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Cycling the city: spatiotemporal patterns of shared bicycle use in Vienna

Introduction

According to the United Nations, almost 70% of the world's population will live in cities by 2050[1]. There is, therefore, a pressing need to rethink the ways we inhabit and interact with urban spaces, in order to make them more equitable and sustainable. One of the most prominent plans in this direction is the effort to make cities car-free or at least less car-reliant. As urban spaces adjust to accommodate more and more residents, the transportation system must also become more efficient. Part of this consists in optimising public transportation, such as trams, buses and metros. In the last few years, public bikes have also gained popularity as an alternative solution. If cost-effectiveness and accessibility are among the main incentives to use public transportation, health became a reason to switch to open-air alternatives especially during the Covid pandemic[2]. Still, the infrastructure, the cost, safety and integration with other public transportation methods need to be optimised to increase their use. This report analyses the situation regarding public rental bikes in the city centre of Vienna. It first considers the literature to identify the main "pain points" or potential issues in the system. Then, it builds a methodological framework to analyse the data. Afterwards, it assesses the results and finally concludes with discussions and recommendations.

Literature review

A study by Podgórniak-Krzykacz and Trippner-Hrabi[3], based on the Polish city of Łódź found that the main motives for using public bicycles are urban congestions when driving and delays when taking public transport. Bikes offer faster and more flexible movement, especially for shorter

[1] United Nations, Department of Economic and Social Affairs, Population Division. (2018). *68% of the world population projected to live in urban areas by 2050, says UN.* https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html
[2] Teixeira, J. F., Silva, C., & Moura e Sá, F. (2021). The motivations for using bike sharing during the COVID-19 pandemic: Insights from Lisbon. *Transportation Research Part F: Traffic Psychology and Behaviour, 82*, 378–399. https://doi.org/10.1016/j.trf.2021.09.016
[3] Podgórniak-Krzykacz, A., & Trippner-Hrabi, J. (2021). Motives and factors that determine city residents' use of public bicycles: The case of Łódź, Poland. Case Studies on Transport Policy, 9(2), 651–662. https://doi.org/10.1016/j.cstp.2021.03.003

distances. Bikes can also offer a solution to the “first and last mile” gap in public transit - namely that walking to the metro or bus stop, and from the metro to the destination adds a significant time to the commute. About a fourth of the respondents also indicated environmental motivators as part of their reason to commute with public bikes. The barriers to use mostly indicated in the study were poor cycling infrastructure and the connected safety concerns and the inability to return bikes due to full stations (in case locking into dock is necessary). It was also found that poor integration of the bike network with the public transport system negatively affects usage. Operational challenges such as empty or full bike docks, and the subsequent need to rebalance the number of bikes between stations, was also mentioned by Fishman and colleagues[4].

Another work by Karunanithi and others[5] uses machine learning to predict patterns in the demand of public bikes with a geographic focus on Seoul. They found that weather, season, and time of day are the strongest predictors of rental demand.

Another study by Teixeira and others[6], this time focusing on non-users in 5 European capital cities (Budapest, Lisbon, Rome, Vilnius, and Warsaw), equally shows that barriers to use of BSS (Bike Sharing Systems) and ESS (E-scooter Sharing Systems) was influenced more by externalities such as poor infrastructure or perceived lack of safety, than by individual choice. Spatial disparity and - namely only affluent areas being served by the bikeshare network - was also cited as a gap in the current infrastructure in a paper by Jahanshahi and others focused on Auckland[7].

Conclusively, it can be said that enlarging the user base for public bike systems relies more on the supply side than on the demand side: poor infrastructure, faulty integration with other public transit, unbalanced bike docks, climate-temporal patterns and spatial disparity. Improvements in the accessibility, infrastructure, convenience and equitability of BSS can be a way of increasing usage of public use and also inviting more and more diverse individuals to rely on this method for their daily commutes. Because of the need to analyse this phenomenon from an infrastructure and network perspective, this work aims at contributing to this effort through a location-based services (LBS) approach.

