users and other

indicators

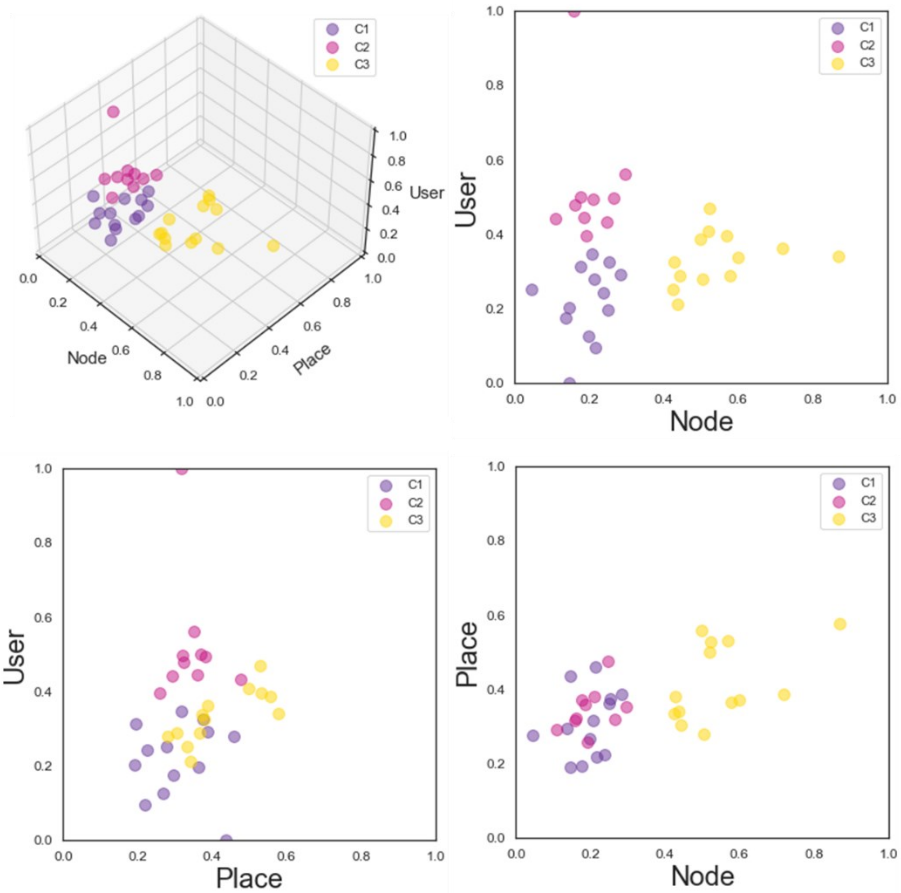


Figure 18. Scatter plot of all station areas and the three clusters in the extended node-place model, representing the indexes for the 'Node', 'Place', and 'User' dimensions from both a synthetic and three paired perspectives.

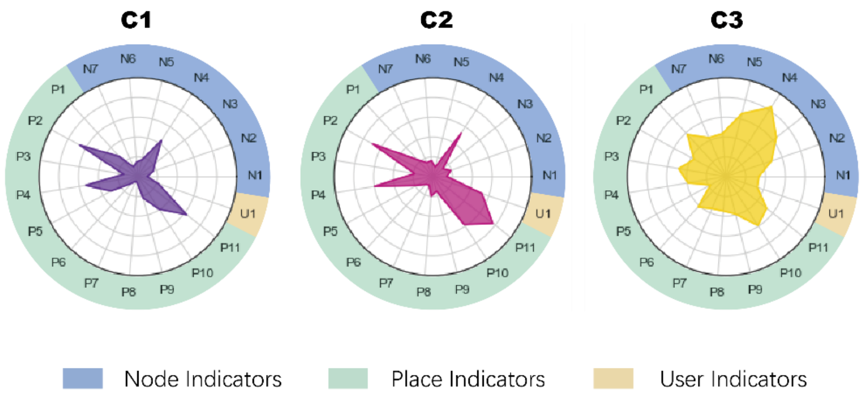


Figure 19. Indicator visualization results for each cluster

Figure 17 shows the correlation between the average household income of older users and the TOD built environment indicators. The Pearson coefficient does not show a significant correlation. Kmeans also divides the stations into three clusters (Figure 18, 19): the stations in the C1 cluster have the lowest average household income of elderly users and the worst built environment. Compared with C1, the TOD built environment is not much different in C2, but the average household income of elderly users is the highest among the three clusters. One possible explanation is that higher household income means more family members or more transportation options, so these elder people do not need to rely on TOD for transportation and daily life. TOD stations in the C3 cluster have the highest level of development, and the average household income of elderly users is about the level of the middle class. This result shows that the gentrification of TOD also intersects with aging. This would also explain why there is no apparent linear correlation shown in Figure 13 - since this relationship is likely to be non-linear.

3.4.5. Discussion

The results of the empirical part of the research show that the TODs within the Tokyo Yamanote Line are indeed unfair in the allocation of resources among users in different age groups. It is embodied in three aspects: 1) Stations with higher aging rates are too poorly connected to multimodal transport, limiting travel for the elderly (such as C1 and C2). 2) TOD stations with a high user aging rate or a better built environment are less diverse in land use, making them difficult to meet the diverse needs of the elderly (such as C1 and C3). 3) The cost of living around TOD stations, which are more livable or have easy access to various resources, is too high, which has a certain repulsive effect on the elderly (such as C2 and C3).

To improve the status quo of age inequality, we should consider increasing the age tolerance of TODs. The functions and design that are beneficial to the elderly will make TOD more effective as a service area for people of all ages. In the current TOD planning and design, many of them are designed based on the "majority" standard, which lacks pertinence when facing vulnerable groups such as the elderly. Therefore, corresponding to the three aspects of the status quo inequality, I put forward three suggestions for “age-friendly TOD”:

1) Better connectivity between transit nodes and multimodal transportation

The unfriendliness of C1 and C2 to the elderly in the node dimension is mainly reflected in the weak connectivity of railways and other modes of transportation. Since rail transit itself cannot directly provide "point-to-point" services, it is very important to effectively improve the accessibility of railway stations. According to the 6th Tokyo Metropolitan Area Person Trip Survey (Tokyo Metropolitan Area Transportation Planning Association, 2021), the proportion of elderly people over 65 years old in Tokyo who choose active travel (walking and cycling) reached 53.9%. Active travel is considered to help increase physical activity levels and improve the quality of life for older adults (Banister & Bowling, 2004; Vale, 2015). Several studies have shown that older people tend to make active travel in activity-friendly environments to ensure access to services and facilities safely and conveniently (Borst et al., 2009; Ewing et al., 2014). Therefore, it is necessary to build complete walking and bicycle facilities, as well as regular bus connection services, so that people can easily reach rail transit stations from different places. This will allow people to reach nearby destinations on foot or by public transportation and obtain diversified products and services, as well as make more effective use of the transportation system. In this regard, Copenhagen’s TOD mode is worth learning. As one of the cities with the highest income per capita in Europe, Copenhagen has very low per capita car ownership. People rely more on public transportation, walking, and bicycles to complete their trips. To ensure the implementation of TOD, Copenhagen improves the service level and competitiveness of public transportation through the integration of different transportation modes. On the one hand, restricting the travel of cars, including controlling the capacity of urban motor vehicle facilities (reducing parking spaces), increasing the internal cost of car transportation (increasing parking fees, taxes), and so on. On the other hand, people are encouraged to use bicycles. Specific measures include setting dedicated bicycle lanes, increasing bicycle parking areas (*Figure 20 d*), and even allowing bicycles to be taken on the subway (*Figure 20 c*). Tokyo is also a large-scale city dominated by a large-capacity public transportation system. It can learn from the development experience of the central city of Copenhagen, improve the local walking environment, set up complete bicycle facilities, and redistribute the right of way to establish a people-oriented, instead of a car-oriented environment.

2) More diverse land use.

