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ANALYSIS OF SHARED BICYCLE TRAFFIC FLOW AND TRAVEL CHARACTERISTICS AT A UNIVERSITY BASED ON THE ARIMA MODEL

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Abstract: To address the uneven spatiotemporal distribution of shared bicycles on university campuses, peak-hour congestion, and insufficient dispatch efficiency, this study targets Guangxi University, aiming to optimize scheduling through demand forecasting. Innovatively integrating univariate and multivariate analyses, it resolves bicycle dispatch challenges while examining student behavioral patterns. Initially, a GAM model revealed that daily rainfall explained 90.08% of ridership variation, with demand exhibiting an exponential decline when precipitation exceeded 8mm. Subsequently, an ARIMA(3,0,0) model confirmed temporal periodicity, and spatial analysis identified academic zones and campus gates as high-demand hotspots. Finally, comparative evaluation of Poisson regression, OLS, and XGBoost multivariate models demonstrated Poisson regression's superiority for daily predictions, while OLS outperformed in hourly forecasting. Conclusions underscore the strong periodicity and weather sensitivity of campus bicycle demand, affirming that precise forecasting enhances dispatch efficacy. Future work should incorporate variables like class schedules to refine the model, providing a methodological framework for intelligent shared-bicycle management in higher education institutions.
Keywords: Shared bicycles; ARIMA model; Multi-factor analysis; Regression prediction

1 INTRODUCTION

Due to factors such as the continual expansion of enrollment in Chinese universities and the construction of new campuses, the area of university campuses has been increasing, leading to a rise in the on-campus travel distance for teachers and students to 2.3 km [1]. Before the advent of shared bicycles, students relied on purchasing private bikes to meet their on-campus transportation needs. However, private bicycles came with significant drawbacks: high upfront costs, vulnerability to theft, difficulties in maintenance after damage, and the proliferation of "zombie bikes" (abandoned bicycles left unused after graduation) [2].

The emergence of the sharing economy and the growing advocacy for low-carbon transportation led to the introduction of the first campus-based shared bicycle system at Peking University in 2014. This initiative pioneered the dockless shared bicycle model, offering a more convenient and efficient mobility solution for students and faculty. To prevent shared bicycles from flowing off-campus, universities implemented a closed-loop operational model in 2016, restricting bike usage within campus boundaries. By 2017, as the dockless model gained widespread adoption, a surge of off-campus shared bicycles began entering campuses uncontrollably. This resulted in random parking, occupancy of public bike zones, and severe disruptions to campus cleanliness and order, prompting some universities to impose complete or selective bans on shared bicycle access [3].

Today, while most universities have established on-campus dockless shared bicycle services with high usage rates, the closed-loop management model has gradually become the dominant trend.

However, frequent media reports of issues such as "malfunctioning bikes piling up in corners," "students privately locking shared bikes," "bike shortages during peak hours," and "disorderly parking" reveal that despite their convenience, shared bicycles have introduced a range of challenges: (1) Uneven spatiotemporal distribution of shared bicycles, leading to unmet demand among students; (2) Congestion and traffic accidents in high-demand areas (e.g., near teaching buildings during class transitions) due to narrow bike lanes and mixed traffic with motor vehicles; (3) Insufficient parking space, resulting in shared bicycles occupying public areas; (4) Aesthetic and environmental degradation caused by disorderly parking; (5) Resource wastage from excessive bike deployment due to inadequate dispatching capabilities. Consequently, developing a scientific and accurate demand prediction model for shared bicycles has become essential to address these issues.

While existing studies have primarily focused on analyzing shared bicycle demand at the urban or provincial scale—often with broad geographic coverage—there remains a notable gap in research specifically addressing the unique challenges faced by individual universities. Currently, no universally applicable research framework has been established to tackle shared bicycle demand issues across diverse campus environments.

Furthermore, the majority of Chinese studies rely on questionnaire-based data collection methods, which often lack the granularity and reliability of empirical data. This limitation can lead to discrepancies between research findings and real-world conditions.