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[4] Fishman, E., Washington, S., & Haworth, N. (2013). Bike share: A synthesis of the literature. *Transport Reviews*, 33(2), 148–165. https://doi.org/10.1080/01441647.2013.775612

[5] Karunanithi, M., Chatasawapreeda, P., & Khan, T. A. (2024). A predictive analytics approach for forecasting bike rental demand. Decision Analytics Journal, 11, 100482. https://doi.org/10.1016/j.dajour.2024.100482

[6] Teixeira, J. F., Diogo, V., Bernát, A., Lukasiewicz, A., Vaiciukynaite, E., & Sanna, V. S. (2023). Barriers to bike and e-scooter sharing usage: An analysis of non-users from five European capital cities. Case Studies on Transport Policy, 13, 101045. https://doi.org/10.1016/j.cstp.2023.101045

[7] Jahanshahi, D., B. Costello, S., Natasha Dirks, K., & van Wee, B. (2024). Toward an Equitable Transport Strategy by Assessing Cycling Initiatives and Identifying Barriers to Implementing Cycling Equity Policies. *Transportation Research Record*, *0*(0). https://doi.org/10.1177/03611981241275559

Finally, the city of Vienna is chosen as a case study for this work. Laa and Emberger[8] provide a detailed history of the development of bike sharing models in the Austrian capital, offering a comparison between station-based and free-floating models. Their research highlights how Vienna's long-standing station-based system, Citybike Wien, has effectively avoided problems such as vandalism and illegal parking through strong operator oversight, user registration, and infrastructure design. In contrast, the introduction of free-floating bike-sharing schemes (FFBSS) in 2017, including operators like oBike and ofo, led to significant issues such as blocked sidewalks, poorly maintained bikes, and a general lack of accountability. These challenges prompted the city to develop and implement a comprehensive local police regulation in 2018, which imposed limits on fleet size, required local business presence, and introduced fines for non-compliance. At this moment in time, an evaluation of the current state of the BSS is due - in order to assess and potentially improve it.

With this objective, this work partly refers to an analysis by Leth and others[9], examining the relationship between Vienna's station-based bike-sharing system, CityBike Wien, and the city's well-developed public transport network to determine whether the two modes act as competitors or complements. Using a full year of operational data from over 1 million trips in 2015, the authors analyse origin-destination pairs, routing options, travel time ratios, and detour factors. They find that CityBike is most frequently used in contexts where it offers a travel time advantage over public transport—often when public transport routes are indirect or require transfers. The average travel time ratio between bike and public transport was around 0.5 to 0.6, indicating that cycling was frequently the faster option. Spatial analysis also reveals that bike-sharing is particularly popular for tangential trips or in areas underserved by direct PT routes, such as student neighborhoods or near multimodal hubs. Despite its potential to substitute for some PT trips, the authors argue that CityBike currently functions more as a supplement than a true competitor, given its relatively small share in the overall modal split and its utility in addressing local gaps in connectivity. The study underscores the role of BSS as a valuable component in integrated urban mobility, especially for enhancing last-mile connectivity and promoting flexible, low-carbon transport alternatives.

Methodology

This work is an LBS-driven analysis of the spatiotemporal dynamics of Vienna's public bike-sharing system. The objective is to build on previous work by complementing it with spatial

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[8] Leth, U., Shibayama, T., & Brezina, T. (2017). Competition or supplement? Tracing the relationship of public transport and bike-sharing in Vienna. GI_Forum, 2017(2), 137–151. https://doi.org/10.1553/giscience2017_02_s137

[9] Leth, U., Shibayama, T., & Brezina, T. (2017). Competition or supplement? Tracing the relationship of public transport and bike-sharing in Vienna. GI_Forum, 2017(2), 137–151. https://doi.org/10.1553/giscience2017_02_s137

analysis (land use, transportation nodes, POIs) and temporal analysis based on times of day; overall, it aims at highlighting imbalances and faults in the system.