The common problem of C1 and C3 is that the land use is mainly residential or commercial, and there is a lack of diversity. Studies have found that physically and socially active people lead healthier lives (Glass et al., 2016; Spinney et al., 2009). Other studies have found that in denser, diverse urban environments, the probability of active travel use by older people tends to be higher (Cheng et al., 2019; Hatamzadeh & Hosseinzadeh, 2020; Y. Zhang et al., 2016). One possible explanation is that areas of high density and mixed land use mean better spatial proximity to various amenities, making walking and cycling a viable alternative for the elderly (Moniruzzaman & Páez, 2016). Therefore, providing a series of neighborhood, health, and entertainment services within walking, biking, and bus routes can strengthen community connections. The richer land use combination allows more outdoor time and stronger community vitality, enhancing the sustainability of TOD. In response to the problem of aging, Singapore built an elderly care complex that integrates retirement apartments, medical and health care, nursery care, childcare, entertainment for the elderly, commerce, hawker centers, and squares next to the subway station following TOD development ideas (*Figure 20 b*). This complex gathers a large number of public facilities in one building and is designed as a diversified vertical village composed of three "layers". The community park on the upper layer provides accommodation for the elderly, as well as a place to socialize, creating a warm and inclusive community. The middle layer medical center is set up to facilitate the residents to seek medical treatment nearby. The community square on the ground layer is a completely public environment that connects people of all ages and eliminates the loneliness of the elderly. This design concept shortens the distance between medical and health, social activities, commerce and other convenience facilities, strengthens the connection between multiple generations, and promotes active aging. For Tokyo, Singapore is a case worthy of reference.

Figure 20.

a) Optimization suggestions for "aging-inclusive" TODs

b) Kampong Admiralty in Singapore

*(*Source*: from https://woha.net/zh/#Kampung-Admiralty)*

c) Bicycles can be taken on the subway

*(*Source*: from http://www.visitdenmark.com/denmark/how-get-denmark)*

d) Bicycle parking facilities

(Source*: from https://www.sohu.com/a/113351816_467374)*

*e) Affordable housing next to the station (*Source*: from BRIDGE Housing)*

3) Affordable housing cost

Although C2 and C3 have more opportunities to obtain services and resources, high land and housing prices are prohibitive. Lower housing cost is important to consider while implementing TOD plans. Regarding the negative correlation between the average age of users and the value of TOD, one possible explanation is that high-value TOD is rejecting the elderly population. The original concept of TOD emphasizes the realization of affordability by reducing housing and travel costs and improving the accessibility of vulnerable groups such as the elderly and children. However, the existing research results have proved that TOD brings a phenomenon that runs counter to affordability: the increasing housing prices around public transportation stations have caused renters or people who mainly rely on public transportation for travel to face a dilemma of having to choose between housing and travel. Therefore, an effective policy is through government subsidies, and developers to provide affordable housing around TOD (*Figure 20 e*). For example, Los Angeles, through its "Joint Development Program" (Metro Joint Development Program), aims to create affordable housing that accounts for 35% of the total housing, and allows developers to discount land prices as high as 30% of the ordinary market price (proportional to the number of affordable housing). In the long term, such policies can help improve the economic sustainability of TOD.

3.5. Conclusion and Limitation

3.5.1. Conclusion

As an efficient and sustainable development method, TOD can effectively improve the quality of life and reduce the travel costs of users. Among them, singles, entrepreneurs, couples without children, the elderly, and low-income families are the most likely to seek TOD. As the aging problem becomes more and more serious, the proportion of the elderly in society will continue to increase in the future. When the elderly cannot drive or travel long distances to obtain diverse products and services, they will become dependent on TOD. Therefore, how to better meet the travel and life demands of the elderly through TOD planning and construction, and provide more complete public services for the elderly, has attracted more and more attention. This research attempts to establish a social equity performance evaluation and analysis method for urban TOD. Correlation coefficient analysis, Gini coefficient, and cluster analysis are used to measure the equity of TOD development level among people of different ages, and to propose corresponding strategies for TOD future development. The result shows:

1) The inequity of resource allocation in TOD is universal among all users, and the inequity of node value is greater than that of place value. 2) Inequity in TOD resource allocation may be age-related. 3) TOD stations were divided into three clusters: residence-oriented aging TOD, livable middle-age TOD, and commuter-oriented young TOD. 4) Age inequity in TOD usage is intersected with gender inequity and socioeconomic inequity. In response to the age inequities revealed by the TOD typology, I also make several recommendations for the development of "age-friendly TOD". Our work can help the transportation and urban planning planners grasp the current status of TOD development, understand the travel conditions of the elderly, and clarify the future direction of

infrastructure development, thus better meeting the challenges brought by aging.

3.5.2. Limitation

Although I achieved the above meaningful results, there were also some limitations:

1) The cell phone location data I use comes from phone carriers, which means that the user sample may be biased. The proportion of children and the elderly may be underestimated. Also, I selected only seven days of data, which is insufficient to reflect seasonal changes in population dynamics. I did not discuss weekends and weekdays separately, possibly ignoring the cyclical changes in TOD usage.

2) Due to data limitations, this chapter only considers TOD stations on the JR Yamanote line and part of the JR Chuo line. Since the study area is in the center of Tokyo, the differences between stations may be relatively small, and some slight errors may change the results of the study.

Due to the above limitations, follow-up studies can include: 1) Exploring the spatiotemporal changes in inequity using trajectory data over a larger time span. 2) Combine with census data, etc. to correct the sample bias of trajectory data. 3) More diverse research objects could be included, such as subway lines passing through suburbs and the city center.

4. Understanding Inequity in Artificial Light at Night (ALAN) Exposure: A Case Study in Tokyo

4.1. Introduction

Night light pollution caused by artificial light sources changing the level of the natural night light is one of the most obvious pollutants in cities (Cinzano et al., 2001). At present, many studies have revealed that night light pollution is related to a variety of human diseases (Pauley, 2004; Raap et al., 2015; Smolensky et al., 2015).

Japan has been cautious in preventing the overuse of ALAN. To create a good light environment and prevent global warming, Japan has formulated the guideline of light pollution countermeasure since 1998 and completed the revised version in 2006 (The Ministry of the Environment, 2021). With the popularity of LED lighting, Japan's Ministry of the Environment revised this guideline again in 2021 to adapt to the characteristics of the new lighting form(The Ministry of the Environment, 2021). In preparation for the 2020 Tokyo Olympics, the Office of the Governor for Policy Planning of Tokyo formulated a basic policy of lighting up public facilities in 2018 to control outdoor ALAN(Office of the Governor for Policy Planning, 2018). To improve awareness and practice, it is necessary to understand whether there are social exposure inequities in ALAN. However, in a busy city like Tokyo with an average daily subway passenger flow of 7.55 million (March 2020) (Tokyo Metro Co, 2020), personal mobility cannot be ignored. Whether travel behavior has an impact on the estimation of ALAN exposure and its inequity as it does on other environmental pollution remains to be studied.

In this chapter, based on the quantification results of ALAN in Tokyo, Japan using remote sensing images, combined with mobile phone positioning big data, I analyzed the ALAN exposure and its inequity in different demographic groups. I have explored three questions: 1) How does ALAN exposure differ between individuals and between different population groups in Tokyo? 2) How does travel behavior affect ALAN exposure and inequity? 3) Are there geographic differences in the impact mechanism of travel behavior on ALAN exposure and inequity estimates?

4.2. Framework and Case Study

4.2.1. Framework

Figure 21 shows the framework of this chapter. I extracted the average pixel brightness value of the VIIRS imagery in each grid boundary of the mobile phone positioning big data as night-time light (NTL) intensity. Then I divided the mobile phone location data into two time periods (dynamic and static) for analysis. I first measured individual ALAN exposure inequity in Tokyo at dynamic and static periods separately using the Gini coefficient. Then I calculated and compared the difference between the two periods in average ALAN exposure for demographic groups of different ages, genders, and places of residence. Finally, I aggregated the grid data to the district level to examine whether there are geographic differences in ALAN exposure inequity and the impact of travel behavior on it.

