Analysis of Factors for Pedestrians' Spatial Distribution in Sakae District of Nagoya Using Mobile Phone Location Data

Yufan Zhang, Toshiyuki Kaneda, Akira Ota

(Yufan Zhang, Graduate Student, Graduate School of Engineering, Nagaoya Institute of Technology, Gokiso, Showa, Nagoya, Japan, y.zhang.394@stn.nitech.ac.jp)

(Toshiyuki Kaneda, Doctor of Engineering, Graduate School of Engineering, Nagaoya Institute of Technology, Gokiso, Showa, Nagoya, Japan, kaneda@nitech.ac.jp)

(Akira Ota, Doctor of Engineering, Faculty of Urban Life Studies ,Tokyo City University, Tokyo, Japan, otaa@tcu.ac.jp)

1 ABSTRACT

Recently, mobile phone location data containing the activities of different urban residents can be employed for an urban study. Compared with field research, mobile phone location data have a larger volume, wider range, and higher frequency. It can provide fresh data to support urban research. Most analyses of the spatial distribution of pedestrians employ linear or log–log models using least squares, but the drawback is that the number of pedestrians and the number of counts do not always follow a normal distribution and the least-squares method is vulnerable to outlier effects. Thus, the use of generalised linear model (GLM) with maximum likelihood estimation for the analysis of the factors influencing pedestrian distribution makes sense. However, these models lack suitable indicators to rank the factors' strengths. In this study, we employed the Sakae district of Nagoya as the object of the study and divided the factors influencing the spatial distribution of pedestrians into four categories: street attribute factor, land use, space configuration, and transportation accessibility factor. Finally, we employed a GLM to study the factors influencing the pedestrians' distribution. We introduced a mean standardised partial differential value to compare the significance of each variable in the model. The findings showed that the correlation coefficient between forecast and actual values was better for the linear model whereas the mean absolute percent error was better for the negative binomial distribution model. Both models revealed that the integration value generated from the segment angular investigation was substantially correlated with the pedestrian distribution as a space configuration indicator.

Keywords: Mobile Phone Location Data, Pedestrians, Generalized Linear Model, Segment Angular Analysis, Urban Planning

2 INTRODUCTION

The quantitative analysis of the spatial distribution of the number of pedestrians has great significance in the 21st century. Recently, in addition to conventional outdoor survey data, the three cellular carriers in Japan have recently begun commercial services of mobile phone location data in urban areas. Owing to the large scope and volume of mobile phone location data collection, it is predicted that new advances in the quantitative analysis of the pedestrian numbers' spatial distribution will be introduced.

In addition to street attribute factors, facility volume (land use) factors, and transportation accessibility factors, space configuration factors based on the space syntax (SS) theory, quantifying urban form, have received attention as factors influencing the spatial distribution of pedestrian counts. Desyllas et al. (2003), Araya et al. (2005), Ozbil et al. (2015), Shimizu et al. (2019), and Kaneda et al. (2020) confirmed the involvement of the SS theory in the spatial distribution of the number of pedestrians as a factor of urban form.

However, in the above research, when investigating pedestrian count distribution factors, models that compute predictions using the least-squares method, like linear and log–log models, are employed. Although models using the least-squares method have the benefit of simple extraction of the factor structure, they have the drawback that the pedestrians' number, which is the number of counts, is not always normally distributed and is vulnerable to a singular value, making it meaningful to investigate the generalised linear model (GLM) that employs the maximum likelihood method. The study by Stavroulaki et al. (2019) revealed that the negative binomial regression model is better than a linear model when pedestrians are the study's subject.

In this study, mobile phone location data, which are count data, are employed as an indicator of the spatial distribution of the number of pedestrians, and the factors influencing the spatial distribution of pedestrian counts are the street attribute factor, facility quantity factor, traffic accessibility factor, and the integration value obtained from the segment angular analysis in SS theory as the urban area form factor. Model equations are selected by employing a linear model and a negative binomial regression model. The two models will then be compared to investigate the factors contributing to the spatial distribution of the number of pedestrians in the Sakae Station area of Nagoya City and to examine the applicability of the negative binomial regression model.

2.1 Study Area

Nagoya City, with a population of approximately 2.3 million, has two major commercial and business clusters: the Nagoya Station and Sakae Station area. The Sakae Station area as a study target is a 150 ha area, including Nishiki, Izumi, Sakae 3-Chome, and Sakae 4-Chome, based on the "Sakae Area Urban Development Project" of Nagoya City (Fig. 1).

