

Evolving Patterns of Bike-Sharing Demand in Los Angeles: Spatiotemporal Trends and Planning Implications*

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Abstract

Bike-sharing systems are increasingly vital for promoting sustainable urban mobility, particularly in cities where car dependency remains deeply entrenched. In the context of Los Angeles, understanding the spatial and temporal distribution of bike-sharing demand is essential for enhancing system efficiency and supporting sustainable transportation objectives. This study aims to address existing research gaps by examining quarterly variations, seasonal trends, and neighborhood-level disparities in bike-sharing usage between 2022 and 2024.

The research employs a spatiotemporal analysis framework, utilizing Multiscale Geographically Weighted Regression (MGWR) models to capture localized patterns of demand. Through the integration of spatial clustering methods and regression analysis, the study explores how factors such as infrastructure accessibility, commuter behaviors, and seasonal dynamics influence bike-sharing adoption across the city.

The findings reveal a consistent increase in bike-sharing demand over the study period, with pronounced peaks during the spring and summer quarters. High-demand areas, including North Hollywood, Westwood, and Downtown Los Angeles, exhibit persistent spatial clustering, reflecting the role of tourism, improved station availability, and evolving mobility patterns. The results further indicate a strengthening spatial dependence in demand, suggesting a more structured and predictable network over time.

These insights contribute to advancing the understanding of urban mobility trends in Los Angeles and provide practical guidance for policymakers and urban planners aiming to optimize bike-sharing infrastructure and integrate it more effectively within the city's transportation framework.

Keywords: Sustainable Urban Mobility, Bike-Sharing Systems (BSS), Spatiotemporal Analysis, Urban Mobility Patterns, Multiscale Geographically Weighted Regression (MGWR),

Introduction

Background and Context

As cities worldwide seek to address increasing congestion, environmental concerns, and the limitations of car-dependent transportation networks, bike-sharing systems have emerged as a viable solution for promoting sustainable urban mobility (Yan & Chen, 2024). These systems provide an affordable, efficient, and environmentally friendly

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alternative to traditional transport modes, enhancing first- and last-mile connectivity, reducing carbon emissions, and encouraging active travel behaviors (Bi et al., 2024).

Los Angeles, a city historically shaped by automobile-centric infrastructure, has bike-sharing as part of its broader transportation strategy to foster a more sustainable and multimodal urban mobility framework (Cheba & Saniuk, 2016). However, despite these efforts, the temporal and spatial dynamics of bike-sharing demand remain insufficiently understood (W. Chen et al., 2023). A nuanced analysis of how bike-sharing trips fluctuate across different time periods and locations can provide critical insights for optimizing system efficiency and expanding accessibility (Link et al., 2020).

This study employs a spatiotemporal approach to analyze Los Angeles' bike-sharing system between 2022 and 2024, focusing on quarterly variations in demand and evolving spatial distribution patterns (Torrissi et al., 2021). Using Multiscale Geographically Weighted Regression (MGWR) ols, gwr, the research identifies key trends and explores the factors influencing bike-sharing usage (Grau-Escolano et al., 2024). The findings aim to support data-driven decision-making for urban planners and policymakers, ensuring that bike-sharing systems contribute effectively to sustainable urban transport strategies (Henriksson et al., 2022).

Research Significance and Gap

Although prior studies have examined bike-sharing adoption and operational efficiency, limited research has explored the interaction between temporal fluctuations and spatial distribution patterns in cities with deeply entrenched car-centric travel habits, such as Los Angeles (Zhang et al., 2021). Existing studies have primarily focused on short-term or isolated factors influencing usage trends. This research expands on these perspectives by:

- Analyzing seasonal and quarterly variations in bike-sharing demand across multiple years.
- Identifying spatial clusters of high demand and their evolution over time.
- Applying spatial regression technique (MGWR, ols, gwr) to assess localized variations in demand and key influencing factors.

