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Planning for bicycle parking: Predicting demand using stated preference and count data

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ABSTRACT

Predicting bicycle parking demand is critical to optimizing parking facilities and thereby promoting cycling. Unfortunately, previous studies have not considered facility type and location when predicting bicycle parking demand, which is critical to meeting user needs, especially in scenarios with multiple parking options, such as on university campuses, as in our case study. The paper presents a predictive model for bicycle parking demand using a synthetic population derived from building space utilization data, a mobility survey, parking facility data, and results from a stated preference experiment on bicycle parking preferences. We evaluate the model's quality using count data from 2022 and 2023 and the influence of including facility types (front wheel racks, u-racks, bicycle parking stations) and whether they are covered. We also analyze the influence of beeline-based distances to reach a facility and to get from the facility to the destination and examine how to weigh them.

Incorporating facility types and coverage substantially improves the model's predictive accuracy, but only if the model's sensitivity to walking distances between facilities and buildings is increased. This suggests that stated preference experiments on bicycle parking choice behavior may underestimate cyclists' sensitivity to walking distances. In contrast, accounting for cycling detours to reach a facility does not contribute to prediction quality. Thus, when cyclists have multiple parking options, it is crucial to consider walking distances for realistic predictions. Furthermore, user-centered planning requires careful consideration of parking facility attributes and the specific preferences of target cyclist groups when determining the size and location of parking facilities.

1. Introduction

Improving bicycle parking infrastructure is essential to promoting cycling, in addition to measures for moving bicycle traffic (Heinen and Buehler, 2019). Although many previous studies have analyzed bicycle parking behavior and preferences, no study has yet modeled the demand for individual facilities, taking into account facility type and location.

Designing bicycle parking infrastructure to meet user needs is important for two main reasons. First, in order to promote cycling with its health and environmental benefits, cyclists need to have adequate parking facilities at their destinations (Buehler, 2012; Bueno et al., 2017; Hunt and Abraham, 2007). Second, suppose cyclists do not find adequate facilities with available capacity there. In this case, they practice 'fly parking', parking their bicycle on street furniture that was not designed for bicycle parking or without locking it to an object, which often blocks sidewalks and hinders people with limited mobility (Gamman et al., 2004; Larsen, 2015; van der Spek and Scheltema, 2015). Because of these parking habits, in this paper, we define parking facilities as any opportunity to park a bicycle, including both designated facilities and fallback facilities such as street furniture or bringing the bicycle to the office, etc. Although the causal relationship between facility placement and fly parking is known, guidelines and planning practices typically calculate the number of required bicycle parking facilities based only on space utilization data or metrics such as the number of workplaces without considering facility placement (APBP, 2015; Barber et al., 2016; BICY, 2011; Blees et al., 2019).

Against this background, we present an approach to model bicycle parking demand at the facility level at RWTH Aachen University, one of the largest technical universities in Germany (45,000 students, 8000 employees). We model bicycle parking behavior based on a stated preference experiment among RWTH students and staff, focusing on privately owned bicycles. By comparing the predictions with actual counts of bicycles parked on two days in 2022 and 2023, we analyze the extent to which the following factors are relevant for predicting bicycle parking demand:

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1. Type of parking facility and whether it is covered.
2. Cycling detour (additional cycling distance to access the parking facility compared to parking the bicycle directly at the destination building entrance).
3. Walking distance between parking facility and destination (building entrance).

We first review previous studies on bicycle parking before describing our methodology, presenting our results, discussing them, and drawing a conclusion.

2. Literature review

Promoting cycling is one approach to increasing the sustainability of mobility, especially in dense urban areas. One way to do this is to improve bicycle parking facilities. For a general review of bicycle parking preferences and behaviors, particularly in the workplace, see Heinen and Buehler (2019).

Studies have shown that improving parking facilities increases the likelihood of commuting by bicycle. Some have found a strong impact (Bueno et al., 2017; Hunt and Abraham, 2007; Noland and Kunreuther, 1995), while others have estimated a small or even statistically insignificant effect (Handy and Xing, 2011; Stinson and Bhat, 2004). Fournier et al. (2023) found that the interest in secure bicycle parking is highest at metro stations and workplaces.