To bridge this gap, this study employs multiple models—including Poisson regression, polynomial regression, and XGBoost—to analyze shared bicycle traffic flow and travel behavior patterns on university campuses. By collecting field data to identify high-demand hotspots, this study systematically compares the performance of these models to determine the optimal solution for predicting bicycle demand in typical high-traffic areas. This approach is critical for achieving accurate demand forecasting, optimizing bike redistribution strategies, and analyzing student mobility behavior.

The insights gained from this research will provide a data-driven foundation for improving shared bicycle management systems on campuses nationwide, addressing the core challenges of supply-demand imbalance while enhancing the sustainability and efficiency of campus transportation networks.

This study focuses on dockless shared bicycles within the campus of Guangxi University. This study collected empirical data through a combination of on-site field surveys and internet-based methods. By identifying high-demand hotspots based on this dataset, it developed a demand prediction model optimized for maximum accuracy. The proposed model aims to improve bike redistribution efficiency, ensuring optimal utilization of each shared bicycle to meet students' riding demands and alleviate the "hard-to-find bikes" problem. Simultaneously, its analysis of the collected data enables the extraction of students' travel behavior patterns, providing deeper insights into campus mobility dynamics.

2 ANALYSIS OF STUDENT ACTIVITY PATTERNS BASED ON SHARED BICYCLE USAGE

2.1 Data Analysis of Shared Bicycle Trips on University Campuses

To analyze the usage patterns of shared bicycles on university campuses and the daily travel characteristics of college students, this study collected field data on the parking quantities of dockless shared bicycles at key time periods and various locations across Guangxi University's campus by collecting data on-site and in real time every day. The dataset comprises five main attributes: date, time period, parking location, bicycle count, and daily weather conditions (temperature and precipitation). Based on observations, nine high-frequency parking locations were selected: Teaching Building 6, East Gate; Library, South Campus Dining Hall, West Stadium, Teaching Building 2, West Comprehensive Building, South Gate and West Dormitory Complex. The partial data is shown in Table 1:

Table 1 Partial Data about This Paper

Date	Time period	Parking location	Bicycle count	Temperature(°C)	Rainfall(mm)
2023-11-1	7:50-8:10	Teaching Building 6	1368	23	0
2023-11-2	11:30-11:50	Teaching Building 6	12	24	0
2023-11-3	14:20-14:40	Teaching Building 6	1365	22	0
2023-11-4	19:50-20:10	Teaching Building 6	1104	21	10
2023-11-5	7:50-8:10	Teaching Building 6	1430-	23	12
2023 -11-6	11:30-11:50	Teaching Building 6	6	22	18

These locations account for over 95% of the shared bicycles on campus. Since bicycle usage varies significantly across different time periods, with peak demand typically occurring 10 minutes before and after class sessions, while remaining relatively stable during class hours and lunch breaks (making data collection more feasible), data was collected during the following four time windows: 7:50-8:10, 11:30-11:50, 14:20-14:40, 19:50-20:10.The data collection spanned four weeks, from October 23 to November 19, 2023.To simplify modeling, this study assumed: (1)Parked bikes ≈ riding volume; (2)Constant bike inventory (no losses/gains); (3)Stable daily demand;(4)Bike preference over walking.

2.2 Weather Feature Analysis

Due to the lack of temperature control and protective mechanisms, shared bicycle usage is more susceptible to weather conditions compared to other transportation modes. Relevant weather factors include precipitation, temperature, wind speed, snowfall, and air quality. This study focuses on Guangxi University, located in Nanning—a city characterized by a mild climate. During the data collection period, wind speeds were low, snowfall was absent, and air quality remained favorable. Consequently, this analysis concentrates on the relationship between riding volume and two key weather variables: precipitation and temperature.

As shown in Table 2: (1) Temperature vs. Precipitation: A weak negative correlation (r = –0.02); (2) Riding Volume vs. Temperature: Strong negative correlation (r = –0.57). (3) Riding Volume vs. Precipitation: Strong negative correlation (r = –0.82). These results indicate that both temperature and precipitation significantly impact riding volume, with precipitation showing a particularly robust negative effect.