By addressing these gaps, this study provides a comprehensive spatiotemporal analysis of bike-sharing demand in Los Angeles (J. Chen & Huang, 2024), offering insights that can inform infrastructure planning, optimize bike-sharing operations.

Research Objectives and Questions

This research aims to investigate the temporal and spatial dynamics of bike-sharing demand in Los Angeles between 2022 and 2024. The key objectives are:

- Analyze Temporal Variations: Identify quarterly demand fluctuations (Q1, Q2, Q3, Q4) and examine seasonal trends over the study period.
- Examine Spatial Distribution Patterns: Assess the geographic distribution of bike-sharing trips and how usage patterns evolve over time.
- Investigate the Impact of Seasonal Trends: Determine the influence of seasonal variations on bike-sharing demand.
- Assess Neighborhood-Level Differences: Explore spatial and temporal disparities in bike-sharing adoption across different neighborhoods in Los Angeles.

To achieve these objectives, the study addresses the following research questions:

1. How does the temporal distribution of bike-sharing trips vary across different quarters (Q1, Q2, Q3, Q4) between 2022 and 2024?

2. What are the spatial distribution patterns of bike-sharing trips in Los Angeles, and how do they evolve over time?
3. How do seasonal variations impact the demand for bike-sharing services?
4. Are there significant spatial differences in bike-sharing usage patterns across Los Angeles neighborhoods?

By answering these questions, this study provides actionable insights to enhance bike-sharing system planning, infrastructure allocation, and policy development, ensuring that bike-sharing remains a sustainable and effective component of urban mobility in Los Angeles (Froehlich et al., 2009).

Literature Review

Refined Literature Review (Aligned with Research Objectives & Questions)

This study applies the Technology Acceptance Model (TAM) and Behavioral Theories (BT) to explore how bike-sharing system demand mediates the relationship between sustainable transportation attitudes and urban planning in Los Angeles (Pan et al., 2023). These frameworks provide a theoretical foundation for analyzing spatial and temporal variations in bike-sharing system usage, quarterly demand fluctuations, and neighborhood-level adoption trends—core aspects of this research (G. Chen & Wei, 2024).

TAM, developed by Davis (1989), identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as key determinants of technology adoption (Samaradiwakara & Gunawardena, 2014). In the context of bike-sharing systems, PU reflects how effectively bike-sharing improves mobility and reduces transportation costs, while PEOU pertains to ease of access, station availability, and user experience. These factors directly align with the research objective of analyzing temporal variations in bike-sharing usage (Q1–Q4) and identifying the key factors influencing adoption patterns in different neighborhoods.

Similarly, Ajzen's (1991) Theory of Planned Behavior (TPB) suggests that attitudes, subjective norms, and perceived behavioral control predict individual behavior. Applied to bike-sharing systems in Los Angeles, this model helps assess how societal norms, accessibility concerns, and environmental attitudes shape bike-sharing demand across different timeframes and locations. As public attitudes toward sustainable transportation evolve, bike-sharing demand fluctuates accordingly, impacting spatial distribution patterns (Jin & Sui, 2024). These insights directly address the research questions on seasonal demand shifts and neighborhood-level variations in bike-sharing system usage (Chen, He, et al., 2023).

Limitations & Justification for Integrated Approach

While TAM and TPB are widely used in mobility research, both models have limitations. TAM does not fully consider external environmental factors, such as urban sprawl, congestion, and socioeconomic disparities—key challenges in Los Angeles' car-centric infrastructure (Chen et al., 2011). Likewise, TPB focuses more on behavioral intentions rather than actual bike-sharing system usage patterns, limiting its ability to predict real-world demand fluctuations (Tru & Ngoc, 2024). Addressing these gaps, this study integrates TAM and BT with spatial-temporal modeling (MGWR) to assess both behavioral and infrastructural factors influencing bike-sharing adoption in Los Angeles (Jaber & Csonka, 2023).

By integrating behavioral theory with spatial-temporal analysis, this study provides data-driven recommendations to enhance bike-sharing system accessibility, optimize station placement, and improve urban mobility in Los Angeles' evolving transportation landscape (Lindenau & Böhler-Baedeker, 2014).