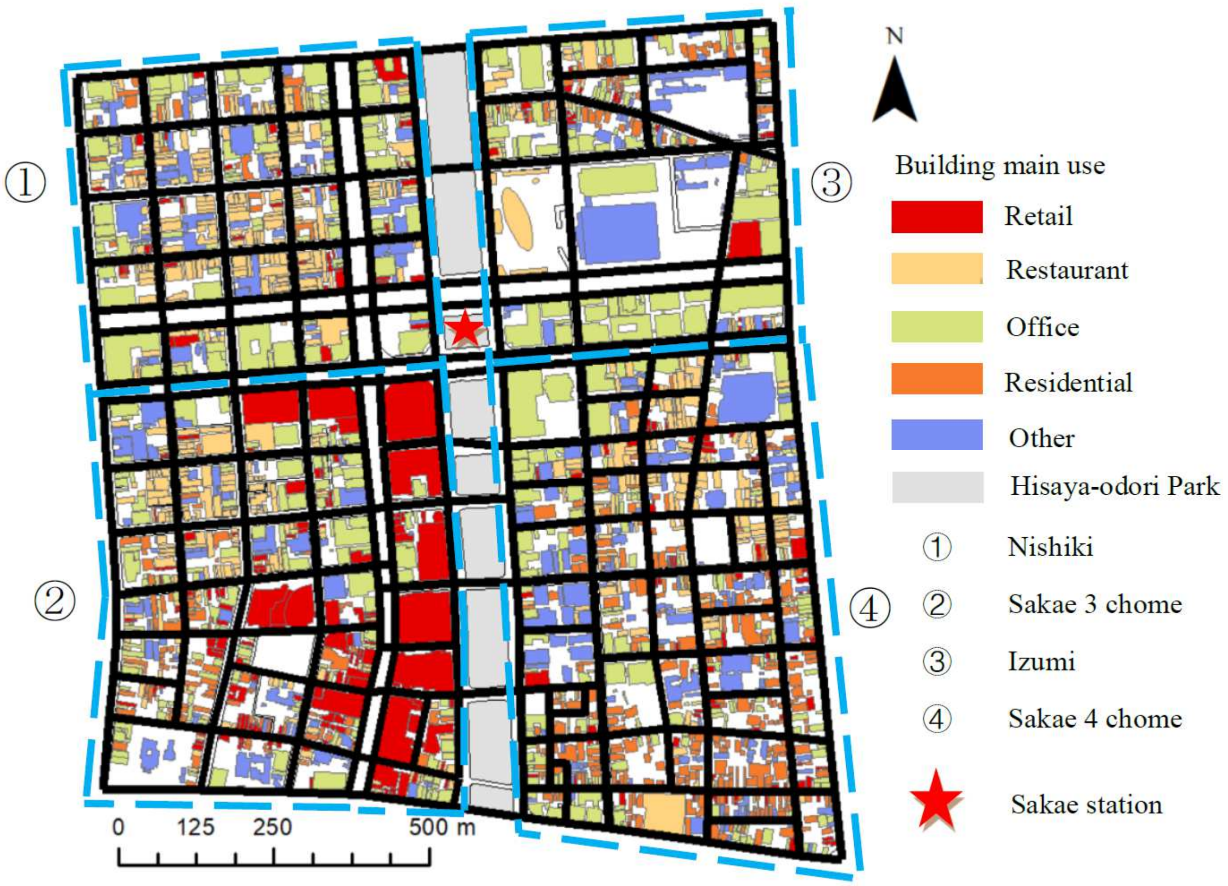


Fig. 1: Distribution of streets and building uses in the Sakae Station area

2.2 Mobile Phone Location Data

In this study, the number of pedestrians was generated from the KDDI Location Analyzer's primary movement line data (KLA). KDDI, a Japanese mobile phone service company, uses GPS location data obtained from its smartphone users to make expanded estimates using the official population statistics. The period from April 1, 2020, to March 31, 2021, was set as the collection period, the data covered the time of day for the aggregation unit from 5:00 to 29:00, the age of users was 20 years or older, and walking was the means of movement.

In the study area, the number of street links with pedestrian number data is 332 because there are some street links where the number of pedestrians cannot be obtained. The average daily value for each weekday is visualised on a map using GIS for the collected data. Looking at the spatial distribution of the number of pedestrians on weekdays and holidays (Fig. 2), the maximum numbers of pedestrians in the street link of Sakae Station on weekdays and holidays are 7090 and 8881, respectively. Furthermore, it can be confirmed that the number of pedestrians in the Nishiki area has decreased on holidays compared to that on a weekday.

The histogram of the number of pedestrians and summary statistics on weekdays and holidays (Fig. 3) indicates that the maximum number of pedestrians is higher on holidays than on weekdays, whereas the minimum number of pedestrians is higher on weekdays than on holidays. The dispersion is larger on holidays than on weekdays, and it can be discovered that the pedestrians' distribution is more concentrated on holidays than on weekdays.