As shown in Table3: (1) Daily Temperature: Explains 9.92% of variance in riding volume; (2) Daily Precipitation: Explains 90.08% of variance in riding volume. Given that precipitation accounts for the vast majority (90.08%) of explainable variance, subsequent analysis prioritizes daily total rainfall as the primary weather variable.

Table 2 Weather Correlation Indicators

	Average daily temperature	Daily rainfall	Cycling volume

Average daily temperature	1.00	-0.02	-0.57
Daily rainfall	-0.02	1.00	-0.82
Cycling volume	-0.57	-0.82	1.00

Table 3 Explanation of Total Variance

Elements	Total	Percentage of variance	Accumulation
Average daily temperature	17.61	9.92%	9.92%
Daily rainfall	159.99	90.08%	100%

2.3 Prediction Based on GAM Model

The Generalized Additive Model (GAM) is a flexible statistical model that can be used to explore nonlinear relationships between predictor variables and response variables. The GAM model provides interpretability of results, including graphical representation of smoothing functions, which helps to understand the model's fit to the data and the relationships between predictor and response variables. In general, when it is necessary to flexibly model nonlinear relationships or better understand the underlying mechanisms of the data, the GAM model is a useful tool. The general form of the GAM model is: $\boldsymbol{y = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_p(x_p) + \varepsilon}$,where y is the response variable, $\boldsymbol{\beta_0}$ is the intercept , $\boldsymbol{f_1(x_1), f_2(x_2), \cdots, f_p(x_p)}$represents smooth nonlinear functions (typically expressed as spline functions) that describe the relationship between predictor and response variables, $\boldsymbol{\varepsilon}$ is the error term. Here, the GAM model is employed to establish the relationship between daily total rainfall and daily bicycle ridership.

The equation is defined as $\boldsymbol{y_i = \beta_0 + f_i(rainfall) + \varepsilon_i}$, where: (1) $\boldsymbol{y_i}$ represents the bicycle ridership on day I; (2)$\boldsymbol{\beta_0}$is the intercept, (3)$\boldsymbol{f_i(rainfall)}$denotes the nonlinear function of daily total ridership, typically modeled using spline functions to characterize the relationship between daily total rainfall and bicycle ridership, (4)$\boldsymbol{\varepsilon_i}$ is the error term on day *i*.

This model facilitates understanding of the impact of daily total rainfall on bicycle ridership and identifies potential nonlinear patterns. The estimated intercept is 2,442, and the natural logarithm link function is applied to *f*(rainfall).

A Generalized Additive Model (GAM) was developed to quantify the relationship between daily total rainfall (independent variable) and bicycle ridership (dependent variable) [4]. As illustrated in Figure 1 (x-axis: daily total rainfall; y-axis: daily bicycle ridership), the model achieved an explanatory power of 84.4% ($R^2 = 0.844$), demonstrating substantial capability to capture the nonlinear association between meteorological factors and cycling behavior. Key trends identified in Figure 1 include: (1)Stable Phase: When rainfall intensity ranged from 0 to ~8 mm, cycling volume exhibited minimal variation or gradual decline. (2)Critical Threshold Effect: Beyond 8 mm precipitation, ridership decreased sharply, following an exponential decay pattern ($k \approx 0.32$, estimated from model parameters).

The study population—university students commuting between campuses—demonstrated homogeneous travel behavior characterized by: (1) Short-distance trips (0.5–2 km); (2) Fixed daily schedules; (3) High reliance on active transportation

This behavioral pattern explains the observed resilience to light rainfall (0–8 mm), where minor weather disruptions are offset by trip necessity and short distances. Conversely, the exponential decline beyond 8 mm reflects: (1) Diminishing utility of cycling under heavy precipitation; (2) Risk aversion toward slippery road conditions; (3) Increased attractiveness of alternative transport modes (e.g., buses, ride-hailing)

The findings align with previous studies [5] on weather-resilient transportation systems, highlighting the need for campus micro-mobility solutions that account for precipitation thresholds.