Research has shown that cyclists prefer sheds to parking racks (Lusk et al., 2014; Moskovitz and Wheeler, 2011; Yuan et al., 2017). However, studies comparing different types of bicycle parking facilities are rare, and most of the aforementioned studies use only the abstract term of availability of (secure) bicycle parking. Lusk et al., 2014 found that on-street parking is not preferred and that some cyclists park in a room at home or at work, although this is also not their preference.

Less literature focuses on the influence of the location of individual parking facilities and is mostly limited to train stations. E.g., Molin and Maat (2015) found that the utility of bicycle parking facilities decreases as walking time increases and that there are segments of cyclists with different parking preferences in terms of sensitivity to walking distances and pricing. Arbis et al. (2016) found that an increase of 100 m in walking distance corresponds to a 20% decrease in the use of bicycle lockers. Papers and guidelines recommend short distances between parking facilities and buildings because otherwise, users will do ‘fly parking’ at furniture not intended for bicycle parking or parking wildly on sidewalks, causing the aforementioned difficulties for pedestrians and people with limited mobility (Dufour, 2010; FGSV, 2012; Gamman et al., 2004; Larsen, 2015).

Molin and Maat (2015) also concluded that bicycle parking is not only an issue at train stations and that estimating preferences for other locations that attract many visitors is an important topic for further research. This also applies to universities.

Although we know that cyclists are very sensitive to walking distances, previous models that predict the parking demand do not focus on individual facilities and their characteristics as this paper does, e.g.:

- Xu et al. (2012) developed a model for a university campus in Beijing based on time series and attraction rates at the building level.
- Pfaffenbichler and Brezina (2016) analyzed the citywide demand for public bicycle parking facilities in Vienna based on mode shares at the city district level, but not for individual facilities.

- Veillette et al. (2018) modeled the demand for bicycle parking at the grid cell level for the city of Québec.
- Ito et al. (2023) modeled statistical area-based demand for the city of London and noted the lack of consideration of parking facility type as a limitation of their study.

Using individual parking preferences and focusing on the level of specific parking facilities according to their location and facility type, this paper presents an approach to modeling parking behavior using a methodology that none of these studies have used.

3. Methodology

Fig. 1 shows our approach to modeling bicycle parking decisions. First, we created a *synthetic bicycle commuter population* of university students and employees who commute by bicycle based on a *mobility survey* (bicycle mode share) and RWTH *student and employee statistics* (number of students and employees). We mapped the population to buildings using *building location and space usage* data. Thus, our total demand includes the number of relevant students and employees per building.

Second, we used a GIS (ArcGIS Pro) to calculate *cycling detours and walking distances* from parking facilities to the building entrances of their destinations based on the distribution of *residential addresses* in the mobility survey, *parking facility data,* and the building locations. Third, we used a mixed logit model to analyze a *stated preference experiment* for bicycle parking. Fourth, we applied the estimated *parking preferences, cycling detours, and walking distances* to the *synthetic bicycle commuter population* in order to predict bicycle parking choices and, thus, total *parking demand* per facility. Fifth, we compared the predicted bicycle parking occupancy to the bicycle parking *count data* by conducting a *model fit analysis*. Finally, based on the discrepancies between the predicted and measured occupancy rates, we returned to the parking preferences and adjusted the weighting of the walking distance and cycling detour parameters to more accurately reflect actual bicycle parking behavior.

3.1. Synthetic bicycle commuter population

To apply our approach to the RWTH campus, we needed a synthetic bicycle commuter population that included (a) group affiliation (students, professors, scientific employees, administrative and technical staff (ATS)), (b) geographic direction of residence (i.e., origin of commute trip) and, (c) building of work or study place (i.e., destination of commute trip). We used the results of a university mobility survey ($n = 3841$) sent out to all students and employees in June 2022 to generate 12,918 bicycle commuters. We then assigned them to buildings using space utilization data based on a dataset of all rooms in university buildings and their use (lecture hall, office, etc.). After filtering out some buildings without parking facilities in their surroundings, we had 12,530 cyclists in 209 buildings.