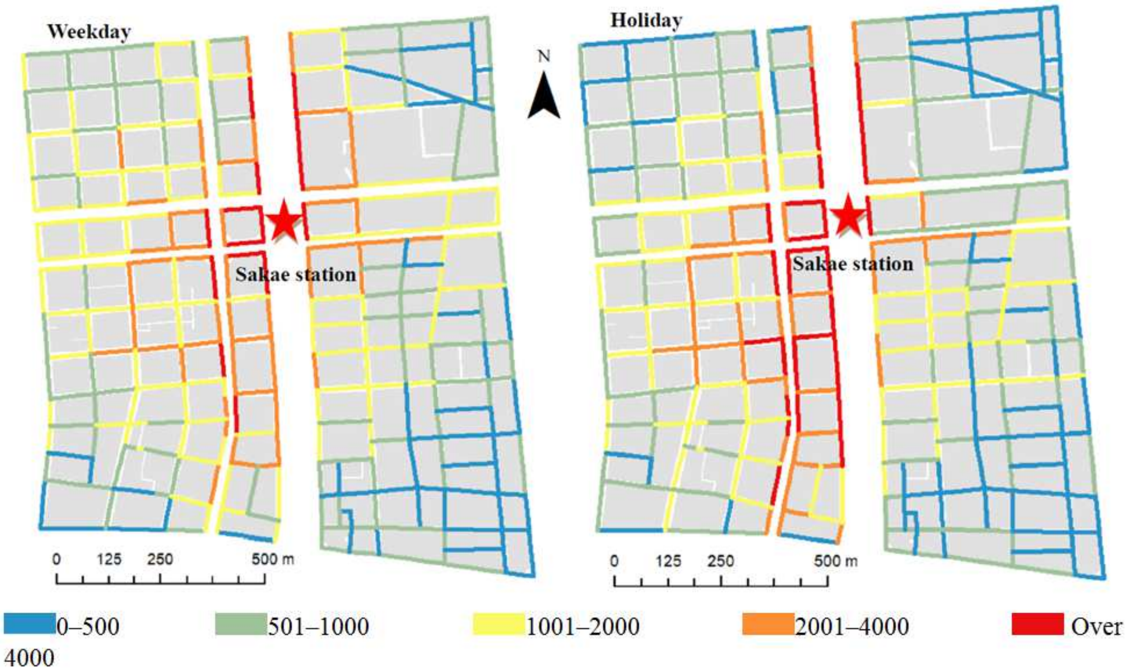
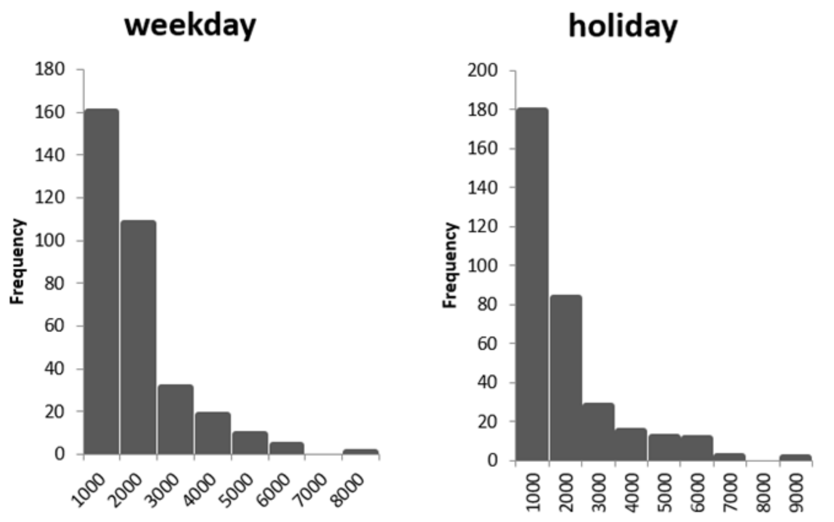


Fig. 2: Spatial distribution of pedestrians (persons/day)



Mean	1362
Sum	452296
variance	1225728
minimun	138
maximun	7090

Mean	1431
Sum	475168
variance	1959837
minimun	117
maximun	8881

Fig. 3: Histogram of the number of pedestrians and summary statistics (persons/day)

3 CANDIDATE EXPLANATORY VARIABLES

In this study, the number of pedestrians was employed as the objective variable, and 13 variables were created as candidate explanatory variables (Table 1). We classified them into four groups of factors: street attribute factor (three variables), facility volume (land use) factor (six variables), space configuration factor (two variables), and transportation accessibility factor (two variables).

