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

Julian Jurcevic [*1] **Martin Eichler** [*2] **Simon Rappenecker** [*3] **Tarik Eker** [*4]

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 significantly across different usage types. [1]

1. Introduction

Sustainable urban traffic relies heavily on the expansion of cycling, which is explicitly promoted by both the state of Baden-Württemberg and the city of Heidelberg 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 identify distinct usage patterns and analyze their sensitivity to external factors.

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 from interval 2016-01-01 until 2025 01-01 was used for prob. clustering

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 for all stations. Locally recorded weather data from the counting stations were excluded due to inconsistencies with official weather data.

[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

2.3. Holiday Data

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

uality: Add res that had to en to clean up

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 dominated by leisure activities. These locations exhibit a single peak in traffic volume around midday or early afternoon.
- *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. Elbow and silhouette analyses indicate a dominant separation between two extreme patterns, while $k = 3$ introduces a stable intermediate cluster with only a minor loss in geometric separation.

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 relevance was assessed using correlation analysis, PCA, and permutation-based importance measures.

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

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

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

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

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

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

Empirical thresholds: $q_{33} = 10.7$°C, $q_{66} = 19.8$°C (temperature), $q_{80} = 7.1$ mm (precipitation).

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 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*.

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.

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

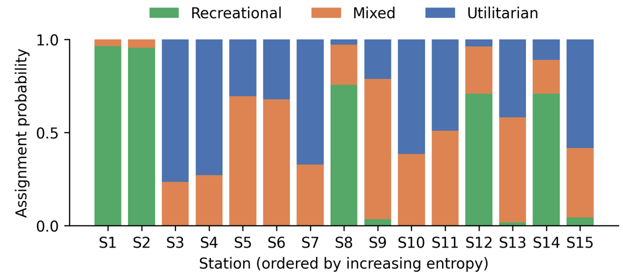
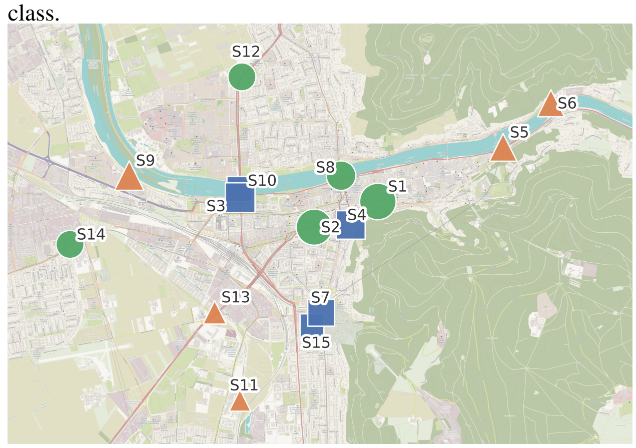


Figure 2. Spatial distribution of bicycle counting stations in Heidelberg. Marker color and shape indicate the dominant usage type. Marker size reflects the assignment probability of the dominant class.



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.

	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%

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.

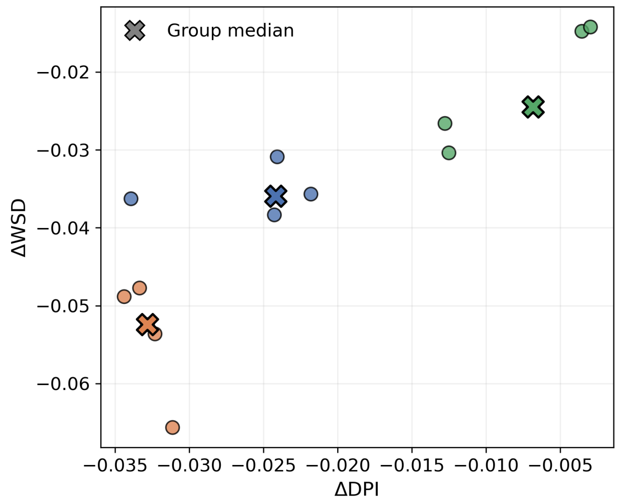
Public holidays substantially reduce bicycle traffic across all usage types (Table 5). Reductions are strongest at recreational and utilitarian stations, while mixed stations are less affected. Beyond volume effects, holidays also weaken weekday commuting peaks and shift usage toward weekend-like profiles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

References

ADFC Rhein-Neckar. Warum wir fahrradstraßen in heidelberg brauchen, 2021. URL https://rhein-neckar.adfc.de. Accessed: 2026-01-05.

Cools, M., Moons, E., and Wets, G. Investigating effect of holidays on daily traffic counts: Time series approach. *Transportation Research Record: Journal of the Transportation Research Board*, (2019):22–31, 2007. doi: 10.3141/2019-04.

Eco-Counter. Zelt evo – inductive loop for mixed traffic. https://de.eco-counter.com/losungen/produkte/zelt-evo-selective, 2025. Accessed: 2025-12-27.

Heinen, E., Maat, K., and van Wee, B. Day-to-day choice to commute or not by bicycle. *Transportation Research Record: Journal of the Transportation Research Board*, (2230):9–18, 2011. doi: 10.3141/2230-02.

Liu, C., Susilo, Y. O., and Karlström, A. The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in sweden. *Transport Policy*, 41:147–158, 2015. doi: 10.1016/j.tranpol.2015.01.001.

Lloyd, S. Least squares quantization in pcm. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982. doi: 10.1109/TIT.1982.1056489.

Mehr Schulferien. Schulferien und feiertage in deutschland – Mehr–Schulferien.de. https://www.mehr-schulferien.de/, 2025. Online-Dienst mit API für Ferien- und Feiertagsdaten (REST API), Version 2.1, abgerufen am January 12, 2026.

Ministerium für Verkehr Baden-Württemberg. Radstrategie baden-württemberg. Technical report, Ministerium für Verkehr Baden-Württemberg, Stuttgart, Germany, 2016.

Miranda-Moreno, L. F., Nosal, T., Schneider, R. J., and Proulx, F. Classification of bicycle traffic patterns in five north american cities. *Transportation Research Record*, 2339(1):68–79, 2013. doi: 10.3141/2339-08. URL https://doi.org/10.3141/2339-08.

Nahverkehrsgesellschaft Baden-Württemberg mbH. Bicycle counting data repository (api v2). https://mobidata-bw.de/fahrradzaehldaten/v2/, 2025. Accessed: 2025-12-27.

Open-Meteo. Historical Weather API Documentation. https://open-meteo.com/en/docs/historical-weather-api, 2025. Accessed: 2025-12-27.

Rudloff, C., Leodolter, M., Bauer, D., Auer, R., Brög, W., and Kehnscherper, K. Influence of weather on transport demand: A case study from the vienna region. Technical report, Austrian Institute of Technology (AIT), Vienna, Austria, August 2014. Technical report.

Stadt Heidelberg. Radstrategie 2030. https://www.heidelberg.de/HD/Leben/radstrategie+2030.html, 2025. Accessed: 2026-01-05.

*Equal contribution [1]Matrikelnummer 7167089, MSc Computer Science [2]Matrikelnummer 6009076, MSc Computer Science [3]Matrikelnummer 6324777, MSc Machine Learning [4]Matrikelnummer 5668988, MSc Computer Science. Correspondence to: JJ <julian-steffan.jurcevic@student.uni-tuebingen.de>, ME <martin.eichler@student.uni-tuebingen.de>, SR <simon.rappenecker@student.uni-tuebingen.de>, TE <tarik.eker@student.uni-tuebingen.de>.

Project report for the "Data Literacy" course at the University of Tübingen, Winter 2025/26 (Module ML4201). Style template based on the ICML style files 2025.