The workflow begins by identifying a reliable data source for station locations and bike availability, enabling geospatial analysis grounded in real-time positioning data. For this work, the focus lies on Nextbike, the leading bike-sharing provider in Vienna. Nextbike is a service operating in numerous cities worldwide, allowing users to rent and return bicycles at designated stations using an app or terminal. Furthermore, the Nextbike API provides real-time access to system data, including station locations, bike availability, and vehicle IDs, enabling developers and researchers to analyze bike usage patterns and system performance. In the next step, a Python-based scraper was developed to collect this information through an API key, and was successfully tested on a purposive sample to ensure accuracy and consistency. Once the data extraction parameters were finalised, the final data was scraped over an extent of around 5 days and then processed and cleaned with Python. First of all, after parsing timestamps and sorting the dataset chronologically by bike number and time, we constructed a new dataset of bike movements by identifying transitions between different stations. This was done by comparing each record's current and previous station per bike, resulting in a table of journeys with defined origin, destination, departure time, and arrival time. Next, the workflow completes this data by geocoding all unique station names using the OpenStreetMap Nominatim API, retrieving latitude and longitude for each origin and destination. These coordinates are merged into the journey data to enable spatial analysis. We then prepared the data for integration into a GIS: we extracted temporal patterns by calculating trip durations and identifying features such as hour of day and day of the week from the departure timestamps. These temporal attributes can be used for plotting daily usage trends, identifying peak hours, and understanding usage behavior over the day. For network analysis, we constructed directed graphs using NetworkX, where each station is a node and trips between them form weighted edges based on frequency. This graph structure allows for exploring connectivity, station importance, and traffic flow across the network. Moreover, since our dataset exhibited significant variability—particularly in journey lengths—a new dataset without outliers was created after the initial cleaning. First, the raw dataset was indexed by origin and destination. Next, a dataset containing journeys and their corresponding lengths was compiled. The interquartile range (IQR) for journey length was then calculated, and values falling outside this range were excluded as outliers. Using the original indexing, a cleaned version of the full dataset—excluding outliers—was reconstructed. This cleaned dataset was used for all subsequent analyses.

The times of day were divided as: morning (07:00–11:00), midday (11:00–16:00), evening (16:00–20:00), and night (20:00–07:00).

The first analysis was carried out once again through Python and it examined bike stations and the number of bikes stored in relation to the capacity of the bike racks. It also looked at the spatial relations between stations with high and low occupancy. To analyze the relationship between stations with high and low occupancy, as well as their spatial relationship, global and local Moran's I spatial autocorrelations were calculated.

The capacity per bike station was extracted from the Wien Mobil bike sharing API[10]. Then, the average number of bikes per station was calculated for the complete dataset, as well as the average occupancy percentage per station. These values served as the input for the spatial autocorrelation analysis. The ESDA library for Python was used, following the method by Arribas-Bel (2019). A neighborhood based on the eight nearest neighbors was defined, and the resulting spatial weight matrix was row-standardized. The expected value and variance of Local Moran's I were taken from Sokal et al. (1988). Based on spatial autocorrelation, each grid cell was classified into one of five categories, following the method proposed by Anselin (1995):

a) High values surrounded by high values (HH)
b) High values surrounded by low values (HL)
c) Low values surrounded by high values (LH)
d) Low values surrounded by low values (LL)
e) Cells with no significance Values of LH and HL indicate spatial outliers, while values of HH and LL indicate clusters.

The same method was used to calculate a second spatial autocorrelation to determine the relationship between arrivals and departures at each station. The number of arrivals was subtracted from the number of departures, and the result was used as input to calculate the relationship between all stations. Furthermore, autocorrelation metrics were calculated for different times of day: morning, midday, evening, and night as defined before.