Methodology

Research Design and Framework

This study employs a quantitative approach, utilizing spatiotemporal analysis and regression modeling to examine bike-sharing system demand in Los Angeles from 2022 to 2024. The Technology Acceptance Model (TAM) and Behavioral Theories (BT) serve as theoretical frameworks for understanding how bike-sharing adoption is influenced by seasonal variations, spatial distribution, and urban infrastructure (Lu et al., 2023).

TAM evaluates the perceived usefulness and ease of use of bike-sharing systems, while BT examines behavioral and societal influences on transportation choices (Davis, 1989; Ajzen, 1991). Integrating these frameworks with spatial regression model (MGWR) allows for a comprehensive assessment of how bike-sharing demand fluctuates across different quarters and neighborhoods in Los Angeles (Calabr'o et al., 2022).

Data Collection and Analysis

Data Sources

This study relies on publicly available secondary data from Los Angeles' bike-sharing system, covering the period from 2022 to 2024. This timeframe was selected to avoid distortions caused by the COVID-19 pandemic, ensuring that the data reflects normalized trends in bike-sharing usage (Teixeira et al., 2023).

The dataset includes:

- Trip Data: Start and end times, trip duration, station locations, and trip frequency.
- Usage Patterns: Aggregated data on usage trends across different quarters and neighborhoods.
- Spatial Data: Geographic distribution of trips across different neighborhoods and station density.
- Environmental Data: Seasonal variations.

These data elements are analyzed to identify spatiotemporal trends in bike-sharing demand and assess variations in adoption across different neighborhoods and timeframes.

Analysis Tools and Techniques

Python is used for data processing, analysis, and visualization, with specific techniques including:

- Temporal analysis
 - refers to the examination of data over time to identify trends, patterns, and variations across different time periods.
- Spatial Analysis
 - Assesses trip density, spatial clustering, and variations in bike-sharing adoption across Los Angeles' neighborhoods.
- Regression Models (MGWR)
 - MGWR (Multiscale Geographically Weighted Regression): Provides a refined analysis by considering multi-scale variations across different neighborhoods.

These techniques allow for a detailed assessment of the spatial and temporal factors influencing bike-sharing system demand in Los Angeles.

Inclusion and Exclusion Criteria

Inclusion Criteria

- Publication Date: Only data from 2022 to 2024 is included to ensure relevance and accuracy.

- **Geographic Scope:** The study focuses exclusively on Los Angeles, as its large-scale urban mobility challenges make it an ideal case for analyzing bike-sharing system adoption.
- **Usage Data:** Includes trip frequency, station locations, and seasonal usage patterns to assess mobility trends.

Exclusion Criteria

- **Pandemic Data (2020–2021):** Excluded to avoid distortions caused by COVID-19-related shifts in transportation behavior.
- **Irrelevant Variables:** Data unrelated to bike-sharing usage, such as public transit ridership without bike-sharing integration, is excluded.

Study Scope and Contribution

The findings will inform bike-sharing system optimization, urban planning strategies, and infrastructure improvements in Los Angeles. By applying spatiotemporal analysis and regression modeling, this study contributes to the growing body of research on sustainable urban mobility solutions.

The map of Los Angeles has been included to provide a clear visual representation of the city's geography and to illustrate where bike-sharing usage is most concentrated. This visualization enhances the understanding of spatial demand patterns, allowing for a more precise analysis of high-usage areas and their relationship to infrastructure, urban mobility trends, and accessibility factors. By incorporating a spatial perspective, this study effectively contextualizes the geographic distribution of bike-sharing demand, supporting data-driven insights for urban planning and policy development.