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When computing the floor-area ratio by land use, when a street has a median strip, the floor-area ratio of one adjacent side block of the street is used as usual, and when there is no median strip, the average of the floor-area ratio of both adjacent side blocks of the street is used.

In this study, (D2) distance to Sakae (m) is logarithmically transformed for analysis using the linear regression model and negative binomial regression model.

		sign	Variable name	Overview	Data source
Objective variable		Y1	Number of pedestrians (weekday)	Average daily street pedestrian counts from April 2021 to March 2022	KDDI location analyzer's primary movement line data
		Y4	Number of pedestrians (holiday)		
Candidate factor variables	Street attribute (A)	A1	Sidewalk dummy	Has no sidewalk: 0, Has sidewalk: 1	Nagoya City road certification map
		A2	Street width (m)	Total width of the road	
		A3	Subway entrance dummy	Has no subway entrance: 0, Has subway entrance: 1	Google maps
	Facility volume factors (B)	B1	Floor-area ratio of retail	All-floor area of retail/block area	Nagoya City planning basic survey data
		B2	Floor-area ratio of restaurant	All-floor area of restaurant/block area	
		B3	Floor-area ratio of offices	All-floor area of offices/block area	
		B4	Floor-area ratio of residential	All-floor area of residential/block area	
		B5	Floor-area ratio of first-floor ratio	First-floor area of retail/block area	
		B6	Floor-area ratio of the first-floor restaurant	First-floor area of restaurant/block area	
	Space configuration factors (C)	C1	Integrated value (R = 400 m)	Integrated value by segment angular analysis with a radius of 400 m	Calculation by DepthmapX
		C2	Integrated value (R＝1200 m)	Integrated value by segment angular analysis with a radius of 1200 m	
	Transportation accessibility factors (D)	D1	Distance to the nearest station	Shortest route distance to the nearest station	Calculation by the shortest path of QGIS
		D2	Distance from Sakae Station (m)	Shortest route distance to Sakae Station	

Table 1: Objective variables and candidate factor variables employed in the analysis

3.1 Floor-Area Ratio

We employed data from the Nagoya City Basic Urban Planning Assessment 2016, a survey of current conditions by building use data, to compute the floor-area ratio of the candidate factor variables employed in this research. We extracted data for four categories, namely, retail, restaurant, office, and residential, and computed the floor-area ratio for each use in each block in the Sakae Station area after calculating the floor area for each use.

Fig. 4 reveals that the maximum floor-area ratio for retail is 800% blocks with more than 50% floor-area ratio are concentrated in the Sakae 3-Chome area. The maximum floor-area ratio for the restaurant is 1193%, and blocks with more than 50% floor-area ratio are concentrated in the Nishiki area and northern part of the Sakae 3-Chome and 4-Chome areas. The maximum floor-area ratio for office is 790%, and several blocks have more than 100% floor-area ratio, blocks with high floor-area ratio for office are concentrated near trunk roads. The maximum floor-area ratio for residential is 427%, and blocks with more than 50% floor-area ratio are concentrated in the Sakae 4-Chome area.

Fig. 4: Floor-area ratio by use

3.2 Space Configuration Index Using Segment Angular Analysis

This study employed the integration value obtained from the segment angular analysis of the SS theory as the space configuration index. The SS theory is a spatial analysis approach that focuses on the topological and geometric relationships of space and uses information on the physical shape of space to quantitatively assess spatial connections and their relationship to human perception and behaviour (Hillier et.al. 1993; Hillier 1996).

We established a segment map of the Sakae Station area using base map information from the Geospatial Information Authority of Japan. A buffer zone of over 1200 m was placed around the periphery of the research area when plotting the segment map by considering edge effects. As for the space configuration index, we used the integration value from the UCL depth map's segment angular analysis.

When conducting the segment angular analysis, specifying the analysis area to meet the purpose is possible, and this area is called the radius. In this study, two types of radius were examined: 400 m (neighbourhood) and 1200 m (wide area).

The analysis findings' spatial distribution (Fig. 5) depicts that the integration value of the intersection is high at a radius of 400 m, but this can be ascribed to the short radial streets around the intersection.

At radius = 1200 m, the integration value of streets in the Sakae Station area is substantial, which is because the streets in the Sakae Station area are grid-plan.