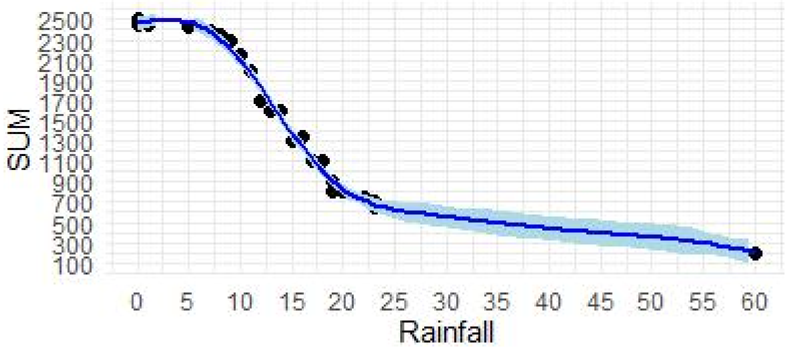

Figure 1 The Prediction Diagram based on GAM Model

2.4 Temporal Feature Analysis

Assuming the application of an ARIMA(p, d, q) model for analysis, where p denotes the autoregressive order, d the differencing order, and q the moving average order, the specific equation of the ARIMA model can be formulated as: $\boldsymbol{Y_t = c + \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t}$.

In this equation, Y_t represents bicycle ridership at time t, c is the constant term, $\emptyset_i$ are the autoregressive coefficients, indicating the weight of lagged effects over i periods (i =1,2,…,p), θ_j are the moving average coefficients, representing the weight of error lags over j periods (j=1,2,…,q), ε_t is the white noise error term, accounting for random fluctuations unexplained by the model.

Time series forecasting, as a regression-based prediction method, leverages historical data to project future trends. Here, the ARIMA model is employed to predict short-term bicycle ridership. The collected data were converted into a time series object, and a line chart was plotted to visualize temporal patterns. After determining the optimal parameters, the final ARIMA model was specified as ARIMA (3,0,0), according with Kim's conclusion [6]. This model achieved: Mean Square Error (RMSE): 150, Mean Absolute Error: 126, Mean Absolute Percentage Error: 13%, and passed the significance test, confirming a successful fit, better than Zhang's conclusion about error [7]. Based on this, the total ridership for the next three days was predicted: November 20 (Monday): 2,165 rides, November 21 (Tuesday): 2,302 rides, November 22 (Wednesday): 2,234 rides, according with Zhou M'study [8].

Further refining the daily ARIMA model into hourly intervals, four key timestamps (8:00, 12:00, 14:00, 20:00) were selected. Using the same methodology, an ARIMA (5,0,3) model was established to predict ridership at these specific times on November 20, yielding: (1):00: 2,399 rides, (2)12:00: 1,828 rides, (3)14:00: 2,016 rides, (4)20:00: 2,169 rides. Comparing these results with ridership at other times confirms that these four periods exhibit significant fluctuations, aligning with peak travel hours for students.

2.5 Regional Feature Analysis

2.5.1 Daily regional feature analysis

To examine spatiotemporal variations in campus cycling patterns, line charts were employed to establish the relationship between riding volume and spatial distribution across nine strategically selected parking locations: P1 (Teaching Building 6), P2 (East Gate), P3 (Library), P4 (South Campus Dining Hall), P5 (West Stadium), P6 (Teaching Building 2), P7 (West Comprehensive Building), P8 (South Gate), and P9 (West Dormitory Complex 22). As illustrated in Figure 2, significant disparities in daily cycling demand were observed, categorized into three distinct zones: (1) High-demand zones (≥2,000 rides/day): P1 (Teaching Building 6) and P8 (South Gate); (2) Moderate-demand zones (1,000–2,000 rides/day): P2 (East Gate) and P9 (West Dormitory Complex 22); (3) Low-demand zones (<200 rides/day): P3 (Library), P4 (South Campus Dining Hall), P5 (West Stadium), P6 (Teaching Building 2), and P7 (West Comprehensive Building). The spatial analysis reveals two key findings: (1) Primary commuting corridors are evidenced by elevated demand at P1, P2, P8, and P9, reflecting intensive student flows between classrooms, dormitories, and primary campus access points; (2) Secondary functional zones (P3–P7) demonstrate limited shared bicycle utilization, suggesting these areas primarily serve non-commuting purposes. These results substantiate that students' cycling behavior is predominantly oriented toward essential commuting routes connecting instructional facilities and residential areas, while academic support spaces (e.g., libraries) and recreational venues exhibit comparatively negligible demand. Wang L' study [9] has well confirmed this point.