Later, we weighted each commuter according to the frequency of bicycle commuting estimated from the mobility survey (e.g., 0.2 for one day per week and 1 for daily commuting). Finally, we calculated the number of parked bicycles per facility using a simultaneity factor based on time-series data from the national household travel survey (Mobility in Germany 2017) to account for the temporal overlap of parking processes. We multiplied our results by a factor of 0.6 to account for vacation days, business trips, and sick days.

3.2. Stated preference experiment

For our analysis, we use the results of a web-based stated preference experiment conducted among students and employees of RWTH in July 2022 ($n = 2960$). In this experiment, participants had to choose one of the following alternatives for parking their bicycles:

- Indoor parking in the building where they work or study (if possible in the status quo), which is equivalent to indoor parking as a fallback behavior (Lusk et al., 2014)
- A traffic sign pole representing ‘fly parking’
- Uncovered parking rack
- Covered parking rack

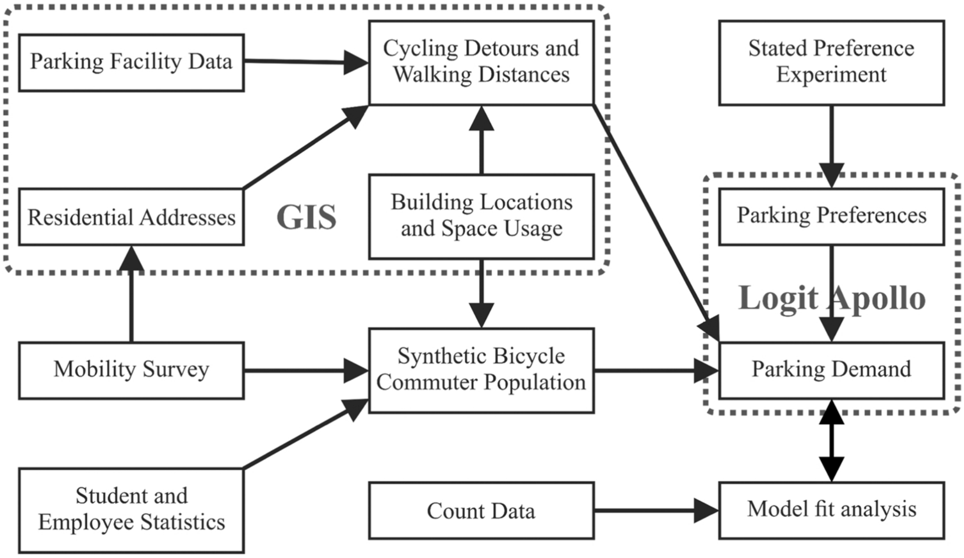


Fig. 1. Overview of the approach.

- Bicycle parking station

These alternatives were associated with different cycling detours, walking distances, and prices, allowing us to analyze the attributes' influence with a mixed logit model using the R package Apollo (Hess and Palma, 2022). We restricted the distances so that, for example, the posts of a traffic sign were always close, as fly parking options are in reality, while bicycle parking stations could be further away. The price was only assigned to bicycle parking stations because the implementation of charging for conventional bicycle parking seems unrealistic. An example choice set is given in Fig. 2. To generate choice sets, we used Ngene and applied an efficient design that minimizes the d-error using coefficients from a pretest. When assigning choice sets to participants, we applied blocking to avoid unbalanced groups of choice sets.