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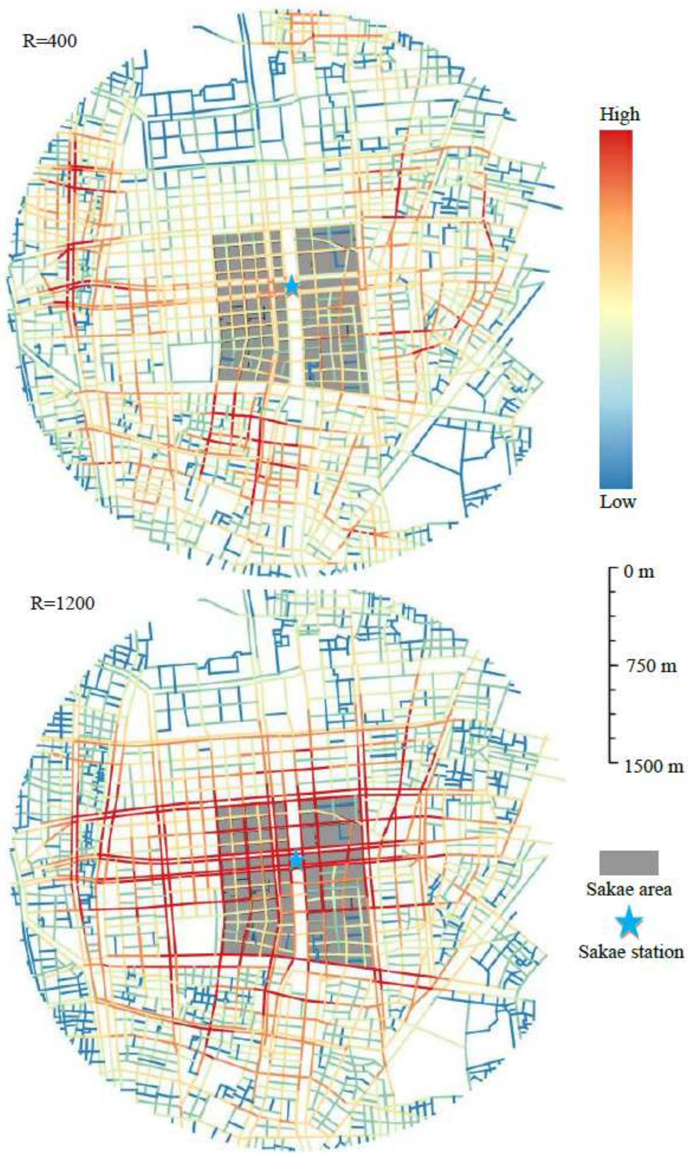

Fig. 5: Integration value by segment angular analysis

4 ANALYSIS OF FACTORS

4.1 Statistical Model

4.1.1 Linear model

The calculation formula for the linear model is the following:

$$Y_i = \beta_0 + \sum_{j \in A} \beta_j X_{ij} + \sum_{j \in B} \beta_j X_{ij} + \sum_{j \in C} \beta_j X_{ij} + \sum_{j \in D} \beta_j lnX_{ij}$$

In the linear model, the least-squares method, which reduces the sum of squares of the residuals, is used for the solution.

4.1.2 The negative binomial regression model

In this study, the pedestrian data employed were count data. Because count data do not take negative values, they lack normal distribution and do not frequently satisfy homoskedasticity. In this study, a GLM was considered in analyzing count data. As mentioned earlier, the pedestrian counts' variance is greater than the mean on both weekdays and holidays. In this case a negative binomial regression analysis in GLM should be taken.

The objective variable Y_i for streets i (number of pedestrians on the street i) is assumed to have a negative binomial distribution in a negative binomial regression analysis. The calculation formula for the negative binomial regression model is the following:

$$\Pr(Y_i = k) = \frac{\Gamma(k+\theta)}{\Gamma(\theta)\Gamma(k+1)}\left(\frac{\theta}{\mu_i+\theta}\right)^{\theta}\left(\frac{\mu_i}{\mu_i+\theta}\right)^{k}$$

The expected value μ_i is predicted using the following equation:

$$\ln(\mu_i) = \beta_0 + \sum_{j\in A}\beta_j X_{ij} + \sum_{j\in B}\beta_j X_{ij} + \sum_{j\in C}\beta_j X_{ij} + \sum_{j\in D}\beta_j \ln X_{ij}$$

where β_0 denotes a constant, β_j denotes a partial regression coefficient, and X_{ij} denotes a factor variable.

The GLM attempts to maximize the log-likelihood using the maximum likelihood approach.

4.2 Mean Standardized Partial Differential Value

To compare the strength of each factor in the linear model, standard partial regression coefficients are frequently employed. The standard partial regression coefficient is computed using (marginal increase in the z-score of y)/(marginal increase in the z-score of x_i) and is understood as the slope between standardized variables, i.e., the partial differential coefficient. Therefore, the standard partial regression coefficient is employed in the case of the linear model, but in the case of the nonlinear model, the partial derivative of y depends on each x_i, so the case where each x_i is an average value may be illustrated. In this study, the mean standardized partial differential value is used as an indicator to compare the model equations' factor intensities (Kaneda et al. 2022).