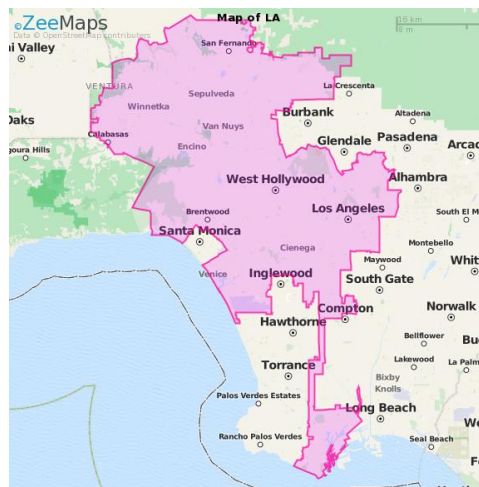


Fig 1. A map of Los Angeles

Temporal Distribution Analysis of Bike-Sharing Demand (2022–2024)

To understand the temporal dynamics of bike-sharing demand, we divided the data into quarters for each year (2022–2024), aligning with the four seasons: Winter (Q1), Spring (Q2), Summer (Q3), and Autumn (Q4). This segmentation provides a clear visualization of seasonal trends and cross-year variations, helping to identify peak usage periods and potential external influences on ridership patterns.

Quarterly and Seasonal Patterns

2022: The data shows a steady increase in demand from Winter (Q1) to Autumn (Q4), with October reaching the highest usage (33,900 trips). While Q3 (Summer) saw significant growth, a decline in December (23,000 trips) suggests a seasonal drop in ridership.

2023: A sharp increase in bike-sharing demand is evident across all quarters compared to 2022. Spring (Q2) and Summer (Q3) recorded the highest growth, with September reaching 49,000 trips. The peak occurred in October (50,100 trips), reinforcing Autumn as a high-demand season. This suggests improved public awareness, infrastructure expansion, or favorable weather conditions sustaining higher ridership.

2024: Demand continued its upward trend, with Spring (Q2) and Summer (Q3) maintaining strong volumes. However, Winter (Q1) showed a remarkable rise compared to previous years (January: 33,900 trips vs. 23,500 in 2023), indicating increasing year-round adoption. Despite an overall upward trend, a notable drop in Q4 (December: 31,500 trips) suggests a seasonal effect or external disruptions.

Cross-Year Trends and Observations

Across all three years, Spring and Summer consistently showed increasing ridership, highlighting weather's impact on bike-sharing demand. Additionally, Q4 peaks in 2023 and 2024 suggest growing user adoption, even in traditionally lower-demand months. While seasonal effects remain influential, the data suggests a long-term increase in bike-sharing acceptance and potential infrastructure improvements enhancing accessibility. This temporal distribution analysis provides insights into shifting usage patterns, setting the stage for further exploration of external and behavioral influences.