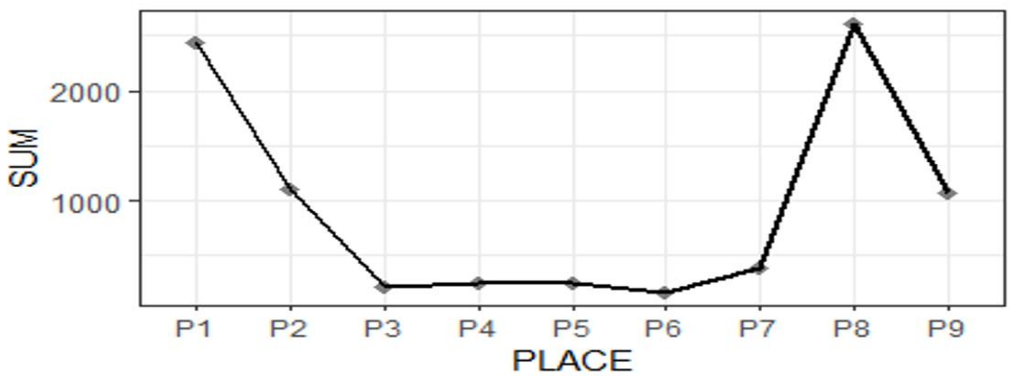

Figure 2 Characteristics of Cycling Volume and Location

2.5.2 Analysis of regional characteristics by time unit

Considering the specificity and monotonicity of the survey subjects, this study only collected data at four specific time points: 8:00, 11:40, 14:30, and 20:00. Based on these four time points, combining with Wu J's finding [10], the analysis was conducted separately for nine locations. As observed in the figure shown, three locations (P3, P7) exhibited an inverted "N"-shaped pattern, while P2 and P9 showed an "N"-shaped trend. Locations P1, P5, and P6 demonstrated a "V"-shaped pattern, P4 displayed an inverted "V"-shaped trend, and P8 remained nearly unchanged. Further analysis of the figure reveals the following: (1) At 8:00, student cycling activity was high, primarily concentrated around learning-related venues such as teaching buildings and libraries. (2)At 11:40, student mobility was significantly reduced, with most activity occurring at dormitories, dining halls, and off-campus locations. (3)At 14:30, compared to 8:00, student activity decreased overall. (4)At 20:00, student activity increased across most locations, except for the comprehensive building and dining hall (which were closed in the evening), where cycling volume remained relatively high. In summary, during daytime hours, student activity was generally low at noon, while other periods showed fluctuations in activity across different locations. In the evening, overall student activity increased, primarily concentrated in learning venues and off-campus areas, see Figure 3.