Once the data was prepared for spatial analysis and visualisation, it was transferred to QGIS. Our analysis examines patterns of bike rentals and returns using heatmaps, origin-destination flows, spatial autocorrelation, and density surfaces. The work defines indicators such as station popularity, average trip duration, and system balancing (supply versus demand), and explores how these vary over time—by hour, day, or season—and space, such as proximity to land use types, public transport nodes, and points of interest. Additional network analysis overlays assess accessibility and connectivity. Temporal analysis investigates peak demand periods, including rush hour and weekend trends, while spatial analysis highlights underused or overburdened stations. This work leverages both static and animated visualizations using QGIS.

[10] https://api-portal.wienerstadtwerke.at/portal/apis/2f86db5c-956e-471c-a741-041cfb0ef438/apiinfo

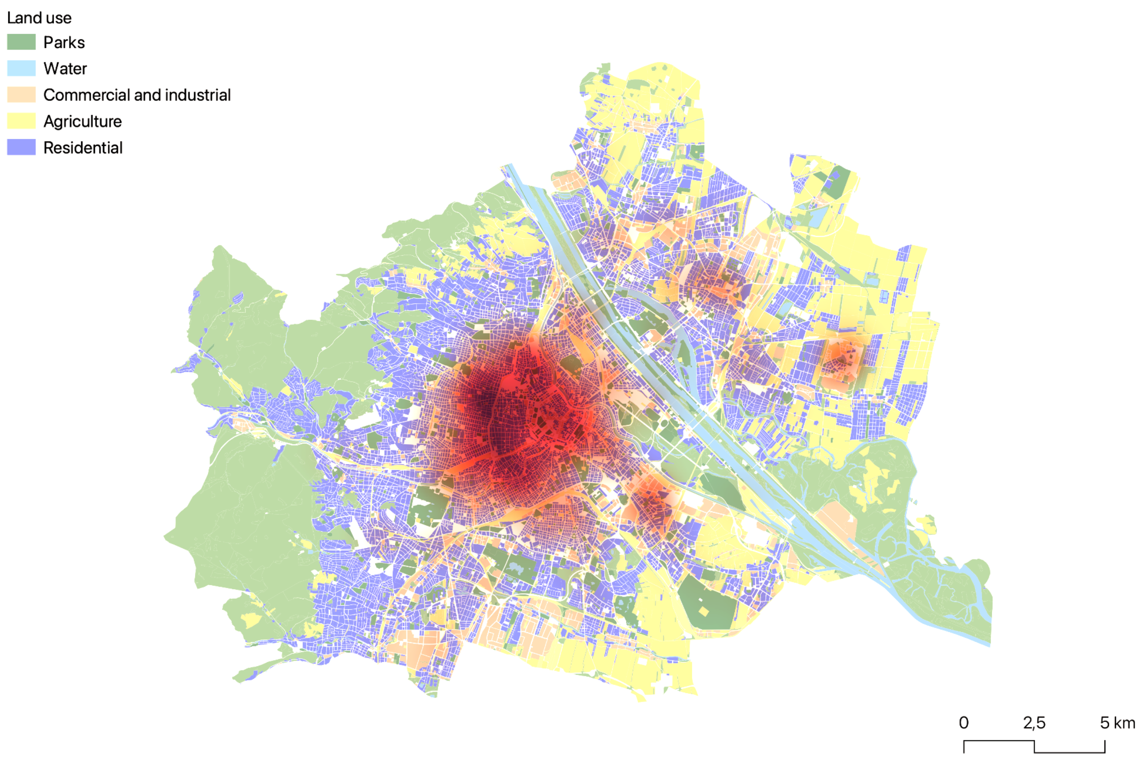
After the visualisations were finalised, results were drawn using empirical observations with a focus on land use, temporal patterns and POIs. This was also assisted by quantitative analysis with the objective of deriving complementary statistical insight from the data.