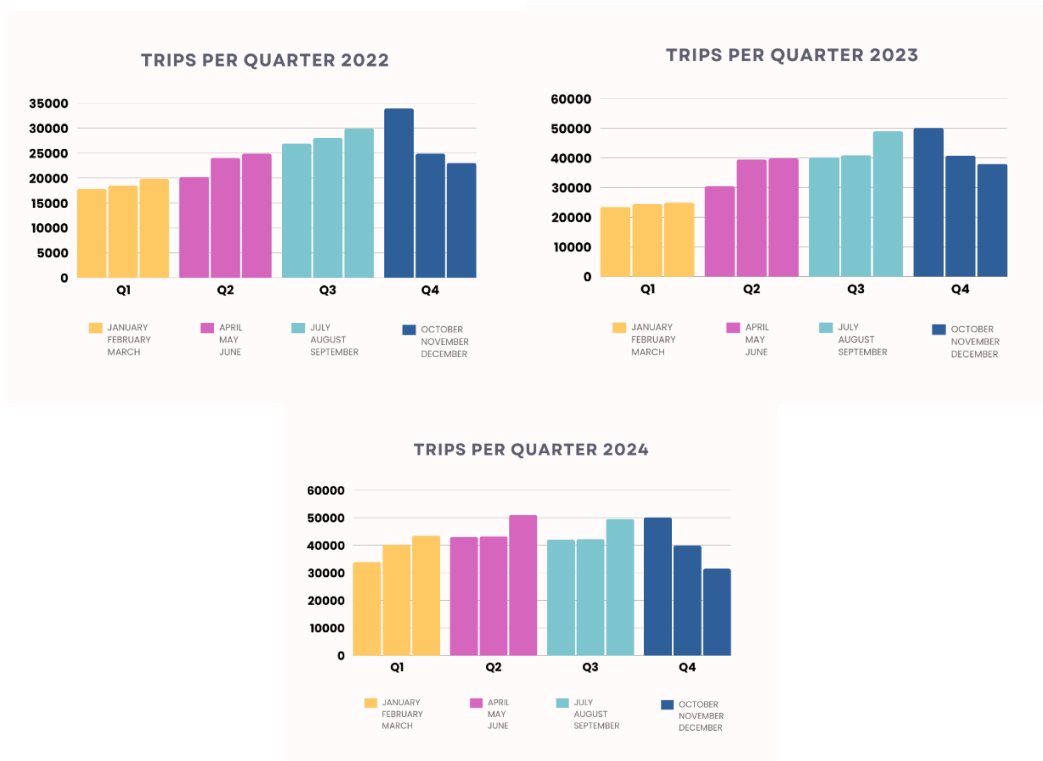


Fig 2. Temporal Distribution Analysis of Bike-Sharing Demand (2022 – 2024)

MGWR Model Analysis and Spatial Interpretation (2022–2024)

The Multiscale Geographically Weighted Regression (MGWR) model was applied to examine the spatial heterogeneity of bike-sharing demand in Los Angeles from 2022 to 2024. By analyzing quarterly trends, this study identifies key demand clusters and spatial dependencies, providing insights into how bike-sharing adoption varies across different urban regions. MGWR allows for localized coefficient estimation, enabling the identification of areas where bike-sharing demand is influenced by infrastructure, accessibility, and seasonal changes.

The analysis focuses on arrival locations, recognizing that demand is not uniformly distributed across the city. High-usage areas such as North Hollywood, Westwood, and Downtown Los Angeles consistently exhibit significant clustering. To improve spatial representation, K-Nearest Neighbors (KNN) clustering was applied to refine demand segmentation, and spatial dependence was further evaluated using Moran's I, AICc, and R² statistics. These measures assess the spatial autocorrelation of bike-sharing trips and the model's explanatory power across different time periods.

Data Preprocessing and Model Implementation

The dataset initially contained all bike-sharing trip records without pre-filtering variables. However, preliminary analysis indicated that some quarters and years exhibited 100% backfitting, suggesting an overfitting issue. Backfitting refers to the iterative process of refining model parameters until they align with observed data patterns. While high backfitting values can indicate strong model performance, a perfect 100% suggests redundancy in variable selection, necessitating data refinement.

To ensure robustness, data cleaning and transformation were performed, including the removal of null values and outliers that could distort model accuracy. The trip duration variable was standardized, and date-time variables were reformatted to enhance temporal precision. Additionally, categorical variables were converted to numerical formats, ensuring consistency in spatial regression analysis.

To improve spatial modeling, KNN clustering was employed, with multiple trials using 6, 10, and 15 clusters. The final selection of 15 clusters provided the most accurate representation of spatial demand distribution, balancing local granularity with regional trends. MGWR models were then trained over 200 iterations per quarter, refining spatial coefficient estimation and improving model accuracy.

