東京における自転車シェアサービスポートの時系列パターンによる分類

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Classifying Bicycle Sharing Service Stations in Tokyo by Temporal Patterns

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Abstract: This research examines the spatial and temporal usage patterns of Bicycle Sharing Services, including Docomo Bike Share and Hello Cycling, in Tokyo using high-resolution station-level data collected over one week at 15-minute intervals. The study employed Principal Component Analysis and identified four dominant temporal patterns, such as commuting peaks on weekdays and leisure flows on weekends. Three distinct clusters were identified using PCA scores for each BSS station: (i) central city residential–industrial commuter origins, (ii) downtown commercial and transit-oriented destinations, and (iii) peripheral residential and suburban local-use stations. The study found a significant association between cluster membership, land use districts, and proximity to a train station using cross-tabulation and the Chi-square test. The spatial distribution of BSS station with cluster membership was examined by mapping. This research, by linking BSS temporal demand characteristics with urban fabric, provides new insights into the integration of BSS within multimodal transport planning.

Keywords: Bicycle Sharing Service (BSS)（自転車シェアリングサービス）, Micromobility Services（マイクロモビリティサービス), Clustering Analysis（クラスタリング分析）, Spatial Analysis（空間分析）

1. Introduction

The rising population densities and rapid urbanization have exacerbated different challenges for different global megacities, such as air pollution (Deshpande & Mishra, 2007) and traffic congestion ((Busari et al., 2021). Bicycle Sharing Services (BSS), in response to these challenges, emerge as an essential component of a multimodal transportation network. This micromobility service, BSS, mitigates the “last mile” and “first mile” issue (Kealy & Wu, 2021) and promoting active transportation to reduce the dependence on private vehicles. BSS has rapidly spread worldwide and become a popular mode of micromobility services (Todd et al., 2021).

However, the efficiency and sustainability of BSS depend on understanding the spatiotemporal usage pattern (Song et al., 2024) which are dynamic and shaped by numerous urban elements. Especially investigating how demand varies temporally and distinguishing between weekday commuting peaks and weekend leisure usage is vital for optimizing BSS operations and infrastructure planning (Xu et al., 2018). The recent BSS system produce location and time specific data, which enables research on each station and the mobility behavior (Beecham & Wood, 2014).

Different studies in the past have investigated the usage pattern and demand (Kim, 2024; Toro et al., 2020; Xie & Wang, 2018) and a few of the studies used clustering to understand the type of BSS stations based on their usage on weekdays and weekends. In particular, the link between temporal demand patterns and their surrounding urban context, such as proximity to a train station and land use, remains unexplored. To address this research gap, the study is required to integrate temporal demand analysis, statistical clustering, and spatial interpretation, an approach this research adopts.

Despite the increase in the popularity of BSS, various studies have examined the temporal demand patterns of spatial station distributions. This research aims to explore the temporal pattern of individual stations on weekdays and weekends. Using 15-minute, individual BSS station data to identify distinct temporal patterns in the case of Tokyo by using two most popular BSS in Japan, Docomo Bike Share and Hello Cycling. This study also examines the statistical relationship between these clusters, proximity to train station and land use districts. Later, this research maps the BSS stations and analyzes the spatial distribution of BSS, revealing the broader urban structure of BSS usage.

2. Temporal Variation of BSS

This research utilizes open data from the bike share map website regarding BSS (Bicycle Sharing Services). For this research, data from both popular BSS Hello Cycling and Docomo Bike Share were used, comprising one week of data in

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October 2023, collected at 15-minute intervals from 7:00 AM to 11:00 PM. The data was filtered to retain valid records, and the data from both BSS services (Hello Cycling and Docomo Bike Share) were merged. Subsequently, the net bike change was calculated. The Net bike change was calculated by subtracting the number of available bikes from the previous interval using a Python Script. The Net bike change is defined as the difference in the number of available bikes at the docking station between two consecutive time intervals. If the value of the Net bike change is positive, it means more bikes were returned to the docking station than were taken. However, if the net bike change is negative, it indicates more bikes were taken from the docking station than returned.

3. Classification of BSS by Temporal Patterns (Weekdays vs. Weekends)

3.1. Methodology

This study employed Principal Component Analysis (PCA). Before running PCA, a scree plot was constructed to show eigenvalues, guiding the selection of the number of PC components. The PCA was conducted with four components to generate eigenvalues, cumulative variance, explained variance ratios, and scores for all BSS stations (IDs). The extracted PCA loadings were used in identifying peak time slots across weekdays and weekends for each PC component. Using these loadings, a loading-time plot was created for each PC component (07:15–23:00), which helped in naming them based on their behavior across time on weekdays and weekends. This research aims to determine the type of BSS stations used by Ward's hierarchical clustering based on PCA scores. A dendrogram was created, and based on linkage distance, the number for k was selected. After confirming the k value, ward clustering with a k value of 3 was employed, and a t-SNE visualization of the BSS stations in a 2-dimensional space was generated. To understand the behavioral pattern of each cluster across time on weekdays and weekends, a figure was created showing the mean net bike change of each cluster over time on weekdays and weekends (7:00 to 23:00).