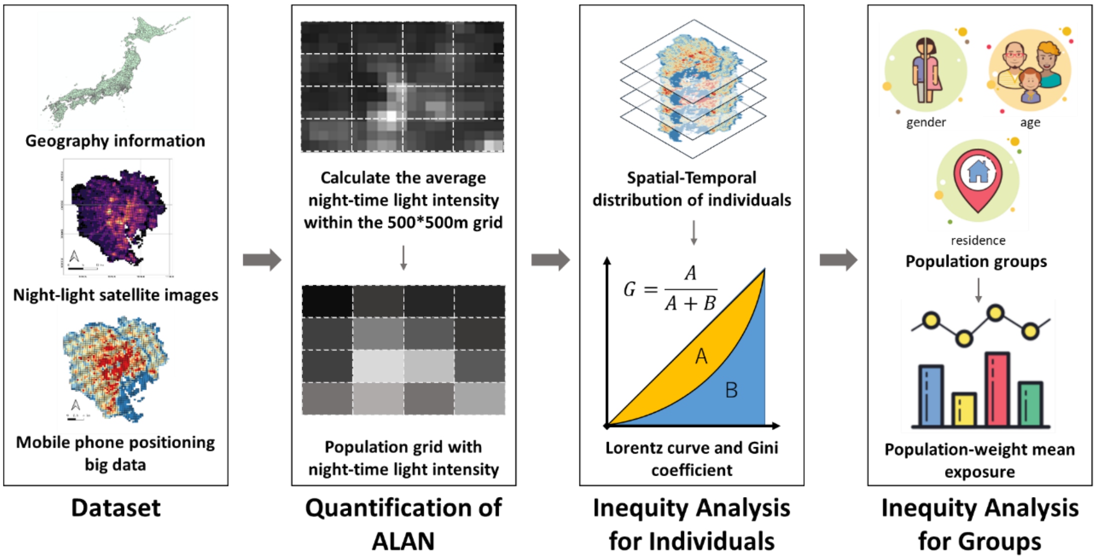


Figure 21. The framework of this chapter

4.2.2. Case study

The case of this chapter is the 23 districts of Tokyo, Japan, with a total area of 621.97 km² and a population of approximately 9.1 million (as counted at the beginning of 2015) (*Figure 22)*.

As the largest metropolitan area in the world (Wendell Cox, 2021), Tokyo is still bright even at night. In Tokyo, light-emitting diode (LED) lighting has quickly replaced outdoor lighting based on fluorescent lamps and mercury lamps due to its high lighting efficiency, low power consumption, and low cost. Due to the popularity of LED, not only electricity bills and management costs have been reduced, but the brightness (illuminance) of the area has also increased, and the residents' sense of security has also been improved (The Ministry of the Environment, 2021). On the other hand, in the case of insufficient research on lighting design, LED may cause excessive brightness and glare, which may also become light damage to the environment, people, flora and fauna, and the night sky (The Ministry of the Environment, 2021). Observing the change in the intensity of light emitted to the sky from the area (approximately 400km^2) centered on the Yamanote Line area in Tokyo, it can be seen that it is increasing at an average of 2 to 3% per year (The Ministry of the Environment, 2021).

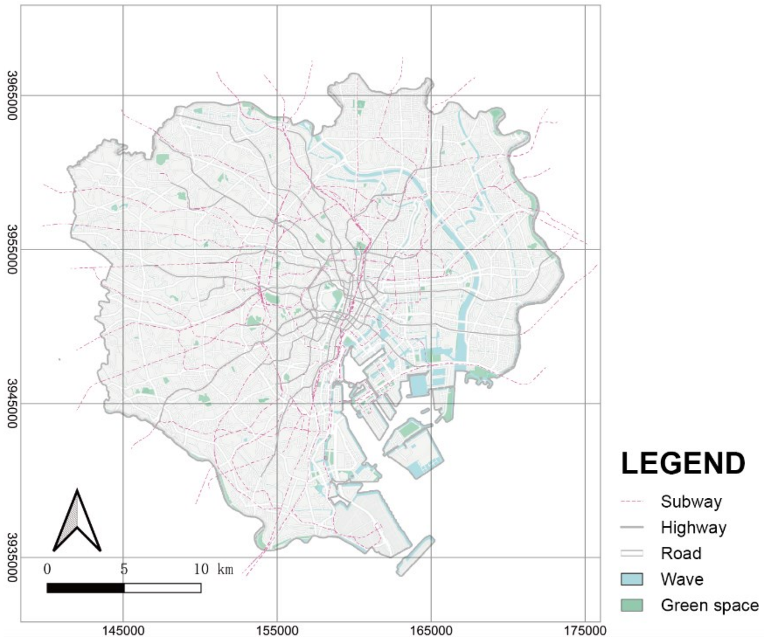


Figure 22. The study area (Tokyo, Japan)

4.3. Methodology

4.3.1. Quantification of NTL intensity

The pixel brightness values of the NPP/VIIRS imagery I used ranged from 3.02nW/cm²/sr to 528.86nW/cm²/sr. To measure the NTL intensity of each grid in the dynamic population data, I used ArcGIS to overlay night-light satellite imagery onto the grid boundaries of the Mobaku data. Since the grid size of Mobaku data is not aligned with that of the night-light satellite imagery, using zonal statistics may result in missing output. So I first convert the VIIRS raster imagery to point vector features using the raster to point function. The number of points is the same as the number of cells, and the cell value is inherited. I then calculated the average NTL intensity of all points contained within each grid boundary using the 'join the attributes of features by their location' function. Units for the NTL intensity are reported in nW/cm²/sr.

4.3.2. Inequity analysis of individuals

To compare the inequity of ALAN exposure among individuals in Tokyo with and without travel behavior, I used the Lorenz curve and the Gini coefficient as evaluations (*Figure 21*). The Lorentz curve is usually used in the field of economics to reflect the equity of economic resource allocation or property distribution, and it is now also used in equity research in many fields (Y. Song et al., 2021; Zhou et al., 2016). In this chapter, I first associate the NTL intensity of the grid with the Mobaku data through the join function of ArcGIS and sort each group of Mobaku data in ascending order of the NTL intensity value. Then I multiply the NTL intensity of each grid by the population to obtain the total ALAN exposure for it. Finally, I accumulated the population and the total ALAN exposure and plotted them on a two-dimensional coordinate system with the population proportion as the x-axis and the total ALAN exposure proportion as the y-axis to obtain the Lorentz curve. The 45° diagonal of the coordinate system is the absolute fair line. The smaller the area enclosed by the Lorentz curve and absolute fair line, the more equal the light pollution distribution at night. Based on the Lorentz curve, the Gini coefficient can be calculated as the ratio of the area A enclosed by the absolute fair line and the Lorentz curve to the area of the right triangle under the absolute fair line (A+B) (*Figure 21*). The value range of the Gini coefficient is between 0 and 1. 0 is absolutely fair, and 1 is absolutely unfair.

$$\text{Gini coefficient} = \frac{A}{A+B}$$

4.3.3. Inequity analysis of population groups

Dynamic population data include the gender and age groups, but the residence information only records the registered residence of the user. To distinguish residents and non-residents in the grid, I overlayed the administrative boundary data on the grid of dynamic population data and used the join function of ArcGIS to add a location attribute to the grid. I then compared the residence information and location information of the populations in the grid, if they matched, the populations were identified as residents, otherwise as non-residents. To address our second question, I calculated hourly population-weighted mean exposure to ALAN for each group over two time periods. I first sliced the dynamic population data by hour, multiplying the population of each group $P_{n,\,i,g}$ within each grid by the NTL intensity L_n. These values within each grid are then summed and divided by the total population for each group in Tokyo. Finally, the hourly population-weighted exposure to ALAN of each group E_g in each time period was obtained by calculating the average ALAN exposure of the group over t hours in the time period. The equation for E_g is as follows:

$$E_g = \frac{1}{t} * \sum_{i=1}^{t} \frac{\sum_n L_n * P_{n,\,i,g}}{\sum_n P_{n,i,g}}$$

where E_g is the hourly population-weighted exposure to ALAN of a population group; L_n is the NTL intensity in grid n; $P_{n,\,i,g}$ is the population of group g in grid n in the i hour of a time period; t is the 6h of a time period.