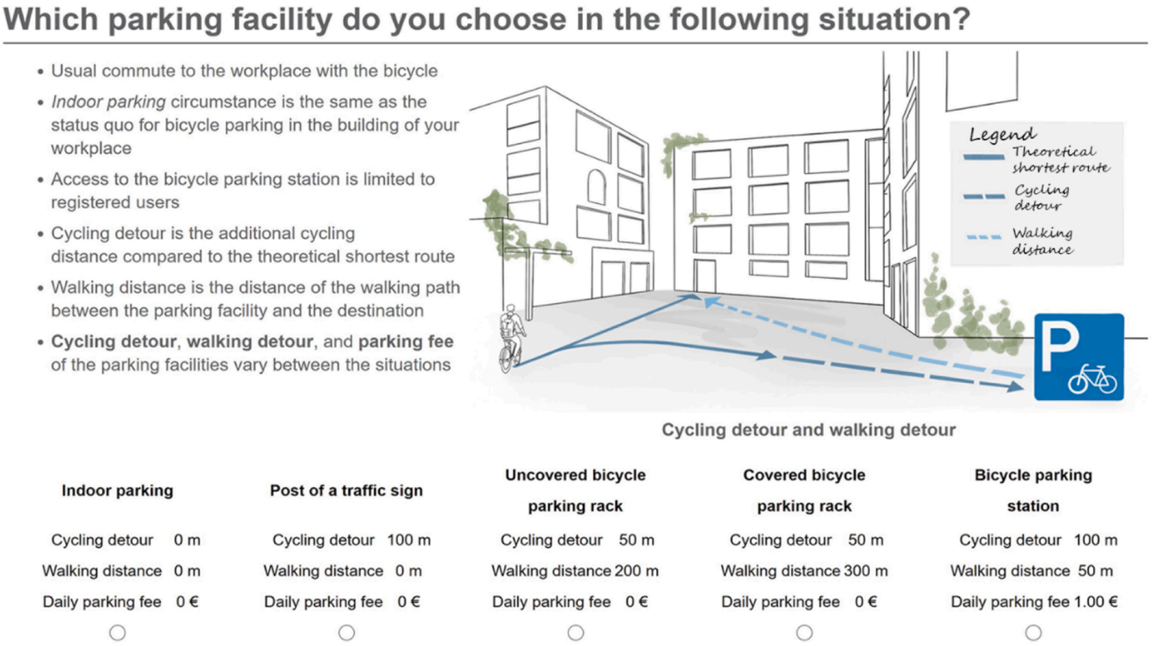
The utility function used was defined as follows:

$$U_{itq} = \alpha_{iq} X_i + \sum \beta_p Y_{itqp} + \varepsilon_{itq} \tag{1}$$

While U_{itq} is the utility of an alternative, which depends on the alternative (i), the situation (t), and the individual (q), ε_{itq} is a Gumbel-distributed error term representing the variation in individual preferences. Furthermore, α_{iq} is an interindividual random coefficient that is multiplied by the facility type (X_i). α_{iq} consists of a mean value (μ_α) and a standard deviation (σ_α) that is multiplied by a normally distributed error term $(\xi_{\alpha iq})$ that is symmetrically distributed around zero.

$$\alpha_{iq} = \mu_\alpha + \sigma_\alpha \cdot \xi_{\alpha iq} \tag{2}$$

While β_p are parameter-dependent (p) standard logit coefficients, they are multiplied by the characteristics of the alternative in the specific situation (Y_{itqp}). This also includes the interactions of characteristics with user-specific attributes, such as the resale value of the bicycle (RV) or the student and employment status. Table 1 presents the coefficients of the estimated mixed logit model, with the exception of the price coefficients, which were not included in the parking demand modeling



Which parking facility do you choose in the following situation?

- Usual commute to the workplace with the bicycle
- *Indoor parking* circumstance is the same as the status quo for bicycle parking in the building of your workplace
- Access to the bicycle parking station is limited to registered users
- Cycling detour is the additional cycling distance compared to the theoretical shortest route
- Walking distance is the distance of the walking path between the parking facility and the destination
- **Cycling detour**, **walking detour**, and **parking fee** of the parking facilities vary between the situations

Cycling detour and walking detour

Indoor parking	Post of a traffic sign	Uncovered bicycle parking rack	Covered bicycle parking rack	Bicycle parking station
Cycling detour 0 m	Cycling detour 100 m	Cycling detour 50 m	Cycling detour 50 m	Cycling detour 100 m
Walking distance 0 m	Walking distance 0 m	Walking distance 200 m	Walking distance 300 m	Walking distance 50 m
Daily parking fee 0 €	Daily parking fee 0 €	Daily parking fee 0 €	Daily parking fee 0 €	Daily parking fee 1.00 €
○	○	○	○	○

Fig. 2. Example choice set.

Table 1
Coefficients mixed logit model.

