Usage Patterns of Bicycle Counting Stations in Heidelberg and the Influence of External Factors

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Abstract

As cycling becomes key in sustainable urban mobility, understanding spatiotemporal traffic patterns is essential for infrastructure planning. While previous studies have classified bicycle traffic, they often rely on predefined, rule-based approaches that may fail to capture hybrid usage behaviors. Addressing this limitation, we present a data-driven approach to classify urban bicycle traffic using hourly data from counting stations in Heidelberg, Germany. We derive features to quantify the shape of traffic patterns across various timescales. Subsequent k-means distinguishes distinct usage patterns: *utilitarian*, *recreational*, and *mixed*. Finally, we investigate the influence of external factors, such as weather and public holidays, which varies substantially across different usage types. [1]

1. Introduction

Sustainable urban traffic relies heavily on the expansion of cycling, which is explicitly promoted by the city of Heidelberg as part of their long-term mobility strategies (Stadt Heidelberg, 2025). To translate these strategies into infrastructure, planners require an understanding of when and why people cycle, not just how many.

Trip purpose is commonly inferred from spatiotemporal bicycle counts; however, existing rule-based approaches struggle to capture hybrid usage patterns (Miranda-Moreno et al., 2013).

Furthermore, cycling demand is highly sensitive to external factors. Precipitation, temperature, and public holidays can influence traffic patterns (Liu et al., 2015; Rudloff et al., 2014; Cools et al., 2007). Since commuters are more weather-resilient than leisure riders, these effects vary by usage type (Heinen et al., 2011).

To address these questions, we analyze hourly bicycle counts from 15 stations in Heidelberg (Figure 2) using a data-driven approach.

[1] Source files are publicly available in the project repository.

Table 1. Data quality and traffic statistics for Heidelberg bicycle counting stations.

ID	Station	Mean [bikes/d]	Std	Avail. [%]
S1	Plöck	4180	1832	91.5
S2	Kurfürstenanlage	1257	630	91.8
S3	Ernst-Walz-Brücke	6179	3344	100.0
S4	Gaisbergstraße	4239	1651	94.7
S5	Schlierbacher Landstr.	786	389	60.2
S6	Ziegelhäuser Landstr.	872	389	58.3
S7	Rohrbacher Str.	2426	1251	95.7
S8	Theodor-Heuss-Br.	7902	2865	100.0
S9	Mannheimer Str.	1964	845	83.2
S10	Ernst-Walz-Brücke alt	3240	1517	99.9
S11	Hardtstraße	1690	640	79.4
S12	Berliner Str.	705	245	92.3
S13	Bahnstadtprom.	2759	1203	63.7
S14	Eppelheimer Str.	909	452	95.6
S15	Liebermannstr.	4101	1456	71.9

Our contributions are threefold: (i) an interpretable station representation based on established temporal traffic indices and their combination across time scales; (ii) unsupervised clustering to distinguish utilitarian, recreational, and mixed usage patterns; (iii) a usage-type–specific analysis of weather and public holiday effects.

2. Data

2.1. Bicycle Counting Data

The bicycle counting stations in Heidelberg are densely and centrally distributed across the urban area. For our analysis, hourly bicycle counts from 15 permanent monitoring stations installed between May 2014 and January 2020 were used. The stations provide hourly bicycle counts using inductive loop sensors (Eco-Counter, 2025). The data are publicly available via the MobiData BW open data platform (Nahverkehrsgesellschaft Baden-Württemberg mbH, 2025).

Data quality was assessed by marking incomplete days and potential sensor failures. Table 1 summarizes data availability and basic traffic statistics.

2.2. Weather Data

Hourly weather data were obtained from the Open-Meteo API (Open-Meteo, 2025). As all stations lie within a single grid cell, a city-wide hourly weather time series was used for all stations. Locally recorded weather data from the counting stations were excluded due to inconsistencies with official weather data.

2.3. Holiday Data

Public holidays and school vacation periods for Baden-Württemberg were obtained from the Mehr Schulferien API (Mehr Schulferien, 2025).