The last step of the workflow consists in the creation of an interactive interface. This expands the scope of the project beyond mere analysis and turns it into a user-friendly tool for policymakers and for the general public to explore the findings of the study. For this purpose, we utilised Streamlit, an open-source Python library designed for the rapid development and deployment of interactive web applications. On our app, users are enabled to visualize spatiotemporal patterns, trajectories, key statistics and text insights. The platform's declarative API and compatibility with common geospatial libraries like geopandas and folium facilitates the display of maps, statistical summaries, and time-of-day filtering. The product also functioned as a research aid as it facilitated the map-based drawing of empirical results.

Results and discussions

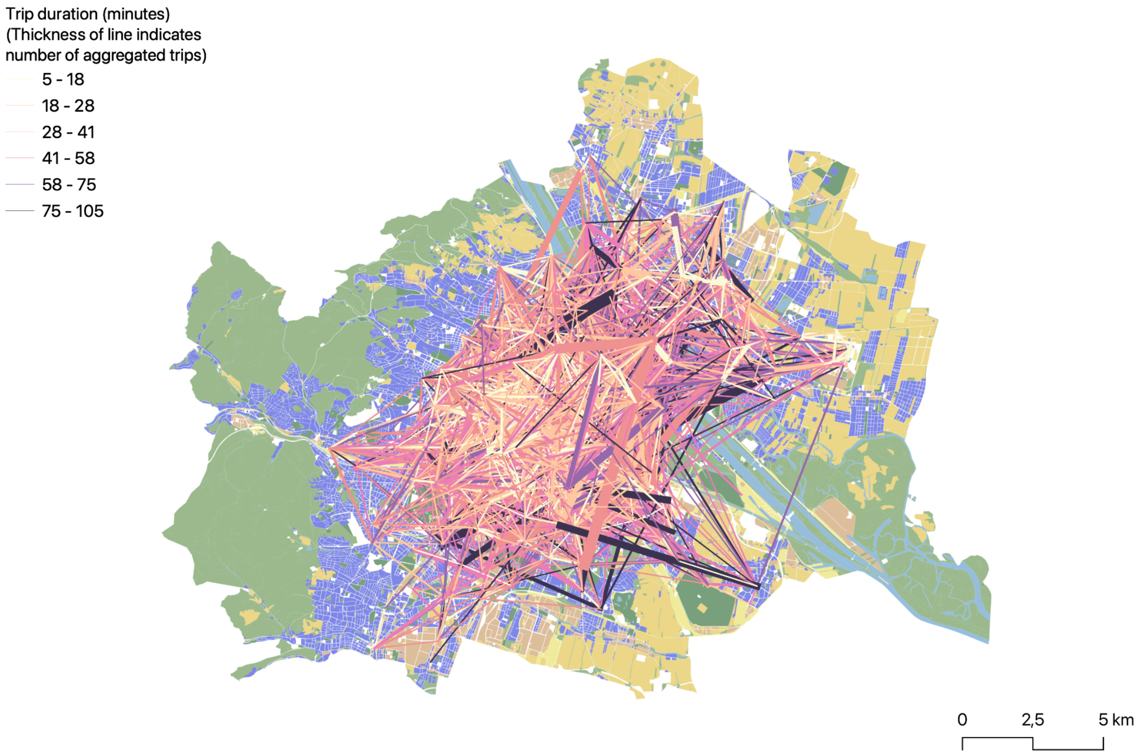
These results are drawn from observations on 254 bike share stations belonging to the NextBike network. The data was collected over a period of 8 days from May 05 to May 13, 2025. In total 20,572 trips were recorded of an average time of 32,5 minutes. On average, 109.4 trips were taken each hour, with the most trips between 16:00 and 20:00.