Quarterly MGWR Results and Spatial Dependence Analysis

2022: Initial Trends and Spatial Distribution

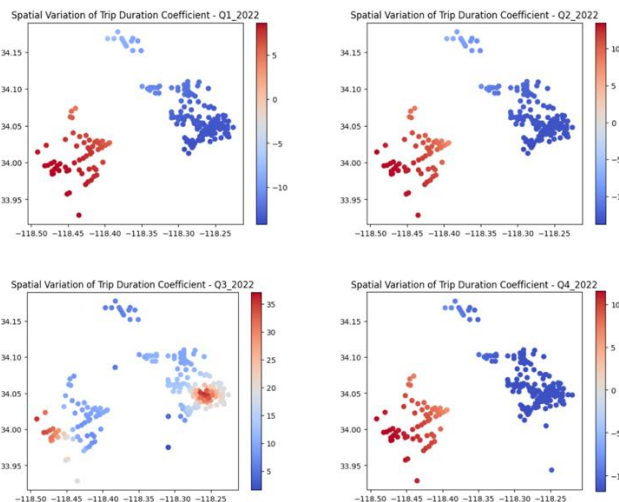


Fig 3. Initial Trends and Spatial Distribution

In the first quarter of 2022, the Moran's I value of 0.1773 with a p-value of 3.79e-28 suggests moderate spatial clustering, particularly in high-traffic areas. The R² value of 35.1% indicates that while spatial factors influenced demand, external variables such as weather and commuter behavior may also contribute. In the second quarter, the Moran's I decreased to 0.1614, with an R² of 22.5%, reflecting a decline in spatial dependence, likely due to increased variability in ridership patterns as weather conditions improved.

During the third quarter, spatial autocorrelation was highest (Moran's I = 0.2449, R² = 43.7%), reinforcing the impact of tourism and outdoor activity on bike-sharing demand. This period corresponded with peak ridership in areas near coastal and entertainment districts. The fourth quarter recorded a Moran's I of 0.1803, with demand shifting towards business districts, reflecting increased commuter-based usage.

2023: Strengthening Spatial Dependence

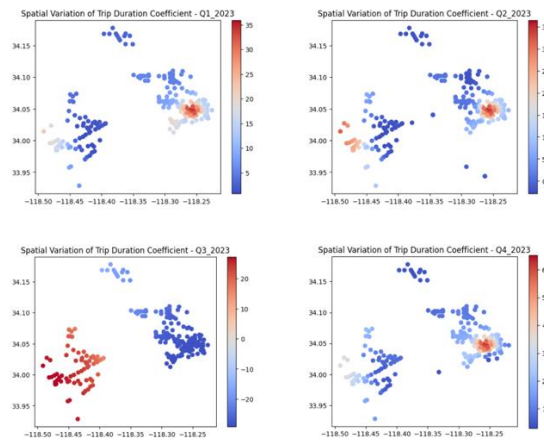


Fig 4. Strengthening Spatial Dependence

In 2023, spatial clustering increased across all quarters, as indicated by higher Moran's I values compared to 2022. The first quarter recorded a Moran's I of 0.1944 and an R² of 37.4%, showing a more structured distribution of demand. By the second quarter, spatial correlation increased further to 0.2362, with an R² of 39.8%, suggesting improved station accessibility in high-demand areas.

The third quarter exhibited a slight decline in Moran's I to 0.1786, potentially reflecting more dispersed bike-sharing usage across the city. However, the fourth quarter recorded the highest spatial clustering (Moran's I = 0.2053, p-value = 1.99e-38), reinforcing autumn as a period of sustained bike-sharing adoption, particularly for commuters.

2024: Enhanced Model Performance and Spatial Predictability

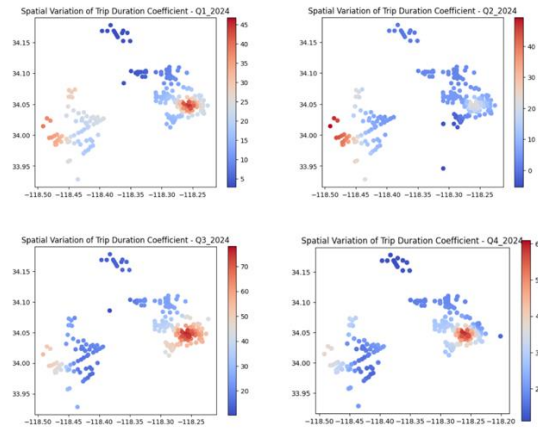


Fig 5. Enhanced Model Performance and Spatial Predictability

By 2024, the MGWR model demonstrated stronger spatial predictability, with higher Moran's I values and R^2 scores compared to previous years. The first quarter recorded a Moran's I of 0.2038 and an R^2 of 44.3%, showing improved spatial clustering and better model fit.