Given a linear model $\ln y = \beta_0 + \beta_1 x_1 + \beta_2 \ln x_2$, where y and x_2 are logarithmically transformed, because $y = e^{\beta_0} \cdot e^{\beta_1 x_1} \cdot {x_2}^{\beta_2}$, the partial derivative of y for x_1 is

$$\frac{\partial y}{\partial x_1} = e^{\beta_0} \cdot \left(e^{\beta_1 x_1}\right)' \cdot {x_2}^{\beta_2}$$

$$= \beta_1 \cdot e^{\beta_0} \cdot e^{\beta_1 x_1} \cdot {x_2}^{\beta_2}.$$

Here, the partial differential equation $\left(\frac{SD_{x_1}}{SD_y}\right)\frac{\partial y}{\partial x_1}$ modified using the standard deviation of x_1 and y is called the standardized partial differential equation. Because the value depends on each x_i, the value when the average value is substituted for each is called the x-mean standardized partial differentiation coefficient MSPDV for x_1.

$$\left(\frac{SD_{x_1}}{SD_y}\right)\frac{\partial y}{\partial x_1}\bigg|_{x=\overline{x_i}\ for\ all\ i} = \left(\frac{SD_{x_1}}{SD_y}\right)\cdot \beta_1 \cdot e^{\beta_0} \cdot e^{\beta_1 \overline{x_1}} \cdot \overline{x_2}^{\beta_2}$$

Note that the MSPDV for x_2 is

$$\left(\frac{SD_{x_2}}{SD_y}\right)\frac{\partial y}{\partial x_2}\bigg|_{x=\overline{x_i}\ for\ all\ i} = \left(\frac{SD_{x_2}}{SD_y}\right)\cdot \beta_2 \cdot e^{\beta_0} \cdot e^{\beta_1 \overline{x_1}} \cdot \overline{x_2}^{\beta_2 - 1}$$

4.3 Analysis of Results

The correlations between candidate factor variables had an absolute value of 0.7 or above for (B2) floor-area ratio of restaurant and (B6) floor-area ratio of first-floor restaurant (0.714), (C1) integration value (R = 400 m), and (C2) integration value (R = 1200 m) (0.743).

The variance inflation factor (VIF) between each candidate factor variable is computed to investigate multicollinearity. Because combinations of candidate factor variables with a VIF greater than 2 are suspected of multicollinearity, only one of the candidate factor variables is included in the factor analysis.

In the case of (B2) floor-area ratio of restaurant and (B6) floor-area ratio of first-floor restaurant (VIF: 2.037), we used (B6) floor-area ratio of first-floor restaurant and excluded (B2) floor-area ratio of the restaurant because the pedestrians in this study are more likely to be influenced by floor-area ratio of first-floor restaurant than floor-area ratio of the restaurant. Additionally, as for (C1) integration value (R = 400 m) and (C2) integration value (R = 1200 m) (VIF: 2.236), we used (C2) integration value (R = 1200 m) and excluded (C1) integration value (R = 400 m) because the correlation coefficient between (C2) integration value (R = 1200 m) (weekday: 0.525, holiday: 0.414) and pedestrians is greater than (C1) integration value (R = 400 m) (weekday: 0.377, holiday: 0.342).

For each number of pedestrians on weekdays and holidays, linear and negative binomial regression models were analyzed using the candidate factor variables after exclusion. In model selection, the stepwise variable increase and decrease approach was employed to select the model with the minimum AIC.

N = 332	Weekday			Holiday		
	Partial regression coefficient	Standard partial regression coefficient	P value	Partial regression coefficient	Standard partial regression coefficient	P value
Constant	7639.580			7135.664		
(A2) Street width (m)	−10.024	−0.118	0.013	−9.408	0.088	0.096
(A3) Subway entrance dummy	819.531	0.222	0.000	1076.495	0.230	0.000
(B1) Floor-area ratio of retail	1.616	0.247	0.000	3.130	0.379	0.000
(B3) Floor-area ratio of office				−0.927	−0.107	0.011
(C2) Integration value (R = 1200 m)	3.004	0.260	0.000	3.012	0.206	0.000
ln (D2) Distance from Sakae (m)	−1085.455	−0.494	0.000	−997.745	−0.359	0.000
AIC	5257.546			5493.301		
R	0.808			0.743		
MAPE	41.261			64.95		

Table 2: Result of the analysis of factors for the number of pedestrians on weekdays and holidays using a linear model.

