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 special 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 significantly across different usage types. [1]

1. Introduction

Sustainable urban traffic relies heavily on the expansion of cycling. Both the state of Baden-Württemberg and the city of Heidelberg explicitly promote cycling as part of their long-term mobility strategies (Ministerium für Verkehr Baden-Württemberg, 2016; Stadt Heidelberg, 2025). To translate these strategies into infrastructure, planners require a good understanding of traffic behavior. Specifically, they need to know not just how many people are cycling, but when and why.

Trip purposes are typically inferred from spatiotemporal traffic patterns. While previous studies have successfully used hourly and daily counts to distinguish utilitarian from recreational traffic, they often rely on rule-based approaches (Miranda-Moreno et al., 2013). These methods, however, struggle to capture hybrid usage patterns common in urban environments.

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). Therefore, we aim to understand how these factors influence the demand profiles of different usage types in the city of Heidelberg, Germany.

To overcome the limitations of rule-based classification, we present a flexible, data-driven approach. Using hourly counting data from 15 stations in Heidelberg (Figure 2), we first derive features to quantify traffic shapes across daily, weekly, and seasonal timescales. We then apply k-means clustering to identify different usage patterns (*utilitarian*, *recreational*, and *mixed*) and analyze their sensitivity to weather and public holidays.

2. Data

The analysis is based on bicycle traffic counts complemented by weather and public holiday data. In the following, we describe the data sources, preprocessing steps, and quality checks.

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 days with fewer than 12 hourly observations as missing and flagging zero-count days at high-traffic stations (median $>$ 500 cyclists/day) as sensor failures. Table 1 summarizes data availability and basic traffic statistics for all 15 stations (S1–S15), reporting mean daily counts and day-to-day variability (Std).

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

[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

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 in chapter 4, we assign one of the following labels to each cluster:

- *Utilitarian*: Traffic showing strong commuting patterns, with two distinct peaks in traffic volume during the morning and afternoon hours.
- *Recreational*: Traffic dominated by leisure activities. These locations exhibit a single peak in traffic volume around midday or early afternoon.
- *Mixed*: Dual-purpose locations exhibiting both utilitarian and recreational characteristics.

The number of clusters was fixed to $k = 3$ to explicitly reflect these three usage types. Silhouette analysis supports a dominant separation between extreme types, while the third cluster captures intermediate behavior.

To characterise the counting stations, we derive three distinct features that capture traffic patterns across different timescales: daily, weekly and seasonal to exploit the distinct pattern visible in Figure xyz .

Double Peak Index (DPI) Weekday hourly profiles of some stations exhibit a double-peak structure, typically associated with morning and evening commuting. The DPI quantifies this behaviour by identifying dominant morning (5–10 h) and evening (14–20 h) peaks and relating their magnitudes to the average midday level (8–14 h). Stations with clear, balanced commuting peaks yield high DPI values, whereas flat or single-peak profiles result in low scores.

Formally, let p_m and p_e denote the magnitudes of the morning and evening peaks at hours h_m and h_e, and let m be the average midday traffic level. The DPI is defined as

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

where S, Y and D models strength, symmetry and distance, respectively:

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

Weekend Shape Difference (WSD) Differences between weekday and weekend hourly traffic patterns provide an additional discriminator between usage types. To capture this effect, we compare the shape of the weekday and weekend hourly profiles. Let $\mathbf{p}^{wd}$ and $\mathbf{p}^{we}$ denote the weekday and weekend hourly profiles, normalised to sum to one.

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

Seasonal Drop Index (SDI) Finally, we consider long-term patterns. Seasonality provides a discriminator between leisure and utilitarian-oriented stations. The SDI quantifies the relative decline between high and low-usage months. Let I_m denote the monthly index values of a station. Using upper and lower quantiles to ensure robustness against outliers

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

Table 2. Weather class definitions for the event-based analysis.

Class	$T_{\max}$ [°C]	P_{day} [mm]
L	< 10	$= 0$
M	[10, 20)	(0, 5]
H	≥ 20	> 5

the SDI is defined as

$$\text{SDI} = \frac{q_{90} - q_{10}}{q_{90}}$$

High values indicate strong seasonal variation, whereas low values correspond to relatively stable, year-round usage.