In the second quarter, R^2 peaked at 49.6%, indicating that spatial factors became the dominant predictors of bike-sharing demand. The third quarter recorded the highest spatial clustering (Moran's I = 0.2612), reinforcing the impact of summer ridership trends in coastal and tourism-driven regions. The fourth quarter maintained high spatial dependence, with demand shifting towards business hubs as commuter usage increased.

Cross-Year Comparison and Spatial Trends

Across all three years, Moran's I values showed a consistent upward trend, indicating that bike-sharing demand became more geographically clustered over time. This aligns with infrastructure expansions, improved station planning, and increased ridership adoption in key areas. The R^2 values also increased annually, reflecting stronger spatial predictability and more structured demand patterns.

Seasonal variations remained a critical factor in shaping demand. The third quarter consistently exhibited the highest spatial clustering, reinforcing the influence of tourism and recreational activity during summer months. In contrast, the fourth quarter demonstrated a shift toward commuter-oriented demand, particularly in business districts and high-density employment areas.

The declining AICc values across the years indicate improved model efficiency, suggesting that spatial predictors of bike-sharing demand became more stable and reliable. The increasing correlation between station locations and trip arrivals suggests a shift toward a more structured and predictable bike-sharing network.

Discussion: Bike-Sharing Systems: Environmental Benefits, Usage Trends, and Urban Planning Considerations

Bike-sharing systems have emerged as an environmentally sustainable and efficient mode of urban transportation, reducing carbon emissions and easing traffic congestion. As a climate-smart strategy, bike-sharing promotes low-carbon mobility and serves as a viable alternative to private vehicles, particularly in densely populated cities facing transportation challenges such as congestion, pollution, and last-mile connectivity issues. The system is primarily used for short commutes, often within neighborhoods, providing convenient transportation for residents and visitors. In Los Angeles, the Metro Bike Share system operates across Downtown LA, Hollywood, North Hollywood, and the Westside, allowing easy access to bicycles for short, localized trips. The system complements existing public transit options, encouraging a shift toward non-motorized transport and contributing to a more sustainable urban environment (Ye et al., 2024).

The success of bike-sharing in urban centers aligns with findings from international studies highlighting the role of bike-sharing in improving mobility and accessibility (Mahajan & Argota Sánchez-Vaquerizo, 2024). In developing cities such as Chennai, bike-sharing has been analyzed for its potential to alleviate congestion, reduce pollution, and enhance transportation efficiency (Patel et al., 2020). Factors such as weather, trip characteristics, and infrastructure availability influence ridership patterns, demonstrating the importance of data-driven decision-making in optimizing bike-sharing networks. In cities with high congestion, such as Surat, bike-sharing has been proposed as a practical solution for improving mobility in central business districts, where space constraints limit the expansion of traditional transport infrastructure (Patel et al., 2020). The integration of public bicycle-sharing systems in dense urban environments has been shown to enhance livability, reduce short-term parking demand, and support pedestrian-friendly infrastructure.

The spatial and temporal analysis of bike-sharing in Los Angeles reveals that demand is heavily concentrated in high-activity areas such as North Hollywood, West Hollywood, and Downtown Los Angeles, where accessibility and infrastructure support consistent ridership (Paterson, 2014). The Multiscale Geographically Weighted Regression model applied in this study confirms that bike-sharing demand is becoming more spatially structured, with increased clustering in high-usage areas (Zhou et al., 2024). The increasing Moran's I values indicate that spatial predictors have become more dominant, reflecting improved infrastructure planning and user adoption over time (Ngeni et al., 2024).