4.4. Result and Discussion

4.4.1. Descriptive analysis

Figure 23 depicts the spatial distribution of ALAN in Tokyo on a 500*500m grid. Because the numerical distribution of NTL intensity is not uniform, for visual comparison, I use natural discontinuity (Jenks) classification in QGIS. ALAN is most obvious in the highly urbanized central region. Moreover, the distribution of high-light pollution areas is basically along the subway, with the circular Yamanote line as the center, and radially distributed outward along each line. The brightest areas are also the most densely populated places in the dynamic population data, such as Shinjuku, Ikebukuro, Shibuya, Ginza, and Ueno. These places are often very popular shopping streets, and there are still many people visiting at night. In contrast, ALAN in other areas is not so strong.

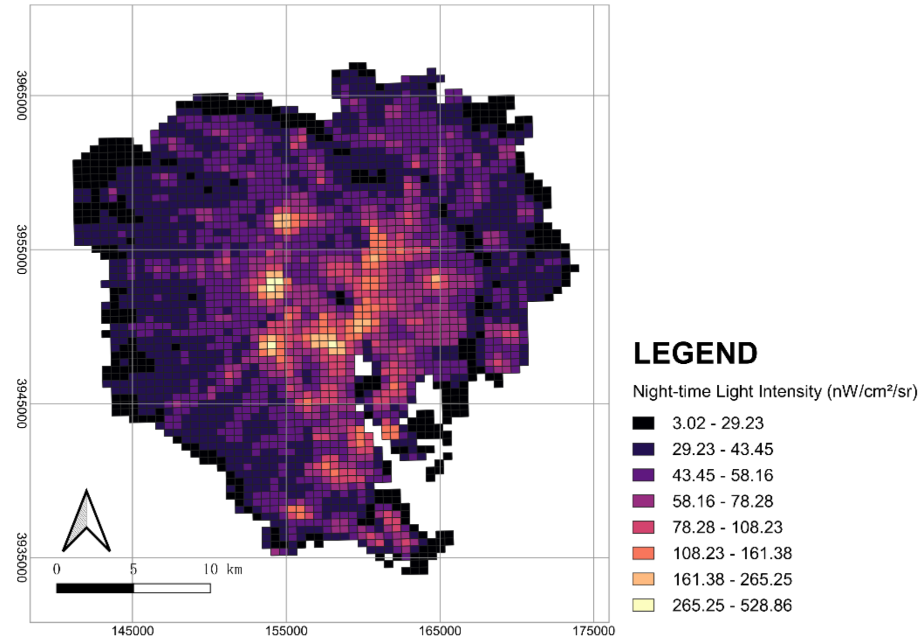


Figure 23. Spatial distribution of NTL intensity

4.4.2. The inequity of ALAN exposure among individuals

Figure 24 reports the Lorentz curve and Gini coefficient of ALAN exposure for all individuals in Tokyo for two time periods (18:00-24:00 and 0:00-6:00). In the figure, the x-axis is the cumulative percentage of the population, and the y-axis is the cumulative percentage of the individual's average ALAN exposure. During the period from 18:00 to 24:00, the Gini coefficient reaches 0.31, and it is reduced to 0.24 between 0:00 and 6:00. . The changing trend of the Lorentz curve and Gini coefficient over time shows that in periods of strong population mobility, the inequity of ALAN exposure will be greater.

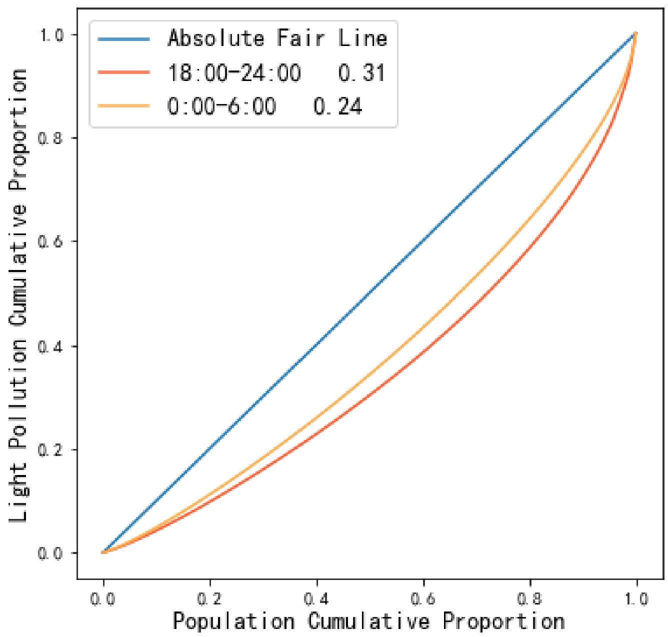


Figure 24. Lorentz curve and Gini coefficient for two time periods

Figure 25 reports the Gini coefficients for two time periods and their difference in the 23 districts of Tokyo. From the perspective of the Lorenz curve and Gini coefficient, there are three outstanding districts: Shinjuku ku, Toshima ku, and Shibuya ku. From 18:00 to 24:00, their Gini coefficients all reached 0.3 or more, and the Shinjuku district even reached 0.43. This means that a small number of people in these areas suffer from disproportionate ALAN exposure. From 0:00 to 6:00, the Gini coefficient of most districts has declined, and the three districts with the greatest inequity also saw the greatest declines. The three "rich districts" of Chiyoda ku, Minato ku, and Chuo ku are exceptions, whose Gini coefficients increased slightly at late night. I speculate that this is because the residential areas in the rich districts are exposed to higher levels of ALAN. In terms of geographical distribution, the districts with higher inequity of ALAN are located in central Tokyo, basically along the Yamanote Line, while districts with lower inequity are more distributed in the suburbs of Tokyo.