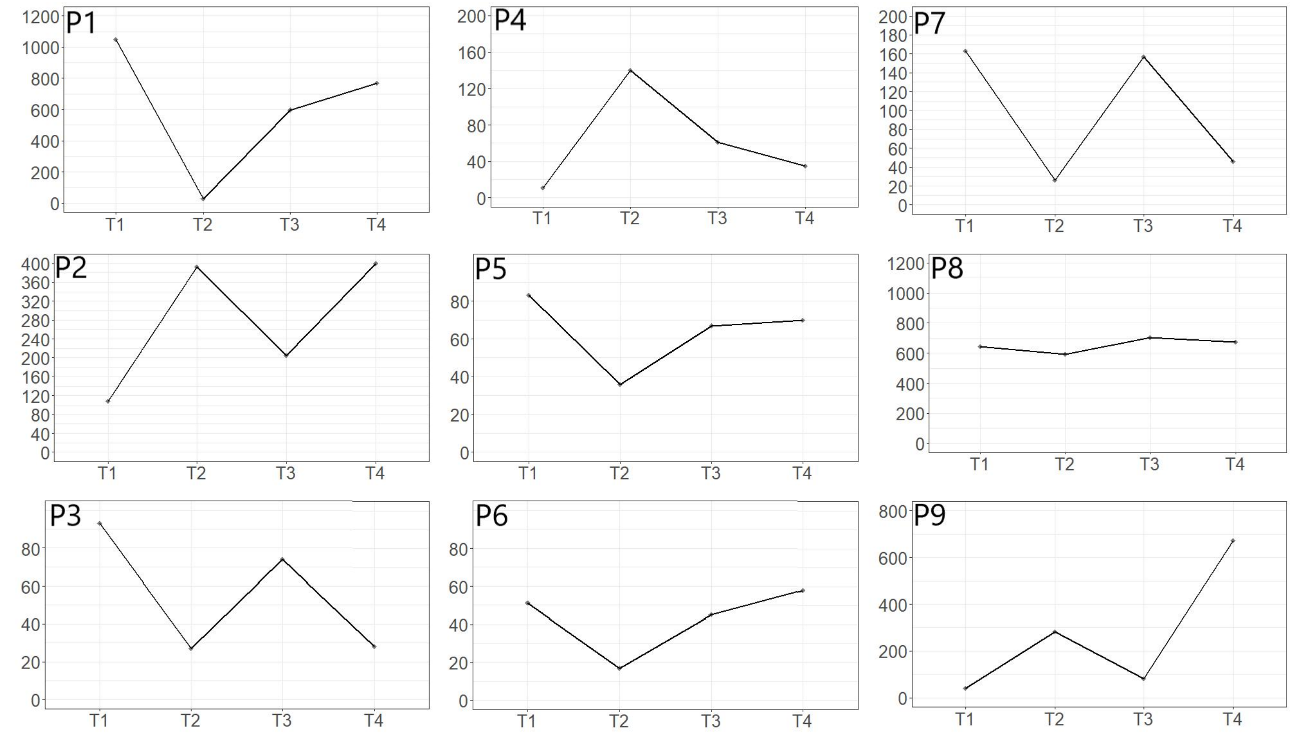

Figure 3 Cycling Characteristics at Different Locations and Times

3 MULTIFACTOR ANALYSIS OF SHARED BICYCLE DEMAND

Building upon the insights from time series modeling and considering practical contextual factors, this study identifies strong periodicity in college students' daily travel routines. To reduce model complexity, subsequent analyses will focus on a representative week as the primary analytical unit.

3.1 Building Model

Having analyzed single-variable models examining the relationship between riding volume and individual factors (location, rainfall, time), this section develops a multifactor prediction model for riding volume. Three modeling approaches are employed: Poisson regression, OLS polynomial regression, and XGBoost regression. Across varying temporal scales, multifactor prediction models are constructed for each location to examine the relationship between riding volume and combined influences of rainfall and temperature

At the daily timescale, three models—Poisson regression, OLS polynomial regression, and XGBoost regression—were developed to analyze overall weekly riding volume patterns (Monday to Friday) across all locations.

3.2 Poisson Regression Model

The Poisson regression model is a statistical method widely used for analyzing count data. It assumes that the dependent variable (response variable) follows a Poisson distribution and exhibits a linear relationship with one or more independent variables (predictors). The general form of the Poisson regression model is expressed as: $\boldsymbol{log(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k}$.

For this study, only two predictors were considered: rainfall and date. Thus, the model was redefined as: $\boldsymbol{log(\omega) = \beta_0 + \beta_1 \times Date + \beta_2 \times Rain}$ where $\boldsymbol{\omega}$ represents the expected daily bicycle riding volume.