3.2. Results

3.2.1. Principal Component Analysis (PCA)

Figure 1 shows the scree plot indicating a sharp decline in eigenvalue from the first to the fourth component. The scree flattening technique, also known as the elbow test, was used to select the number of components to minimize noise.

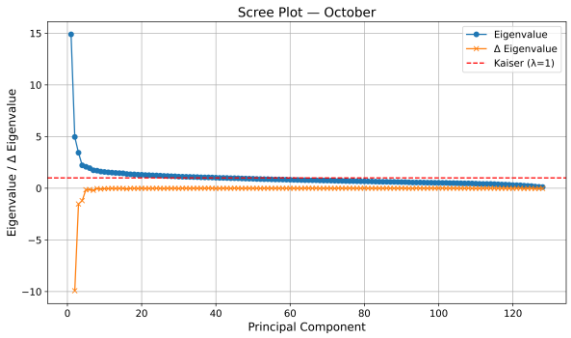


Figure 1: Scree plot for determining the number of principal components

Table 1 below shows the eigenvalues, explained variance ratios, and cumulative explained variance. Components were assigned after analyzing Figure 2, which shows the loading across time on weekdays and weekends for each component.

Table 1: PCA eigenvalues, explained variance ratios

PC	Eigen value	Explained Variance Ratio	Component Name
PC1	14.878	0.1162	Commuting Flow (AM Outflow - Inflow)
PC2	4.9589	0.0387	Morning Activity Peak and Evening Peak
PC3	3.4289	0.0268	Evening inflows and Midday outflow
PC4	2.2209	0.0173	Midday Utilization

As shown in Figure 2a, PC1 on weekdays exhibits significant negative loadings (morning peak, 7:15-9:00), indicating the start of the commute trip, and significant positive loadings (evening peak, 18:00-21:00), indicating the end of the commute trip. The pattern remains almost the same on weekends; the morning shows the start of the trip (outflow), while the afternoon and evening reflect inflows. Similarly, Figure 2b, PC2 on weekdays, captures positive loadings in the early morning (08:00 to 10:00) and late evening (20:00 to 23:00), indicating bike returns during the start and end of the day. While (17:00 to 20:00) shows a significant outflow of bikes, it shows the beginning of the last trip of the commute. On the weekend, the early morning (7:15 to 11:00) shows the outflow of trips, while the afternoon and evening trip shows the trips for leisure activities. Figure 2c shows a similar trend on both weekdays and weekends for PC3. Early morning and evening time (20:00 to 23:00) shows inflow, while negative loadings throughout the day indicate trips for daily activities. Figure 2d, PC4 on weekdays between 11:00 and 14:00 shows significant positive loading, indicating bike use for short trips during lunch

breaks or errands. On weekends, it shows a mixture of positive and negative loadings from afternoon to evening.