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

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

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 according to a centroid-level *utilitarian score*

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

with lower scores labeled as *recreational*, intermediate as *mixed*, and higher as *utilitarian*.

Weather and Event Class Definitions

For the event-based analysis, days were grouped into three classes based on temperature and precipitation (Table 2).

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.

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

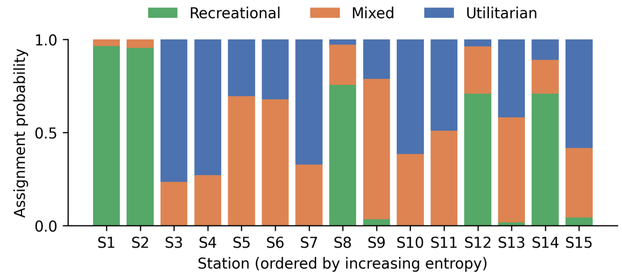
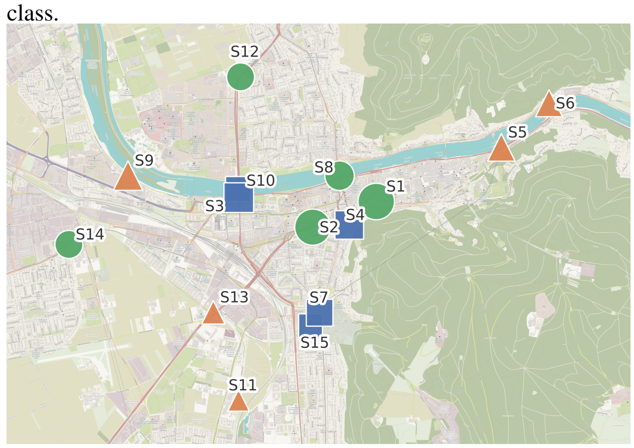


Figure 2. Spatial distribution of bicycle counting stations in Heidelberg. Marker color and shape indicate the dominant usage type. Marker size reflects the assignment probability of the dominant class.



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.

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

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

Type	**Weekdays** L	Δ_M	Δ_H	**Weekends** L	Δ_M	Δ_H
Mix	1447	31%	72%	948	49%	116%
Rec	1034	17%	36%	801	26%	59%
Util	3543	18%	43%	2525	26%	65%

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

Type	**Weekdays** L	Δ_M	Δ_H	**Weekends** 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%

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.

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.

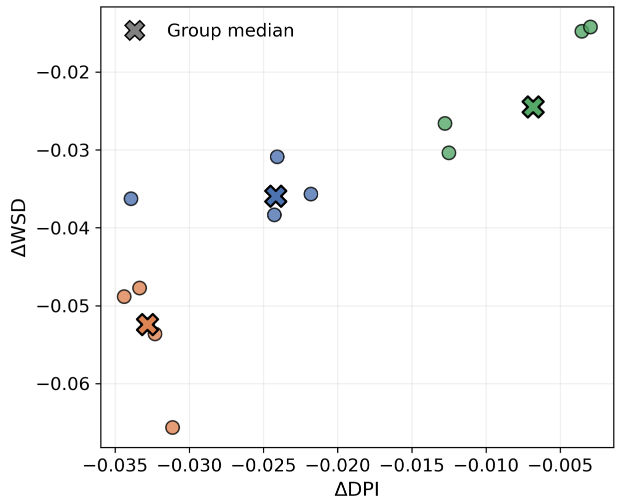
Public holidays substantially reduce bicycle traffic across all usage types (Table 5). Reductions are strongest at recreational and utilitarian stations, while mixed stations are less affected. Beyond volume effects, holidays also weaken weekday commuting peaks and shift usage toward weekend-like profiles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

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

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.



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. 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.

Contribution Statement

Max Mustermann collected and prepared data. Gabi Musterfrau and John Doe performed the data analysis. Jane Doe produced visualizations. All authors will jointly wrote the text of the report.

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