3. Method

Previous works often rely on predefined rules to categorize bicycle traffic (Miranda-Moreno et al., 2013). However, such an approach may fail to capture hybrid usage patterns. We propose a more data-driven, implicit approach. By extracting features that quantify the 'shape' of daily, weekly, and seasonal profiles, we map each station into a multi-dimensional feature space. This allows us to use unsupervised k-means clustering (Lloyd, 1982) to discover different usage types.

In a subsequent step, cluster semantics are assigned post hoc, resulting in the following usage types:

- *Utilitarian (Util)*: Traffic showing strong commuting patterns, with two distinct peaks in traffic volume during the morning and afternoon hours.
- *Recreational (Rec)*: Traffic lacking typical 9-to-5 commuting peaks. While often associated with leisure, in a university city like Heidelberg, this pattern also captures irregular student traffic (e.g., to libraries or lecture halls).
- *Mixed (Mix)*: Dual-purpose locations exhibiting both utilitarian and recreational characteristics.

The number of clusters was fixed to $k = 3$ to reflect the conceptual distinction between utilitarian, recreational, and mixed usage. Although the maximum silhouette score is achieved at $k = 2$ (0.49), $k = 3$ introduces an additional stable cluster (silhouette 0.41) while preserving a clear elbow in the inertia curve.

We represent station usage using three interpretable features capturing intra-day patterns, weekday–weekend differences, and seasonal variability. Features are derived from station-level normalised hourly, daily, and monthly traffic indices (I_h, I_w, I_m) (Miranda-Moreno et al., 2013), and are conceptually aligned with the indicators used therein. The resulting feature space is low-dimensional, volume-invariant, and preserves temporal structure. Feature relationships were explored using correlation analysis and PCA as sanity checks.

Double Peak Index (DPI) Weekday hourly profiles at utilitarian stations often exhibit pronounced commuting peaks. The Double Peak Index (DPI) quantifies this pattern by comparing the dominant morning (5–10 h) and late-day (14–20 h) peaks to the average midday level (8–14 h).

Let p_m and p_e denote the magnitudes of the morning and late-day peaks at hours h_m and h_e, and let m be the average midday level. The DPI is defined as

$$\mathrm{DPI} = \max(S \cdot Y \cdot D,\, 0)\,,$$

where

$$S = \tfrac{(p_m - m) + (p_e - m)}{2},$$
$$Y = 1 - \tfrac{|p_m - p_e|}{\max(p_m, p_e)},$$
$$D = \min\left(\tfrac{|h_e - h_m|}{10},\, 1\right)$$

capture peak strength, symmetry, and temporal separation, respectively.

Weekend Shape Difference (WSD) Differences between weekday and weekend hourly profiles provide an additional discriminator between usage types. Let $\mathbf{p}^{wd}$ and $\mathbf{p}^{we}$ denote the weekday and weekend hourly profiles, normalised to unit sum. The Weekend Shape Difference (WSD) is defined as

$$\mathrm{WSD} = \left\|\mathbf{p}^{wd} - \mathbf{p}^{we}\right\|_2.$$

Seasonal Drop Index (SDI) Seasonality provides an additional discriminator between recreational and utilitarian stations. We quantify long-term variability using the Seasonal Drop Index (SDI), defined from the monthly index I_m. Robust upper and lower quantiles are given by

$$q_{90} = \mathrm{quantile}_{0.9}(I_m), \qquad q_{10} = \mathrm{quantile}_{0.1}(I_m),$$

and the SDI is defined as

$$\mathrm{SDI} = \frac{q_{90} - q_{10}}{q_{90}}.$$

Temporal Clustering

To account for temporal variability in bicycle traffic, k-means clustering is performed on sliding two-year windows with monthly shifts. Feature vectors are recomputed separately for each window.

For each station s and usage type u, the empirical cluster membership probability is defined as

$$P(u \mid s) = \frac{1}{N_s} \sum_{i=1}^{N_s} \mathbb{1}\big(c_i(s) = u\big),$$

Table 2. Independent temperature and precipitation class definitions.

Class	$T_{\max}$ [°C]	P_{day} [mm]
L	$< q_{33}$	$= 0$
M	$[q_{33}, q_{66})$	$(0, q_{80}]$
H	$\geq q_{66}$	$> q_{80}$

Classes are defined independently for temperature and precipitation and applied only to the respective analysis. Empirical thresholds: $q_{33} = 10.7$°C, $q_{66} = 19.8$°C (temperature), $q_{80} = 7.1$ mm (precipitation).

where $c_i(s)$ denotes the cluster assignment in the i-th run and N_s the number of valid runs.