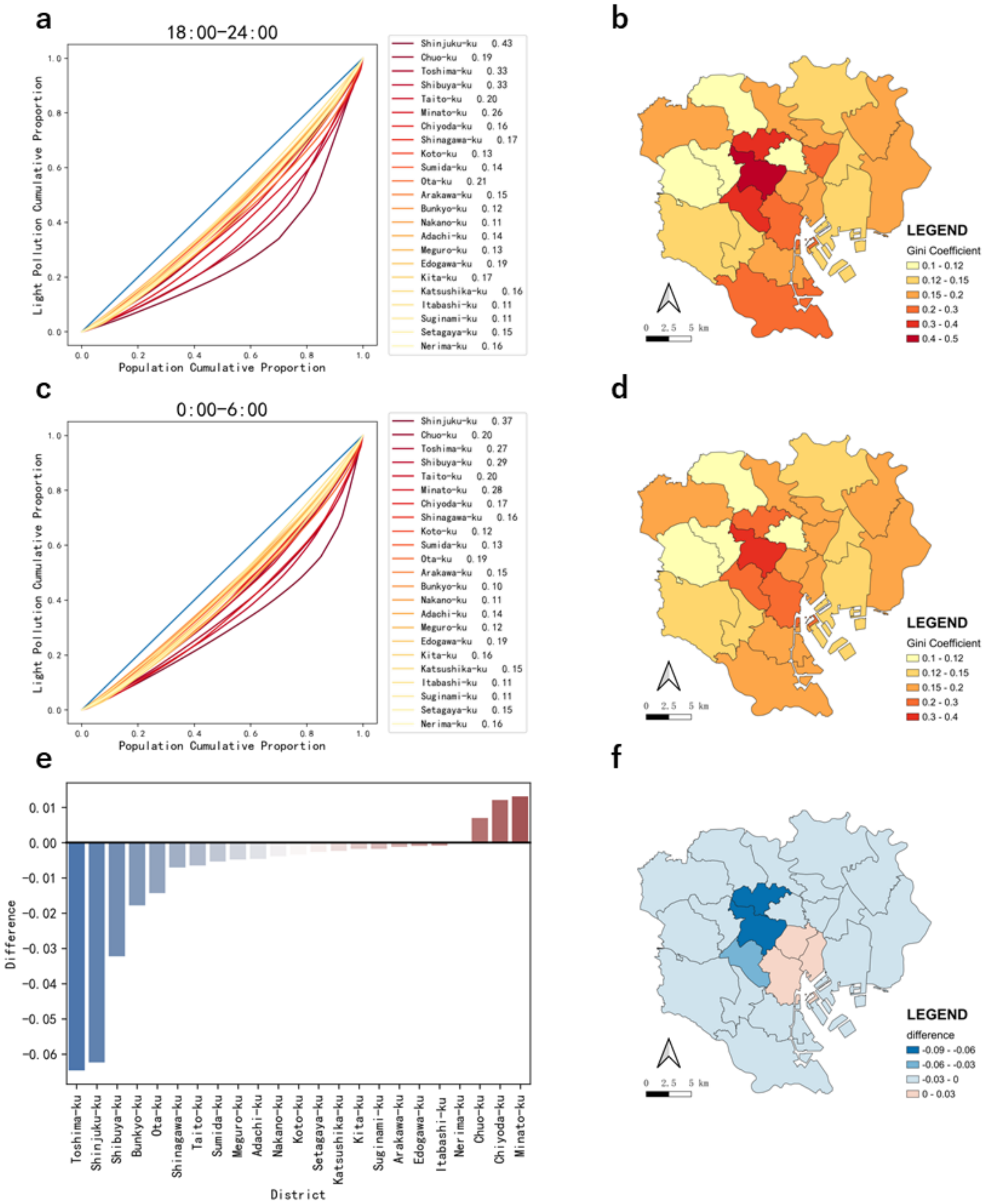


Figure 25. a. c. Lorentz curve and Gini coefficient of each district in two time periods.
b. d. Spatial visualization of Gini coefficients for each district in two time periods.
e. The difference in the Gini coefficient of each district between two time periods.
f. Spatial visualization of Gini coefficients difference for each district between two time periods.

4.4.3. ALAN exposure among different age groups

Figure 26 reports the population-weighted mean exposure to ALAN of different age groups in two time periods. It shows that population-weighted mean exposure to ALAN is negatively correlated with the age of the user group, and younger people are exposed to higher intensity of ALAN. During the period from 18:00 to 24:00, the >15-20 years old group has the highest ALAN exposure level, with an average level of 76.6 nW/cm²/sr per hour; while the >70-80 years old group has the lowest exposure level, with an average level of 51.9 nW/cm²/sr per hour. From >15-20 years old to >70-80-year-old, as the age increases, the ALAN exposure level decreases successively. But the >0–15-year-old group is an exception. Although it is the youngest group, the mean ALAN exposure of it is not the highest, but close to that of people aged >50-60. From 0:00 to 6:00, ALAN exposure decreased in different magnitudes across all age groups. Groups with higher ALAN exposure intensity also have a greater reduction. For example, ALAN exposure decreased by 18.9 for >15-20 years old, while only 0.7 for >70-80 years old. This makes the inequity of ALAN exposure among different age groups less notable at late night.

Figure 27 shows the visual results of population-weighted mean exposure to ALAN of different age groups in the 23 wards of Tokyo during two time periods. During the same time period, it can be found that the difference in ALAN exposure among age groups in central Tokyo is greater than that in the marginal areas of Tokyo. A similar phenomenon can also be found in a single group, that travel behavior will have a greater impact on changes in ALAN exposure in central Tokyo. This shows that there are regional differences in the inequity of ALAN among different age groups.

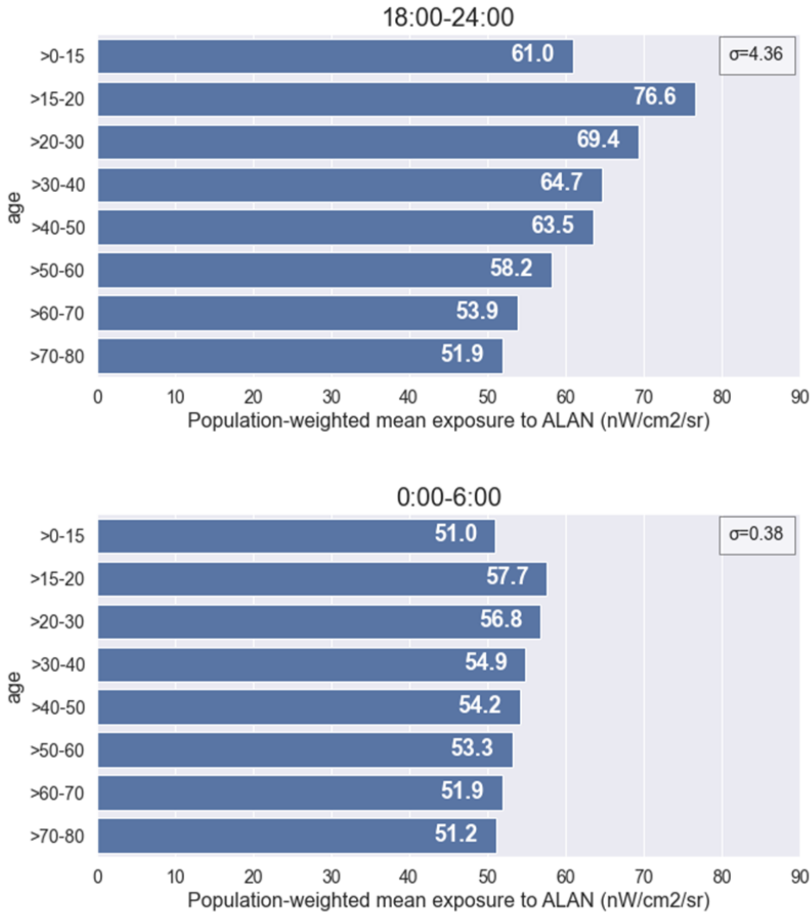


Figure 26. population-weighted mean exposure to ALAN for different age groups in two time periods

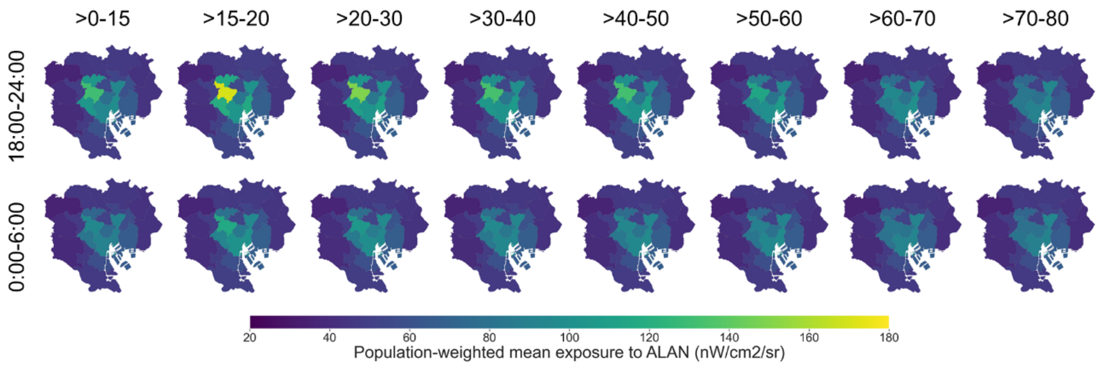


Figure 27. population-weighted mean exposure to ALAN for different age groups of each district in two time periods

4.4.4. ALAN exposure among different gender groups and residence groups

Figure 28 shows the population-weighted mean exposure to ALAN of males and females for two time periods. The figure shows that average ALAN exposure is very similar between different gender groups, and there is no inequity. During the period from 18:00 to 24:00, the population-weighted mean exposure to ALAN for the male was 66.4 and for the female was 62.6. During another time period, the average ALAN exposure for men and women respectively dropped to 55.5 and 53.8. Since the difference in ALAN exposure between the two gender groups is only about 5%, there is almost no inequity in ALAN exposure among people of different genders.