1. Density and network analysis: distribution of bike stations



From a first simple density visualisation using a heatmap we can notice that the spatial distribution of Vienna's public bike-sharing stations is markedly monocentric, with a strong concentration of stations within and immediately surrounding the Gürtel ring road. The visualization confirms that the central districts—particularly those encompassing Karlsplatz, Stephansplatz, and Westbahnhof—host the densest clusters of stations. Conversely, peripheral areas, especially in the southeastern and southwestern districts (e.g., Simmering, Meidling), show a thinner and more dispersed presence. A network centrality analysis (based on degree metrics of connectedness) reinforces this spatial hierarchy. Stations in the city center exhibit significantly higher centrality values, serving as primary hubs in the network. This spatial pattern suggests a hub-and-spoke structure, where central stations function as connectors, and peripheral stations serve more localized, feeder roles. Interestingly, Floridsdorf in the north shows a secondary node of moderate connectivity, while southern districts remain underserved. It appears that the bike sharing network is integrated with the public transit system, with central nodes located in the vicinity of important U-Bahn stations. This could suggest a last-mile usage of shared bikes to complete a commute or a trip between the desired destination and the closest available means of transportation.

2. Temporal and directional trends



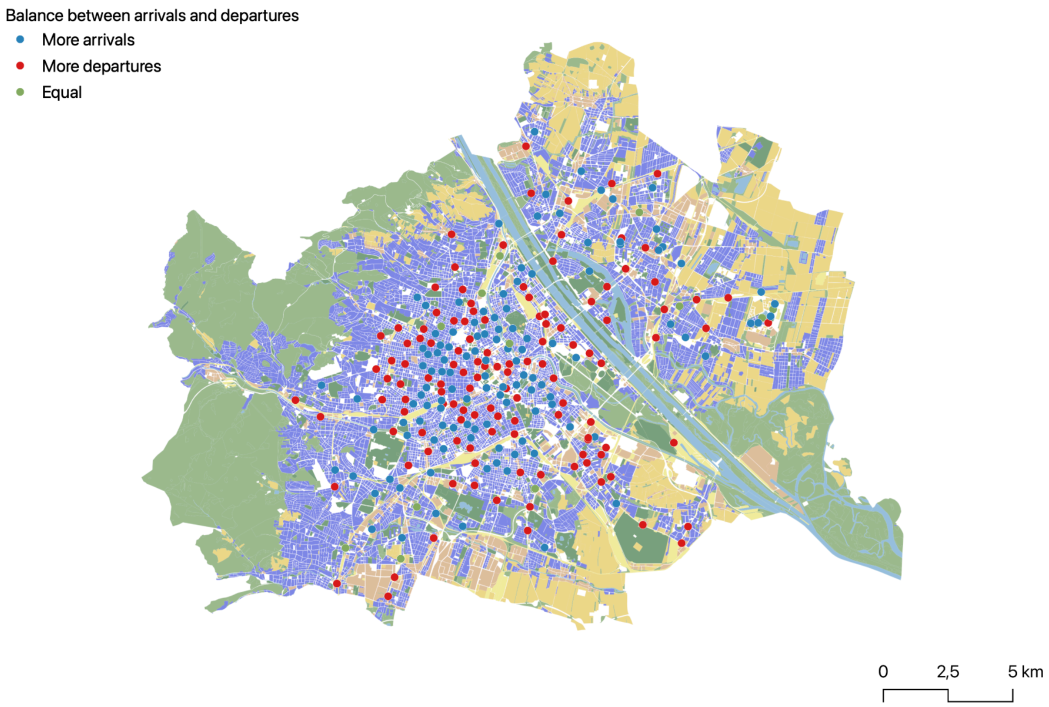
Quantitative and spatial analysis of 20,572 shared bicycle trips in Vienna reveals a highly structured, temporally rhythmic, and spatially uneven pattern of urban mobility. When disaggregated by time of day—morning (07:00–11:00), midday (11:00–16:00), evening (16:00–20:00), and night (20:00–07:00) — distinct variations in trip flow directionality, duration, and interaction with land use emerge.