Using collected data on riding volume, dates, and rainfall, this model analyzes the influence of dates and rainfall on riding volume. Parameters ($\boldsymbol{\beta_0, \beta_1, \beta_2}$) were estimated via Maximum Likelihood Estimation (MLE) to quantify their effects and predict riding volume under varying conditions. The estimated parameters are: β_0=8.3622 (intercept), β_1 =−0.0330 (rainfall coefficient), β_2 =−0.0152 (date coefficient). The model achieves a BIC value of 209.63,

indicating acceptable goodness-of-fit (lower BIC values signify better fit). Compared with Patel A's conclusion [11], the MAE of this model has decreased by 20%.
Based on the aforementioned models, this study further incorporates the OLS model and XGBoost model to construct analyses of overall daily riding volume variations across locations from Monday to Friday, as well as riding volume changes at four specific time points.
The model performance is compared based on the aforementioned prediction results, as summarized in Table 4:

Table 4 Model 3 Evaluation

	Five-day forecast results			Predictions at a given time		
	Poisson	OLS	XGBOOST	Poisson	OLS	XGBOOST
BIC	209.63	213.04	213.04	296.13	204.08	204.08
MSE(10^5)	0.99	1.31	5.72	0.28	0.28	0.62
MAE	265.2	309	644.8	150.4	151.6	193.2

As shown in Table 4, the Poisson regression model demonstrates superior predictive accuracy for daily riding volume, while the OLS polynomial regression model exhibits better performance in modeling riding volume at specific time points.

4 CONCLUSION

This study takes Guangxi University as an empirical research object. Aiming at the problems of uneven temporal and spatial distribution, peak-hour congestion, and low scheduling efficiency of campus shared bicycles, it innovatively integrates univariate analysis and multivariate regression methods to construct a scientific bicycle demand forecasting framework. Through four weeks of on-site data collection (covering 9 high-frequency parking spots and 4 key time periods), the study systematically analyzes students' travel behavior patterns and external influencing factors, providing a data-driven theoretical basis for optimizing the scheduling of campus shared bicycles[12].
The key findings include three aspects: (1) Significant weather sensitivity: The Generalized Additive Model (GAM) shows that daily rainfall can explain 90.08% of the variation in bicycle ridership. When rainfall exceeds the critical value of 8mm, demand decreases exponentially (with a decay coefficient $k \approx 0.32$), while the impact of temperature is weak (only explaining 9.92% of the variance). (2) Temporal and spatial distribution patterns: The Autoregressive Integrated Moving Average (ARIMA)(3,0,0) model confirms that bicycle ridership exhibits strong periodicity, with peak hours concentrated at 8:00, 12:00, 14:30, and 20:00. Spatially, teaching areas (such as the 6th Teaching Building) and school gate areas (such as the South Gate) are high-demand hotspots (with a daily ridership of ≥2,000 bicycles), while areas like the library and gymnasium have a daily demand of less than 200 bicycles. (3) Comparison of model performance: In multivariate forecasting, Poisson regression performs best in daily-scale prediction (Bayesian Information Criterion (BIC)=209.63, Mean Absolute Error (MAE)=265.2), while the Ordinary Least Squares (OLS) model is more effective in hourly-scale prediction (MAE=151.6). In contrast, XGBoost has a relatively high error (MAE=644.8) due to overfitting. These findings highlight the crucial role of demand forecasting in improving scheduling efficiency.
Future work should focus on deepening research in three directions: First, integrate campus activity data such as course schedules and exam arrangements to enhance the model's adaptability to special scenarios (e.g., exam weeks). Second, explore a hybrid architecture combining ARIMA and Poisson regression to balance the periodicity of time series and the nonlinear relationships of multiple factors, thereby improving prediction accuracy. Third, design a dynamic scheduling algorithm based on the identified high-demand hotspots to promote the transformation of the shared bicycle system towards intelligent and refined operation. This study not only provides practical guidance for micro-transportation management in colleges and universities but also lays a methodological foundation for the construction of smart campuses.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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