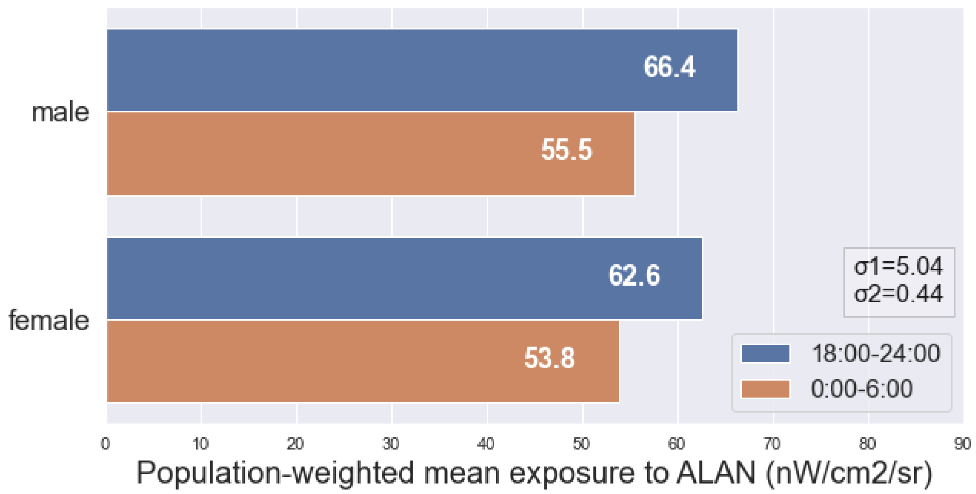


Figure 28. Population-weighted mean exposure to ALAN for different age groups in two time periods.

Figure 29 shows the visualization of the population-weighted mean exposure to ALAN of different genders in Tokyo's 23 wards at two time periods. No inequities in ALAN exposure between gender groups were found in the 23 districts, regardless of the time period. In terms of geographic differences in average ALAN exposure among population groups, results were similar for gender groups and age groups, with higher average ALAN exposures in central Tokyo.

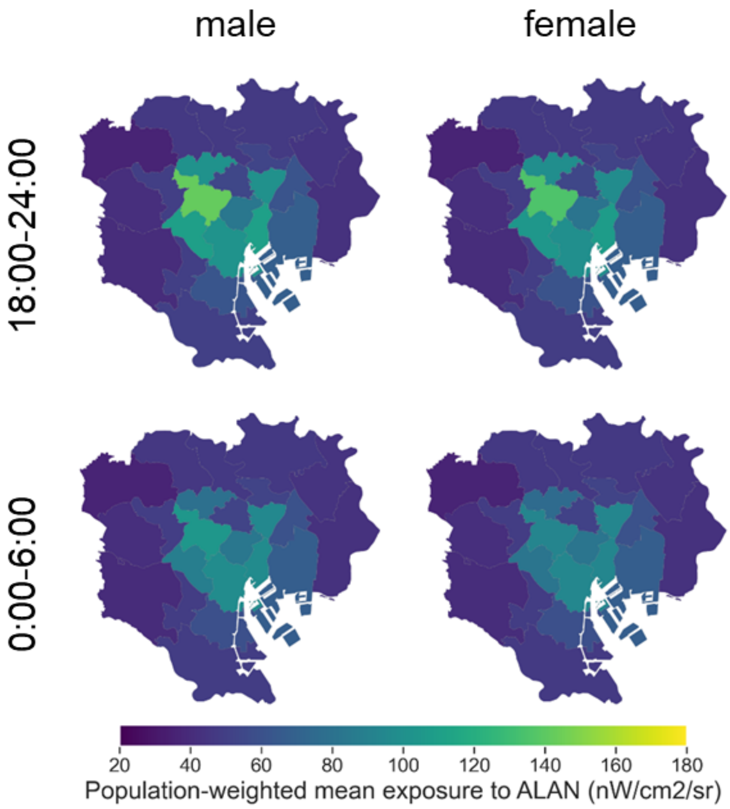


Figure 29. Population-weighted mean exposure to ALAN for different age groups of each district in two time periods.

Figure 30 shows the population-weighted mean exposure to ALAN of residents and non-residents in two time periods. In comparison, it is significant that the population-weighted mean exposure to ALAN of non-residents is higher than that of residents. During the period from 18:00 to 24:00, the average ALAN exposure of non-residents reaches 100.7, which is 87.2% higher than the 53.8 of residents. During 0:00 to 6:00, there is little change in the average ALAN exposure of the residents, while the average ALAN exposure of non-residents has experienced a substantial reduction of 32.9, and the difference between them also reduced to 28%. In general, non-residents experience higher ALAN exposure than residents, but the inequity will decrease late at night.

Figure 31 shows the spatial distribution of the population-weighted mean exposure to ALANof residents and non-residents in each district of Tokyo during two time periods. It can be seen that the ALAN exposure of residents and non-residents in the marginal area of Tokyo is relatively close, and the difference between them is mainly concentrated in the urban center. In the center of Tokyo, even in the same district, non-residents' ALAN exposure is much higher than that of residents. This shows that non-residents in the central area are highly concentrated in places with high-intensity ALAN.

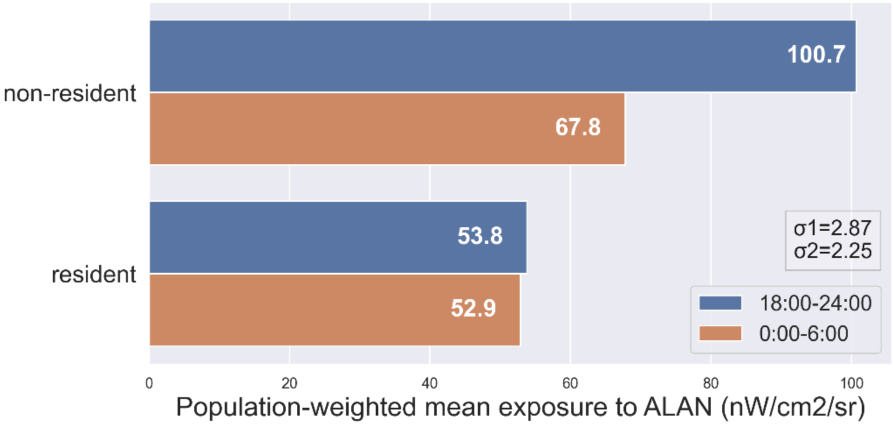


Figure 30. Population-weighted mean exposure to ALAN for different residence groups in two time periods

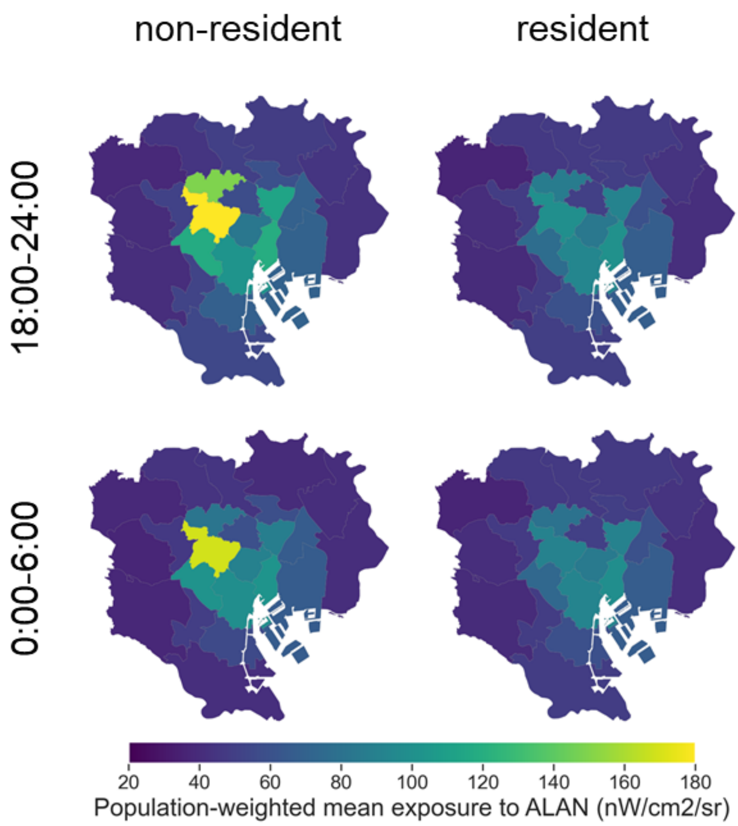


Figure 31. Population-weighted mean exposure to ALAN for different residence groups of each district in two time periods

4.4.5. Discussion

The empirical research results show that there is indeed an unequal phenomenon of ALAN exposure in Tokyo. For individuals, a small number of people in Tokyo suffer a disproportionate amount of ALAN exposure, and this proportion continues to decline slowly at night. One possible explanation is that although high-ALAN areas are often located in prosperous urban areas and have high population densities, these areas are limited in area and the overall population is only a minority in the entire Tokyo metropolis. Among these people, many commuters and tourists are attracted by a large number of job opportunities, leisure and entertainment, and scenic spots provided by the city. At night, as commuters and tourists leave, fewer people stay in areas with high ALAN, so ALAN exposure tends to be equal.