Since k-means produces unlabeled partitions, cluster semantics are assigned post hoc by ordering clusters using a centroid-level *utilitarian score*

$$\text{DPI} + \text{WSD} - \text{SDI}.$$

Prior work characterises utilitarian stations by pronounced weekday commuting peaks, strong weekday–weekend contrast, and comparatively weak seasonality (Miranda-Moreno et al., 2013). Clusters with higher scores are labeled *utilitarian*, intermediate scores as *mixed*, and lower scores as *recreational*. As centroid ordering is performed in the same feature space used for clustering, these labels should be interpreted as descriptive summaries of the clusters rather than as an independent external validation.

Weather and Event Class Definitions

For the event-based analysis, days were grouped into three classes based on temperature and precipitation using data-driven quantile thresholds (Table 2). Here, quantiles are computed over the empirical city-wide distribution of daily weather observations and serve solely to define comparable event classes.

Low-condition days (L) serve as baseline, and relative changes in mean daily bicycle counts for class $X \in \{M, H\}$ are computed as

$$\Delta_X = \frac{\bar{C}_X - \bar{C}_L}{\bar{C}_L} \times 100.$$

4. Results

This section presents the results of the proposed clustering approach and analyzes the spatial distribution of station usage types as well as their sensitivity to external factors.

4.1. Station Usage Types and Spatial Structure

Figure 1 presents the probabilistic usage type assignments. Cluster labels correspond to the usage types defined in Section 3 and are assigned based on the centroid-level utilitarian score. Some stations show near-deterministic assignments with low entropy (e.g., S1–S3), while others exhibit more balanced probabilities, indicating temporally variable usage.

Figure 1. Probabilistic usage type assignments of bicycle counting stations.

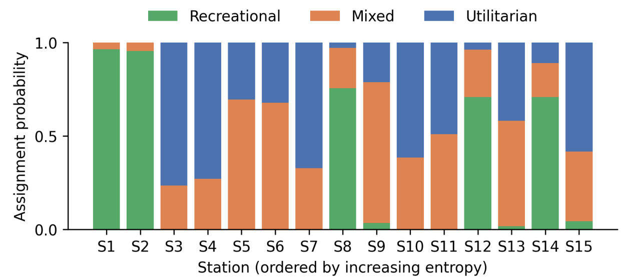
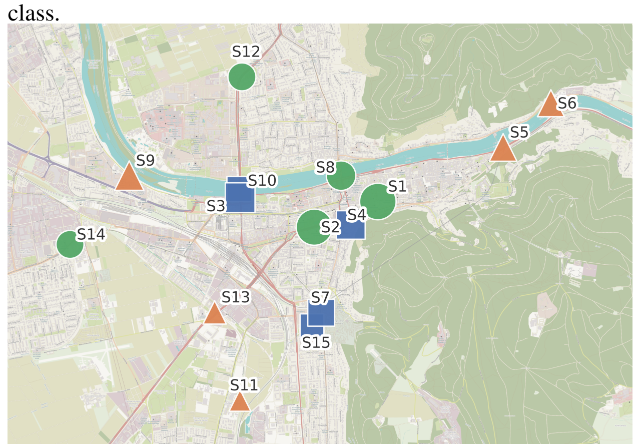


Figure 2. Spatial distribution of bicycle counting stations in Heidelberg. Marker color and shape indicate the dominant usage type. Marker size reflects the assignment probability of the dominant class.



In the following analysis, each station is assigned its dominant usage type, defined as the class with the highest assignment probability. Figure 2 visualizes the spatial distribution of stations by dominant usage type.

Utilitarian stations are primarily located along major traffic corridors and key commuting links. For example, Ernst-Walz-Bridge (S10) serves as Heidelberg's central river crossing, while Gaisbergstraße (S4) is a designated bicycle priority corridor intended to relieve bicycle traffic from the parallel Rohrbachstraße (S7) (ADFC Rhein-Neckar, 2021).

Mixed stations predominantly occur in transitional urban zones. Stations such as S5, S6, and S9 connect several residential districts to the city center and combine utilitarian demand with recreational usage due to their location along the Neckar river. Similarly, S13 is located along a corridor linking Kirchheim to the city center and bordering extensive green areas.