From a behavioral perspective, the Technology Acceptance Model and the Theory of Planned Behavior provide insight into bike-sharing adoption trends. The Technology Acceptance Model suggests that perceived usefulness and ease of use influence adoption patterns (Davis, 1989), with seasonal trends reflecting higher ridership during spring and summer when weather conditions are favorable. Infrastructure improvements further enhance ease of use, contributing to higher ridership during peak commuting periods. The Theory of Planned Behavior explains adoption through attitudes, social norms, and perceived behavioral control, indicating that the rise in year-round demand, particularly in the first quarter of 2024, reflects an increasing perception of bike-sharing as a reliable, everyday commuting option rather than a seasonal alternative (Naumov et al., 2021).

The findings reinforce the importance of data-driven urban planning in optimizing bike-sharing systems (Fazio et al., 2021). City planners and policymakers must focus on station placement, infrastructure expansion, and accessibility enhancements to sustain and increase ridership. As bike-sharing becomes an integral component of sustainable urban mobility, future research should incorporate socioeconomic variables and policy interventions to refine demand predictions and improve the spatial efficiency of bike-sharing networks (Sun & Ertz, 2020).

Conclusion

This study provides a comprehensive spatiotemporal analysis of bike-sharing demand in Los Angeles from 2022 to 2024, revealing significant insights into its temporal variations, spatial distribution, and influencing factors (Tian et al., 2023). The findings confirm that bike-sharing demand is not uniform across time and space, with seasonal fluctuations and geographic clustering shaping its adoption (Zhao et al., 2022). High-demand areas, including North Hollywood, Westwood, and Downtown Los Angeles, consistently exhibited strong spatial clustering, highlighting the impact of infrastructure availability, accessibility, and commuting behavior (Ma et al., 2023).

The Multiscale Geographically Weighted Regression model confirmed increasing spatial dependence over time, as reflected in rising Moran's I values (Chen et al., 2023). This suggests that bike-sharing demand in Los Angeles has become more structured, with stronger correlations between station locations and ridership trends. The observed increase in year-round demand, particularly in winter months, indicates that bike-sharing is evolving from a seasonal mode of transport to an integral component of urban mobility (Carrese et al., 2021). This shift can be attributed to improved infrastructure, public awareness, and behavioral adaptation, as explained through the Technology Acceptance Model and the Theory of Planned Behavior.

From a policy and urban planning perspective, the results emphasize the need for data-driven decision-making in optimizing bike-sharing networks. Strategic station placement, infrastructure expansion, and integration with existing transit systems will be crucial in sustaining growth and improving accessibility. The study highlights the importance of seasonal demand forecasting and spatial optimization, ensuring that bike-sharing systems remain efficient, inclusive, and aligned with the city's long-term sustainability goals (Qiu & He, 2018). Future research should explore

external socioeconomic and policy variables to refine demand predictions and further enhance the spatial and temporal efficiency of bike-sharing systems in urban environments (Dill et al., 2022).

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Appendix

Quarter	Moran's I	P-Value	AICc	R ²
2022 – Q1	0.177324	3.797573e-28	3052.066275	0.351267
2022 – Q2	0.161396	1.156313e-23	3188.362930	0.224776
2022 – Q3	0.244952	4.234021e-30	3348.776921	0.437355
2022 – Q4	0.180307	1.065603e-29	3296.605050	0.207025
2023 – Q1	0.194446	7.343131e-34	3178.383456	0.373756
2023 – Q2	0.236211	9.965514e-29	3495.337385	0.397825
2023 – Q3	0.178575	3.728284e-29	3564.881146	0.226990
2023 – Q4	0.205308	1.997452e-38	3508.568316	0.378230
2024 – Q1	0.203818	1.332816e-37	3416.680683	0.442782
2024 – Q2	0.176605	2.000081e-29	3565.414001	0.496143
2024 – Q3	0.261203	2.984743e-34	3560.717760	0.466616
2024 – Q4	0.185632	1.736488e-31	3419.718604	0.432047

Fig 6. Quarterly MGWR Model Performance and Spatial Autocorrelation