Unequal exposure to ALAN has also been discovered in different age groups. Among people of different ages, young people and middle-aged people are often exposed to higher intensity ALAN, while children and the elderly who are more sensitive to ALAN are not affected by environmental injustice. This is similar to the EJ research conclusion of Lagonigro et al. (2018) on noise pollution. From the perspective of housing, the elderly may be more inclined to live in places with less ALAN, because they are physiologically more sensitive to ALAN. On the contrary, young and middle-aged people tend to work in cities, and most of them will rent houses nearby for commuting convenience. This leads to a higher average ALAN exposure for young and middle-aged people. From the perspective of travel, I found that the difference in ALAN exposure between different age groups is more obvious in the time period of 18:00-24:00 when people are engaged in nightlife. During the period of 0:00-6:00, when most people have returned home, the difference among different age groups has been significantly reduced. I suggest this is caused by differences in travel patterns among different age groups. On the one hand, there are differences in the mobility of people of different ages. For example, children aged >0-15 are usually not allowed to move alone, and the elderly are difficult to move due to the decline in physical functions. Young adults aged >15-60 have greater mobility, so they have more opportunities to be exposed to higher intensity of ALAN. On the other hand, people of different ages also have different night travel purposes. For example, young people are keen on entertainment and consumption, and they tend to go to prosperous areas with higher ALAN intensity. The elderly like to walk and relax, and they will choose destinations with lower ALAN intensity for travel.

For the ALAN exposure research of different genders, I conclude that although the ALAN exposure of men is slightly higher than that of women, men and women basically achieve environmental equity. This phenomenon is similar across time periods and districts, indicating that travel behavior has little effect on inequity between gender groups.

From the analysis of residents and non-residents, I found that the population-weighted mean exposure to ALAN of non-residents can reach up to twice that of residents. I suppose that people's choice of where they live and where they travel may be a reason. In Tokyo, the geographical distribution of residential areas is relatively uniform, so most residential areas are free from high ALAN. However, people's travel destination choices tend to have a strong convergence. Our analysis of the non-resident population in the mobile phone positioning data and the grid's NTL intensity found a clear correlation between them (Figure 32). This shows that people may choose to go to areas with higher ALAN intensity when traveling at night because these places will have more opportunities to meet the needs of travelers. As time goes by, the number of people traveling continues to decrease, and the spatial distribution of travelers tend to be scattered. Therefore, the difference in ALAN exposure between residents and non-residents is gradually shrinking.

Figure 32. Joint plot of non-resident population and NTL intensity during 18:00-24:00.

In the experiment on individual inequity or group inequity, I all found obvious regional differences. Compared with Tokyo's fringe, in several districts in central Tokyo, inequity of ALAN exposure and the influence of travel behaviors on it is more obvious. Perhaps it is because the intensity of ALAN in these areas has a larger span and crowd activities are more active.

Our research results have brought several inspirations. First, in the study of the inequity of ALAN exposure, if personal mobility is not taken into account, it will cause erroneous estimates. This is consistent with the conclusions of some EJ studies on air pollution (Fallah-Shorshani et al., 2018b; Shekarrizfard et al., 2017a, 2017b). Many previous EJ studies have used the resident population to estimate environmental pollution exposure, assuming that everyone stays at home and does not travel, but obviously, this assumption is unrealistic. In this chapter, the dynamic population data of 0:00-6:00 can be approximately equal to the residential population, and the period of 18:00-24:00 is regarded as the dynamic population. By comparing the statistical data of these two time periods, it is not difficult to find that the use of a dynamic population usually results in a higher estimate of ALAN exposure and inequity, because the average ALAN exposure suffered by non-residents is higher than that of residents. But this does not mean that the use of static population data will definitely cause underestimation, which has a lot to do with personal mobility.

Second, the inequity of ALAN exposure in Tokyo that I found may promote a better understanding of Japan's health differences. Because ALAN has been confirmed to have a statistical correlation with a variety of human diseases. Future research can explore whether Tokyo's ALAN exposure inequity and personal mobility interact with the health differences of different population groups. For example, whether the incidence of insomnia at different ages may be related to ALAN exposure, and how does personal mobility affect the differences between individuals. To deepen understanding and strengthen practice, it is necessary to evaluate the impact of unequal exposure to

ALAN on human health in the future when individuals are moving.

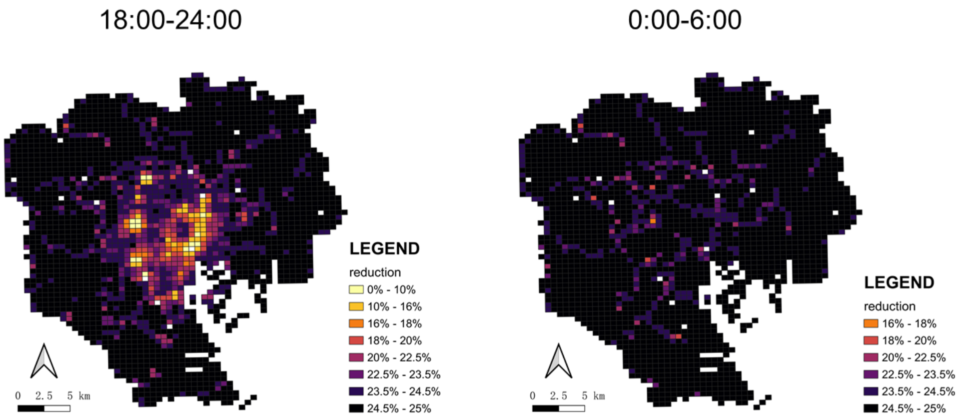


Figure 33. The reduction rate of NTL intensity with lighting time management

4.4.6. Policy recommendation and simulation

To minimize the impact of ALAN on the human body, I put forward several suggestions on how to carry out light pollution prevention and control:

1) Take proper light distribution control. To suppress light leakage and glare of outdoor lighting fixtures, light shields and flow hoods using light shields or reflectors can be installed on the lighting fixtures. In addition, the appropriate amount of light and light color can be selected according to regional characteristics, surrounding environment, and lighting purposes.

2) Implement lighting time management. Since lighting is necessary when people are present, lighting time management can be performed according to the needs of lighting. Nowadays, many outdoor lighting lamps use timers and illuminance sensors for lighting management. In addition, through the use of human-sensing sensors, lighting can be controlled more appropriately, helping to suppress environmental impact and prevent global warming.

I use mobile phone positioning big data to simulate the scene by using human sensors to manage lighting time. The current smart lighting usually outputs a power of 100% when the sensor senses a person or a car and reduces it to 75% when the sensor does not sense it. I assume that when there are 20,000 non-residents in a 500*500m grid, the output power of outdoor lighting is 100%. When the number of non-residents is 0, the outdoor lighting output power is 75%. Accordingly, the intensity of ALAN was re-adjusted and the exposure difference was re-evaluated.