N = 332	Weekday			Holiday		
	Partial regression coefficient	Mean standardized partial differential value	P value	Partial regression coefficient	Mean standardized partial differential value	P value
Constant	9.840			8.75		
(A1) Sidewalk dummy	0.199	0.063	0.078	0.333	0.059	0.030
(A2) Street width (m)	−0.012	−0.136	0.000	−0.016	−0.123	0.000
(A3) Subway entrance dummy	0.178	0.048	0.049	0.363	0.088	0.003
(B1) Floor-area ratio of retail	0.001	0.216	0.000	0.002	0.277	0.000
(B3) Floor-area ratio of office	0.000	0.063	0.013			
(B4) Floor-area ratio of residential	−0.001	−0.058	0.028	−0.002	−0.088	0.005
(B6) Floor-area ratio of first-floor restaurant	0.005	0.071	0.005	0.005	0.061	0.033
(C2) Integration value (R = 1200 m)	0.003	0.277	0.000	0.004	0.284	0.000
ln (D2) Distance from Sakae (m)	−0.593	−0.218	0.000	−0.434	−0.144	0.000
AIC	5001.229			5182.148		
R	0.785			0.656		
MAPE	40.915			63.310		

Table 3: Result of the analysis of factors for the number of pedestrians on weekdays and holidays using negative binomial regression.

Therefore, in linear model analysis, a five-variable model for weekdays and a six-variable model for holidays were chosen (Table 2). The variables adopted in the weekday model were on the order of increasing absolute value of the standard partial regression coefficient: ln (D2) distance from Sakae (m) (standard partial regression coefficient: −0.494), (C2) integration value (R = 1200 m) (0.260), (B1) floor-area ratio of retail (0.247), (A3) subway entrance dummy (0.222), and (A2) street width (m) (−0.118).

In the holiday model, the following parameters were used on the order of increasing absolute value of the standard partial regression coefficient: (B1) floor-area ratio of retail (0.379), ln (D2) distance from Sakae (m) (−0.359), (A3) subway entrance dummy (0.230), (C2) integration value (R = 1200 m) (0.206), (B3) floor-area ratio of office (−0.107), and (A2) street width (m) (−0.0880).

Therefore, in negative binomial regression model analysis, a nine-variable model for weekdays and an eight-variable model for holidays was selected (Table 3). The variables used in the weekday model were on the order of increasing absolute value of the mean standardized partial differential value: (C2) integration value (R = 1200 m) (partial derivative: 0.277), ln (D2) distance from Sakae (−0.218), (B1) floor-area ratio of retail (0.216), (A2) street width (m) (−0.136), and (B6) floor-area ratio of first-floor restaurant (0.071).

In the holiday model, the following parameters were used on the order of increasing absolute value of the standardised partial differential value: (C2) integration value (R = 1200 m) (0.284), (B1) floor-area ratio of retail (0.277), ln (D2) distance from Sakae (−0.144), (A2) street width (m) (−0.123), and (B4) floor-area ratio of residential (−0.088).

Both in the linear and negative binomial regression models, (C2) integration value (R = 1200 m) was adopted at 1% importance in both weekday and holiday scenarios, proposing the integration value's effectiveness as a space configuration factor for pedestrians in this study.

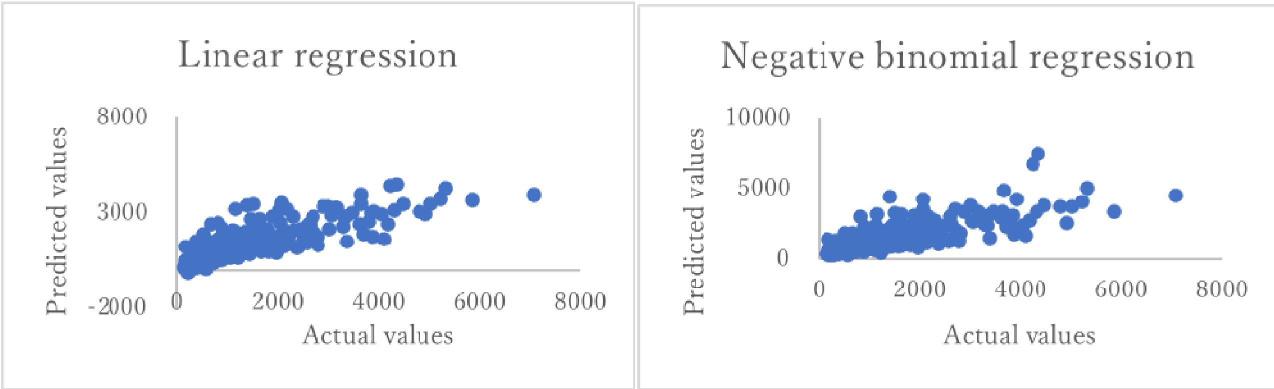

Fig. 6: Scatterplot of the predicted and actual values of the weekday model (R = 0.808, R = 0,785).