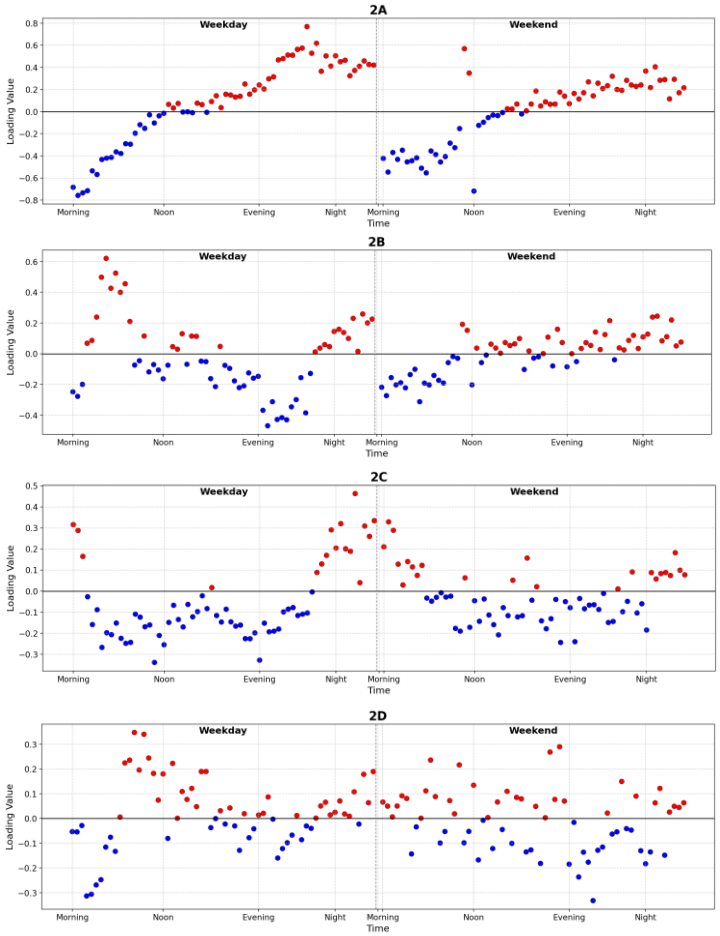


Figure 2: PCA loadings versus time on weekdays and weekends

3.2.2. Clustering Analysis

Later, Ward's hierarchical clustering method was employed using PCA scores. Based on which three distinct clusters at a meaningful linkage distance were selected. The majority of BSS stations (n = 2,750) are in Cluster 2, while Clusters 0 (n = 209) and 1 (n = 248) represent smaller but behaviorally distinct groups.

3.2.3. Cluster Visualization and Temporal Profile

Figure 3 below was created using the mean net bike change of each cluster across time intervals on weekdays and weekends. Cluster 0 on weekdays shows a significant negative mean net bike change in the morning (7:15 to 9:00) and a significant positive mean net bike change in the evening (18:00 to 21:00), confirming the commute start and end trip. Cluster 1 exhibits an opposite trend to Cluster 0, characterized by significant inflow in the early morning (7:15 to 9:00) and significant outflow in the evening (18:00 to 21:00) on weekdays and weekends. This indicates that the user commutes to work by bike, using those in cluster 0, and parks them in the station located in cluster 1. On weekends, Clusters 0 and 1 both show peaks indicating the start and end of the first trip to leisure or daily activities. While Cluster 2 indicates only slight fluctuation throughout the day or balanced inflow and outflow trips.

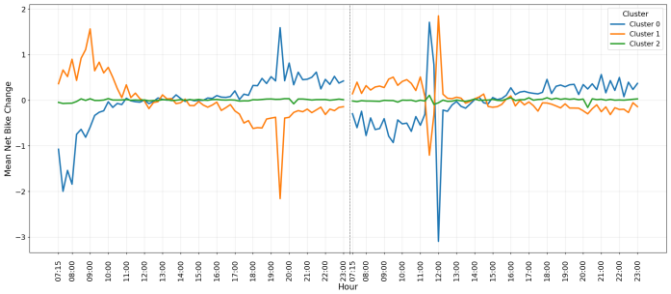


Figure 3: Mean net bike change profiles of clusters

4. Urban Spatial Characteristics of BSS Clusters

4.1. Methodology

Once assigning cluster numbers to each BSS station, cross-tabulations and Chi-Square Tests of Independence (performed in SPSS) were employed to investigate the association between cluster membership and two factors: (i) land-use district category (residential, commercial, industrial), and (ii) train station proximity (≤800 m vs. >800 m). To understand the spatial distribution of BSS across Tokyo, the final clusters with station ID were mapped using GIS as shown in Figure 5.

4.2. Results

4.3. Association of Cluster with Land Use District and Train Station Proximity

After cluster analysis, cross-tabulation, and a chi-square test were employed to confirm the statistical association between clusters and land use district categories and proximity to train stations. Figure 4 below shows the cluster membership with land-use categories and train station proximity, revealing that both factors have statistically significant associations with cluster membership (land use: $\chi^2 = 175.056$, df = 4, $p < .001$, Cramer's V = 0.165; station proximity: $\chi^2 = 25.446$, df = 2, $p < .001$, Cramer's V = 0.089). As shown in Figure 4, most stations in this cluster 0 are in Tokyo's downtown area, which explains the significant morning outflow and evening inflow on both weekdays and weekends (as shown in Figure 3). These BSS stations serve the residents of the inner city, especially those living in mixed-use areas and in proximity to a train station (as shown in Figure 4, where 82.3% of stations are within an 800m distance). Therefore, Cluster 0 is serving as the *Central City Residential-Industrial Commuter Stations*.

Cluster 1 is also situated mainly in the downtown area of Tokyo. However, it exhibits an opposite temporal trend to Cluster 0 (as shown in Figure 3), with a significant inflow in the morning (at the end of the first trip) and outflow in the evening

(at the start of the last commute trip). The analysis also revealed that 62.1% of the stations are in commercial land use districts and 89.9% within 800m proximity of the train station. This cluster serves as a *Downtown Commercial and Transit-Oriented Destination*. However, Cluster 2 is spread across Tokyo, dominating the outer edges of the Tokyo Metropolitan Area. As shown in Figure 4, most stations (52.7%) are in residential land use districts. The use of BSS stations or the inflow and outflow of Cluster 2 is lower than that of Clusters 0 and 1. This might be due to short or local trips. Cluster 2 serves as *Peripheral Residential and Suburban Local Use*.