Morning trips are predominantly inbound and commuting-focused, averaging 30.77 minutes in duration, with a median of 24.97 minutes and a majority of trips directed toward the central districts from residential neighborhoods such as Favoriten, Meidling, and Simmering. This clear directionality suggests commuting behavior, often linked to work or educational activities. Midday trips, by contrast, exhibit a more dispersed pattern with reduced directionality, shorter travel distances, and a mean duration of 35.23 minutes—slightly longer than the evening average but heavily influenced by outlier leisure or recreational trips, while the median remains at 29.99 minutes. These midday trips often remain within or adjacent to the central Gürtel-bound districts and include increased movement toward green recreational areas such as Prater and Schönbrunn. Evening usage, corresponding to the most spatially saturated and radial flow pattern, represents the daily peak in shared bicycle activity. During this time, trips average 34.18 minutes with a large spread (IQR: 19.9–45 minutes), reflecting outward commuting from central work and educational hubs to peripheral residential zones. At night, the network becomes more locally looped in districts within the city center, associated with nightlife and social functions (e.g., the 6th to 9th). The shortest mean duration (28.54 minutes) is observed, suggesting localized movements or return trips after public transport has ceased.

3. Spatial and land use trends

Across all time periods, trajectory analysis confirms that the central districts, particularly the Innere Stadt and those immediately along the Gürtel, function as the system's primary attractors and dispersal nodes. This monocentric structure is further supported by empirical land use classification based on origin and destination coordinates. Approximately 82% of all trips begin and end within the central urban core—a dense zone of mixed land uses including commerce, culture, education, and multimodal transit. Residential areas serve as secondary mobility anchors, accounting for 14.2% of trip origins and 13.8% of destinations, particularly influential in morning inbound and evening outbound flows. Peripheral farmland zones, primarily located in the eastern and northern edges of the city, represent only 2.3–2.4% of trip interactions, highlighting the system's strong urban dependency and lack of utility in low-density areas. Most notably, commercial and industrial zones—despite their geographic footprint and employment significance—account for just 0.1% of all origin and destination points, suggesting a misalignment between spatial economic activity and shared mobility access. This mismatch may stem from infrastructural gaps, modal preference patterns such as car or transit commuting, or sociocultural factors like shift work and cycling infrastructure deficits. Overall, the empirical results confirm that Vienna's bike-sharing system is firmly embedded in the urban center and adjacent residential districts, with limited reach into functionally important but underserved zones such as industrial peripheries.

4. Balance and efficiency of system



An analysis of station-level departures and arrivals reveals significant imbalances over time. For instance, stations near Karlsplatz, the Museumsquartier, and university campuses tend to shift roles throughout the day, experiencing more departures in the morning and more arrivals at night, reflecting their function in commuting and social activity cycles. Stations with low arrival and departure numbers tend to be on the outskirts of the city. These include the AIT Austrian Institute of Technology in the 21st district, Alterlaa in the 23rd district, and Alaudagasse in the southern part of the 10th district. The number of trips per time of day ranges from over 150 for high-frequency stations to zero for low-frequency stations.

Table xy: Selection of stations with high number of departures and arrivals, and their general trends by time of day

Station	**Status morning**	**Status midday**	**Status evening**	**Status night**
Hauptbahnhof	More arrivals	More departures	More departures	More arrivals

Karlsplatz - TU Wien	More arrivals	More arrivals	More departures	More departures
Praterstern	More departures	More arrivals	More arrivals	More departures
WU-Campus - Südportalstraße	More arrivals	More arrivals	More departures	More departures
Museumsquartier	More arrivals	More arrivals	More departures	More departures

Local autocorrelation also shows clustering of HH and LL cells in some areas. Overall, the HH clusters (11 cells total) are in the northwest, and there is one larger LL cluster (21 cells total) by the Danube in the northeast. Otherwise, there are just individual significant stations. The patterns of clusters change throughout the day. In the morning, there is a clear LL cluster in the center while some HH cells are present at the periphery. At midday, there is still an LL cluster in the center, though it is slightly more focused in the south (16 stations are LL), and there is no clustering of HH cells (7 stations total). In the evening, there are barely any clusters. At night, the LL cluster is replaced by an HH cluster in the center surrounded by several smaller LL clusters. These clusters may reflect undersupply or limited demand and highlight areas for potential infrastructure expansion.