Figure 33 shows the percentage of ALAN reduction for each grid after lighting time management. It can be seen that this measure is very effective for most areas where light pollution is not strong and can achieve a protection rate of more than 20%. For areas with strong light pollution, the effect gradually becomes obvious over time, and the protection rate can reach about 15% in the second half of the night.

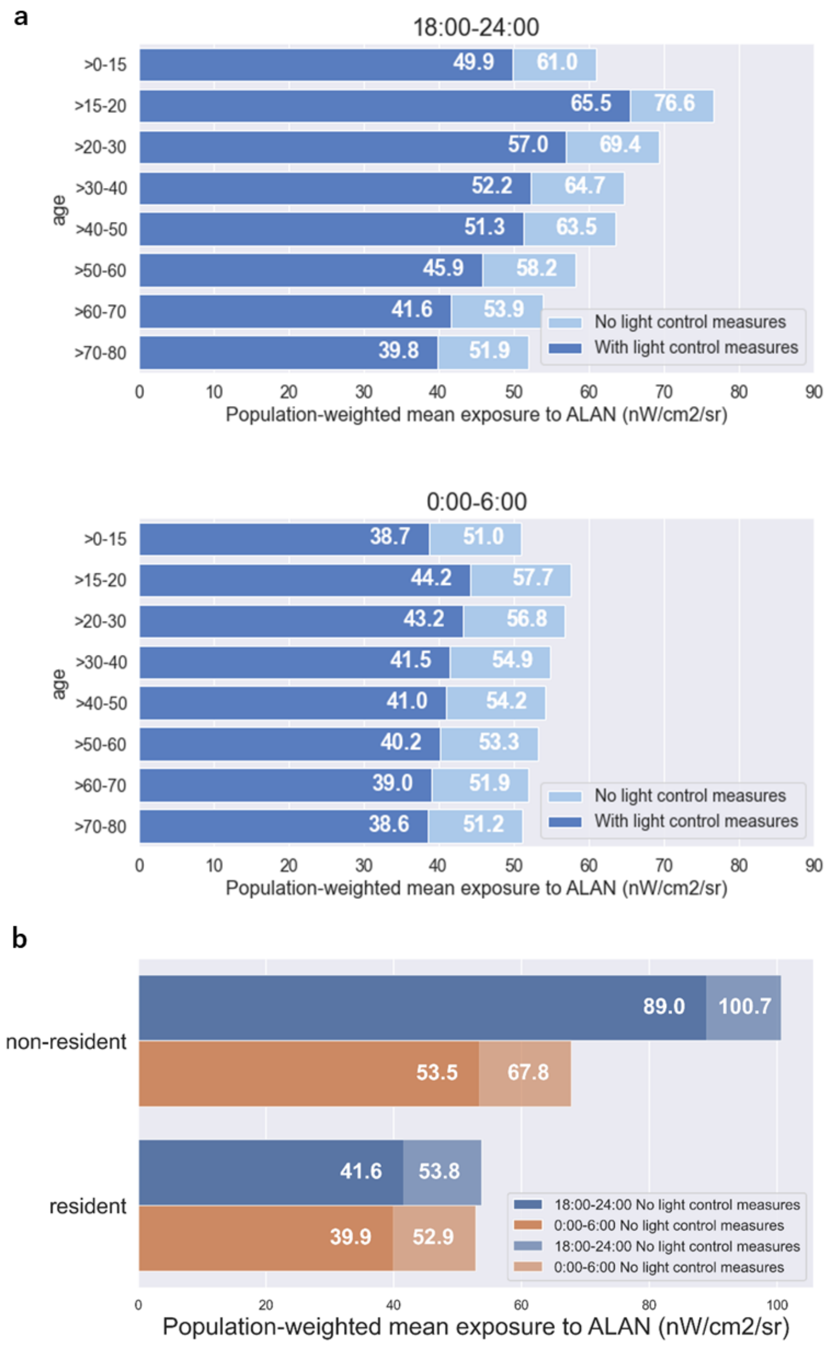


*Figure 34. Population-weighted mean exposure to ALAN for each **a.** age and **b.** residence group with and without light control measures*

Figure 34 shows the difference in ALAN exposure for each age, gender, and residence group after lighting time management. It can be seen that different age groups and gender groups can effectively reduce their ALAN exposure. Compared with non-residents, residents benefit more from this measure, and per capita, exposure has dropped by nearly 25%. It can be said that lighting time management can effectively reduce the impact of night lights on residents.

4.5. Conclusion and Limitation

4.5.1. Conclusion

Based on other researchers, this chapter used mobile phone positioning data for the first time to conduct an EJ study of ALAN. Considering the temporal changes of the population, this chapter uses night-light remote sensing to estimate ALAN and discusses whether the ALAN in Tokyo, Japan is unequal among different groups from the aspects of age, gender, and place of residence. The results show that there is indeed a considerable degree of inequity in ALAN in Tokyo. Among user groups of different ages, people aged 15-20 have suffered the most exposure to ALAN. The elder groups are exposed to weaker ALAN, and children and the elderly under 15 are not affected by the inequity of ALAN. There is almost no inequality in ALAN between user groups of different genders. The average ALAN exposure of non-residents and residents showed obvious inequity, and the non-residents were significantly higher than the residents. In addition, we also found that there are regional differences in the inequities among different groups. Central Tokyo tends to be more unequal than marginal areas, and its inequity is more affected by time.

In further discussion, I found that over time at night, the decrease in ALAN exposure and inequity is related to the decrease in travel behavior. Because the destination of night travel and places with high-intensity ALAN are highly overlapped, the per capita ALAN exposure increases with the increase in travel behavior. The difference in travel patterns between different groups of people makes their average ALAN exposure increase or decrease differently, so the inequity of ALAN will also change accordingly.

Because of the impact of travel behavior on ALAN exposure and the inequity of ALAN, the government should consider controlling the outdoor lighting of high-frequency destinations for night travel when taking policy actions. For example, by controlling the light distribution of light shields, hoods, etc., light leakage and glare from street lamps, billboards, etc. can be reduced. Relevant regulations have also appeared in the lighting control guidelines of "Lighting Up Tokyo"(Office of the Governor for Policy Planning, 2018). This shows that the purpose of research based on environmental justice is being combined with the environmental protection movement, which aims to protect everyone from environmental pollution. To achieve this goal, it is necessary to recognize and understand the differences in exposure of different populations to ALAN. I hope that this research can help scholars and the government better solve the problem of inequity in ALAN exposure.

4.5.2. Limitation

The limitations of this chapter are mainly reflected in the following aspects:

1) This chapter uses mobile phone positioning big data to estimate the population, which means that those who do not have a mobile phone that supports the positioning function are not considered. For example, some children and the elderly may have large deviations when estimating ALAN exposure for these groups. Additionally, I only used seven days of mobile phone positioning data, which means that the effects of seasonal changes in population distribution on ALAN exposure might be ignored. Future research should consider using

location data spanning a longer time period (eg, one year), and incorporating new data or mathematical models to compensate for sample bias introduced by mobile phone positioning data.

2) The NPP/VIIRS images were taken around 1 a.m. local time and do not collect radiation in the blue spectrum. With the trend toward the popularization of LEDs, this means that ALAN levels may be seriously underestimated. Additionally, the nighttime light images I use are synthetic monthly data that do not reflect seasonal changes in ALAN distributions. Further research may consider using annual data or computing the mean of multiple monthly data instead of annual data.
3) The initial EJ research revealed that environmental injustice is related to race, which led the environmental justice movement to environmental racism for a time. However, most of the subsequent EJ studies have shown that the unequal distribution of pollution is actually related to low socioeconomic status. Due to the lack of user economic data, this chapter does not explore whether the inequity of ALAN exposure is related to the user's economic level. If follow-up research can obtain user income data, it can explore the root cause of unequal ALAN exposure.

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２０２２年度　修士論文　モビリティベースの環境正義：公共交通指向型開発（TOD）ステーションの使用と夜間の人工照明（ALAN）曝露における不公平の理解

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