Table 3. Effect of temperature on station usage across usage types.

	Weekdays			Weekends		
Type	L	Δ_M	Δ_H	L	Δ_M	Δ_H
Mix	1383	21%	70%	887	27%	116%
Rec	1009	7%	36%	754	16%	64%
Util	3424	11%	39%	2368	17%	61%

Table 4. Effect of precipitation on station usage across usage types.

	Weekdays			Weekends		
Type	L	Δ_M	Δ_H	L	Δ_M	Δ_H
Mix	2100	−17%	−37%	1587	−19%	−46%
Rec	1510	−9%	−22%	1275	−12%	−29%
Util	4810	−8%	−23%	3823	−13%	−29%

Recreational stations are mainly located in areas with limited commuting relevance and high leisure appeal. For example, Plöck (S1) lies in Heidelberg's historic old town near the Universitätsbibliothek Heidelberg and other university buildings. This results in predominantly tourist- and student-oriented traffic with reduced utilitarian demand.

4.2. Impact of External Factors on Usage Types

We first examine the effects of weather conditions, followed by the impact of public holidays on station usage.

Bicycle traffic increases with rising temperatures across all usage types (Table 3). Mixed stations exhibit the strongest temperature sensitivity, particularly on weekends, while utilitarian and recreational stations show more moderate responses.

Precipitation consistently reduces bicycle traffic across all usage types (Table 4). The strongest declines occur at mixed stations, especially on weekends, whereas utilitarian and recreational stations are less affected.

Overall, weather sensitivity differs systematically by usage type and reflects underlying trip purposes.

Public holidays substantially reduce bicycle traffic across all usage types (Table 5). Reductions are strongest at recreational and utilitarian stations, while mixed stations are less affected. Beyond volume effects, holidays also weaken weekday commuting peaks and shift usage toward weekend-like profiles (Figure 3).

Together, these results highlight that external factors affect not only traffic volume but also temporal usage structure in a type-specific manner.

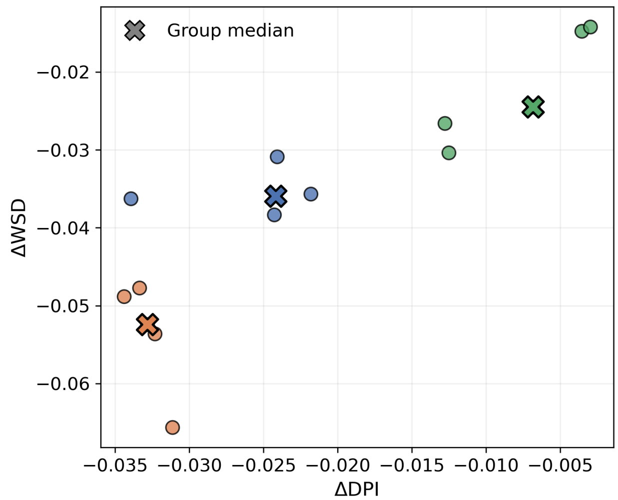
5. Conclusion

This analysis identified distinct bicycle usage patterns across stations in Heidelberg and showed that their spatial distribution and sensitivity to external factors differ systematically.

Table 5. Effect of public holidays on station usage by usage type.

Type	No holiday	Holiday	Δ
Mix	1648	953	−28.6%
Rec	1260	728	−42.2%
Util	3238	2043	−42.8%

Figure 3. Holiday-induced structural changes in station usage.



Utilitarian, recreational, and mixed stations respond differently to weather and public holidays, reflecting underlying trip purposes. Overall, the results highlight that urban bicycle demand cannot be captured by traffic volume alone, but requires consideration of temporal usage patterns and contextual influences. The findings should be interpreted in light of several limitations: the analysis is restricted to 15 stations within a single city, and directional flow information was not considered due to incomplete availability across stations.

Contribution Statement

Simon Rappenecker and Martin Eichler were responsible for the acquisition and preprocessing of the bicycle counting and weather datasets. Julian Jurcevic and Tarik Eker developed the feature engineering framework. All authors contributed equally to the interpretation of the results and the final drafting of this report.

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