Table xy The values Global Moran's I for the departures - arrivals

	Moran's I	**p-value**
Morning	0.14983419923635294	0.001
Midday	0.12071030937388227	0.001
Evening	0.06110375195491316	0.014
Night	0.32855028858877855	0.001
Average	0.030413847747912476	0.121

Table xy LISA of the average local morans for the departures and arrivals

Label	value
Non-Significant	161
LL	14
HH	13
HL	4
LH	2

The picture looks quite different when the capacity of bikes by bike racks per station is analyzed. The station with the highest average occupancy over the entire time frame was Gußhausstraße/Argentinierstraße with 170%. Fourteen stations had an average occupancy of more than 100%, meaning there were, on average, more bikes than static racks available per station. Only four stations had an occupancy of less than 20%. The spatial autocorrelation calculation revealed some spatial patterns in the percentage of occupancy. The results of the global Moran's I calculation were significant and indicated slight clustering with a value of 0.13. Local autocorrelation revealed a total of 14 HH cells, 13 LL cells, 4 HL cells, and 2 LH cells. One main HH cluster is visible in the eastern center, and two LL clusters are visible to the west of the HH cluster. Therefore, there are some relationships between the locations of high- and low-occupancy stations.

Table xy The values for global Moran's I for the percentage of occupancy of bikes per bike racks for each station

	Moran I	**p-value**
Morning	0.09002208226849595	0.004
Midday	0.13050851132582392	0.001
Evening	0.1388085594323936	0.001
Average	0.12613195003131283	0.001

Table xy LISA labels for local Morans for the percentage of occupancy of bikes per bike rack by station

Label	**Value**
Non-Significant	204
LL	21
HH	11
HL	10
LH	8

Implications and recommendations

Limitations

While this study provides valuable insights into the spatiotemporal dynamics of bike-sharing in Vienna, several limitations should be acknowledged:

The dataset spans only 8 days in May 2025. This short time frame limits the ability to identify seasonal trends or account for atypical events (e.g., weather anomalies, public holidays). A longer-term dataset across multiple months and seasons would yield more robust insights into long-term usage patterns.

The analysis is limited to the NextBike system and does not include data from other bike-sharing or micromobility services (e.g., e-scooters, free-floating bikes). This potentially underrepresents the full picture of shared mobility usage and limits cross-platform comparisons.

The real-time data scraping approach, while innovative, depends on API response stability and coverage. Potential gaps in data due to API downtime, inconsistent updates, or geo-ambiguities in station naming could introduce noise or bias into the dataset.

The method of reconstructing trips from sequential station records assumes that all transitions between stations reflect true user movements. However, bike relocations by maintenance crews or system balancing operations could be misclassified as user trips, especially if no metadata distinguishes them.

Additionally, all outliers were removed during preprocessing; however, given the limited context surrounding their origin, their exclusion may have influenced the results and represents a limitation of this study.

The analysis operates at the system and station level, without insight into user demographics, trip purposes, or user behavior. This restricts interpretation, particularly regarding equity and accessibility. Integrating survey data or anonymized user profiles could offer more nuanced findings.

Finally, one limitation of the spatial autocorrelation is that it was not adjusted for multiple testing. A more detailed analysis could apply a method to adjust p-values for multiple testing using a 5% significance threshold, such as the method proposed by Holm (1979).