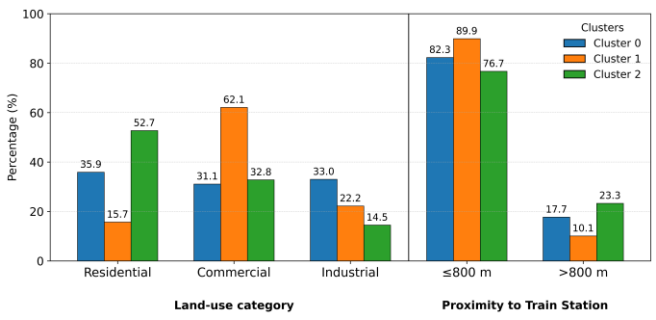


Figure 4: Cross-tabulation of clusters with land-use category and train station proximity

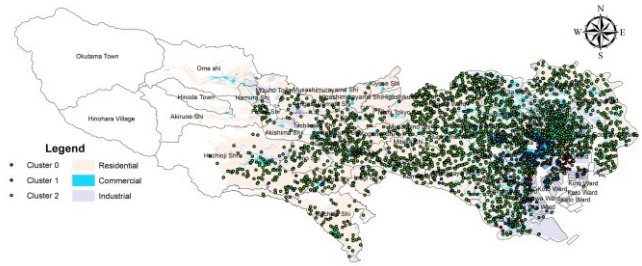


Figure 5: Spatial distribution map of BSS station across Tokyo

5. Conclusion

This research employed Principal Component Analysis (PCA), Clustering Analysis, and Chi-square test on Bicycle Sharing Service (BSS) data. PCA and clustering revealed three distinct BSS station types in Tokyo. Cluster 0 serves as a central city residential, industrial, and commuter origin. Cluster 1 serves as downtown commercial and transit-oriented destinations. Cluster 2 serves as peripheral residential and suburban local-use stations with stable, short trips.

Chi-square tests confirmed a significant relationship between clusters, land use district (residential, commercial, and industrial), and train station proximity (≤800m and >800m), while spatial mapping reinforced these patterns. These findings address a significant research gap by taking each BSS station into account and explicitly linking the temporal demand patterns of BSS stations with their urban context, including land use and proximity to transit. The data used in this research is at 15-minute intervals, meaning that some short inflow/outflow events may not be fully captured; however, the extensive coverage ensures robust and reliable results. In addition, this research utilizes data from the Autumn (October) season only; future research can compare different seasons to determine whether the BSS stations exhibit a similar pattern across different seasons on weekdays and weekends, and whether their cluster membership remains the same or changes.

References

Beecham, R., & Wood, J. (2014). Exploring gendered cycling behaviours within a large-scale behavioural data-set. *Transportation Planning and Technology*, *37*(1), 83-97.

Busari, A., Loto, R., Ajayi, S., Odunlami, O., Folake, A., Kehinde, O., & Olawuyi, O. (2021). Ameliorating urban traffic congestion for sustainable transportation. IOP Conference Series: Materials Science and Engineering,

Deshpande, A., & Mishra, P. (2007). Urbanization, air pollution and human health. *J. Environ. Res. Dev*, *1*(3).

Kealy, A., & Wu, J. (2021). Safety Challenges and Solutions in Bike-Sharing Systems. 2021 IEEE 18th International Conference on Mobile Ad Hoc and Smart Systems (MASS),

Kim, K. (2024). Discovering spatiotemporal usage patterns of a bike-sharing system by type of pass: a case study from Seoul. *Transportation*, *51*(4), 1373-1407.

Song, R., Jiang, J., & Guo, X. (2024). Analysis of Behaviour Pattern of Bicycle-sharing Users Based on Complex Network: a Case Study of Beijing Downtown Area. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 437-444.

Todd, J., O'Brien, O., & Cheshire, J. (2021). A global comparison of bicycle sharing systems. *Journal of Transport Geography*, *94*, 103119.

Toro, J. F., Carrion, D., Brovelli, M., & Percoco, M. (2020). Bikemi bike-sharing service exploratory analysis on mobility patterns. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 197-203.

Xie, X.-F., & Wang, Z. J. (2018). Examining travel patterns and characteristics in a bikesharing network and implications for data-driven decision supports: Case study in the Washington DC area. *Journal of Transport Geography*, *71*, 84-102.

Xu, X., Ye, Z., Li, J., & Xu, M. (2018). Understanding the Usage Patterns of Bicycle‐Sharing Systems to Predict Users' Demand: A Case Study in Wenzhou, China. *Computational intelligence and neuroscience*, *2018*(1), 9892134.