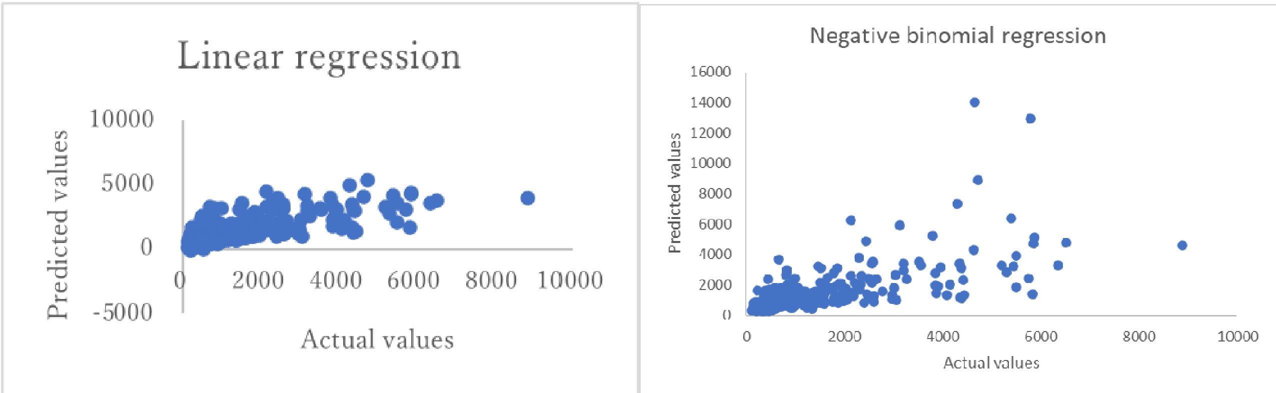

Fig. 7: Scatterplot of the predicted and actual values of the holiday model (R = 0.743, R = 0.656).

Because negative binomial regression cannot compute R^2, we used two indicators for the comparison of the two models: the mean absolute percent error (MAPE) and the correlation coefficient between predicted and actual values.

The calculation formula for MAPE is

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|$$

By comparing the linear model's findings with those of the negative binomial regression model, we discovered that the correlation coefficient between predicted and actual values was better for the linear model (weekday: 0.808, holiday: 0.743), but the MAPE was better for the negative binomial distribution model (weekday: 40.915, holiday: 63.310). The weekday model outperformed the holiday model, regardless of whether it is a linear model or a negative binomial regression

The scatterplot of the actual and predicted values (Figs. 6 and 7) depicts that although the correlation coefficient of the linear model was better for both normal and holiday, the predicted values of the linear model had negative values. Additionally, when compared with the negative binomial regression model, the linear model had a smaller predicted value, which was due to the least-squares method of minimising the sum of squares of the residuals used to solve the linear model.

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5 CONCLUSION

This study attempted to employ the mobile phone location data in the Sakae Station area as an indicator of the number of pedestrians and to investigate the factors influencing the spatial distribution of the number of pedestrians from four aspects: street attribute factors, facility volume factors, transportation accessibility factors, and space configuration factors. In the analysis, the factor structures of the number of pedestrians on weekdays and holidays were compared using linear and negative binomial regression models, and the following conclusions were obtained:

In the comparison of the AIC minimum model between the linear model and negative binomial regression model in the Sakae Station area, By comparing the distribution of the predicted values and the MAPE, we can see that the negative binomial distribution model is superior. The integration value (R = 1200) generated by segment angular analysis as a city form indicator proposes its validity as a factor for pedestrian counts in both models.

Unlike linear models, to compare factor strengths for each variable, negative binomial regression models cannot use standard partial regression coefficients. In this study, we described with an example that the mean standardised partial difference value using the mean of the standardised partial difference (mean standard partial difference) can be used to compare the strength of each factor variable in a negative binomial regression model.

The mean standardised partial differential value for the factor intensities adopted in the negative binomial regression model indicated that on weekdays, the first factor was the space configuration factor, the second factor was the transportation accessibility factor, and the third factor was the facility volume factor. On weekends and holidays, the first factor was the space configuration factor, the second factor was the facility volume factor, and the third factor was the transportation accessibility factor. However, the findings of the linear model depicted that the ranking of factor intensities was distinct from that of the negative binomial regression model: on weekdays, the first factor was the transportation accessibility factor, the second factor was the space configuration factor, and the third factor was the facility volume factor. On weekends and holidays, the first factor was the facility volume factor, the second factor was the transportation accessibility factor, and the third factor was the street attribute factor.

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