		Est.	Std. err.	t-ratio	p-value	
Indoor parking	μ_α	-2.940	0.299	-9.828	<2E-12	***
	σ_α	5.146	0.160	32.237	<2E-12	***
Indoor parking$_{Student}$	β_p	-2.419	0.271	-8.929	<2E-12	***
Indoor parking$_{ATS}$	β_p	1.784	0.375	4.758	1.96E-06	***
Indoor parking$_{RV > 500\ €}$	β_p	1.740	0.300	5.808	6.32E-09	***
Indoor parking$_{RV > 1{,}000\ €}$	β_p	1.304	0.441	2.955	0.003	**
Indoor parking$_{No\ designated\ space}$	β_p	-0.965	0.287	-3.359	7.82E-04	***
Indoor parking$_{Forbidden\ in\ building}$	β_p	-0.894	0.272	-3.282	0.001	**
Indoor parking$_{Forbidden\ at\ department}$	β_p	-0.936	0.420	-2.230	0.026	*
Pole of a traffic sign	μ_α	-2.032	0.075	-26.953	<2E-12	***
	σ_α	1.945	0.072	26.972	<2E-12	***
Uncovered bicycle parking rack	μ_α	fixed				
	σ_α	1.381	0.065	21.104	<2E-12	***
Covered bicycle parking rack	μ_α	0.656	0.066	9.899	<2E-12	***
	σ_α	-1.547	0.065	-23.936	<2E-12	***
Covered bicycle parking rack$_{RV > 500\ €}$	β_p	0.874	0.104	8.368	<2E-12	***
Bicycle parking station	μ_α	0.876	0.164	5.349	8.86E-08	***
	σ_α	2.864	0.085	33.552	<2E-12	***
Bicycle parking station$_{Student}$	β_p	-0.495	0.181	-2.733	0.006	**
Bicycle parking station$_{ATS}$	β_p	-0.620	0.333	-1.861	0.063	.
Bicycle parking station$_{RV > 500\ €}$	β_p	1.489	0.199	7.488	6.99E-14	***
Bicycle parking station$_{RV > 1{,}000\ €}$	β_p	1.258	0.254	4.961	7.03E-07	***
Bicycle parking station$_{Dist.\ to\ RWTH}$ $[km]$	β_p	0.045	0.018	2.551	0.011	*
Cycling detour $[m]$	β_p	-0.006	3.21E-04	-19.104	<2E-12	***
Cycling detour$_{Student}$ $[m]$	β_p	-0.002	3.93E-04	-5.840	5.23E-09	***
Cycling detour$_{Professor}$ $[m]$	β_p	-0.002	0.001	-2.868	0.004	**
Cycling detour$_{ATS}$ $[m]$	β_p	0.001	0.001	1.950	0.051	.
Walking distance $[m]$	β_p	-0.016	4.23E-04	-38.871	<2E-12	***
Walking distance$_{Student}$ $[m]$	β_p	-0.002	0.001	-4.380	1.19E-05	***
Walking distance$_{Professor}$ $[m]$	β_p	0.004	0.001	3.147	0.002	**
Walking distance$_{ATS}$ $[m]$	β_p	0.006	0.001	8.588	<2E-12	***

Significance codes: 0 '***' 0.001 '**' 0.01'*' 0.05 '.' 0.1 ' ' 1

because all facilities on campus are free. All coefficients are significant, at least at the 0.1 p-value level. The reference category was a scientific employee with a bicycle with a resale value of less than 500 € in combination with an uncovered bicycle parking rack.

Overall, the results show that – although there are differences between groups – the type of parking facility, whether it is covered or not, and the walking distance are important for cyclists. Our later findings in this paper will support these results, where we compare predicted and actual bicycle parking on the RWTH university campus. However, the stated preference model also indicates that cycling detours significantly influence the probability of choosing a parking facility. Later on, our application to the campus does not confirm this finding. For more information on the stated preference experiment, see Kohlrautz and Kuhnimhof (2023).

3.3. Parking facility data

We used a dataset of parking facilities at RWTH, including the location and facility type shown in Fig. 3. Due to construction sites on campus and the ongoing replacement of front racks with u-racks, the number of parking facilities varies slightly between 2022 and 2023.

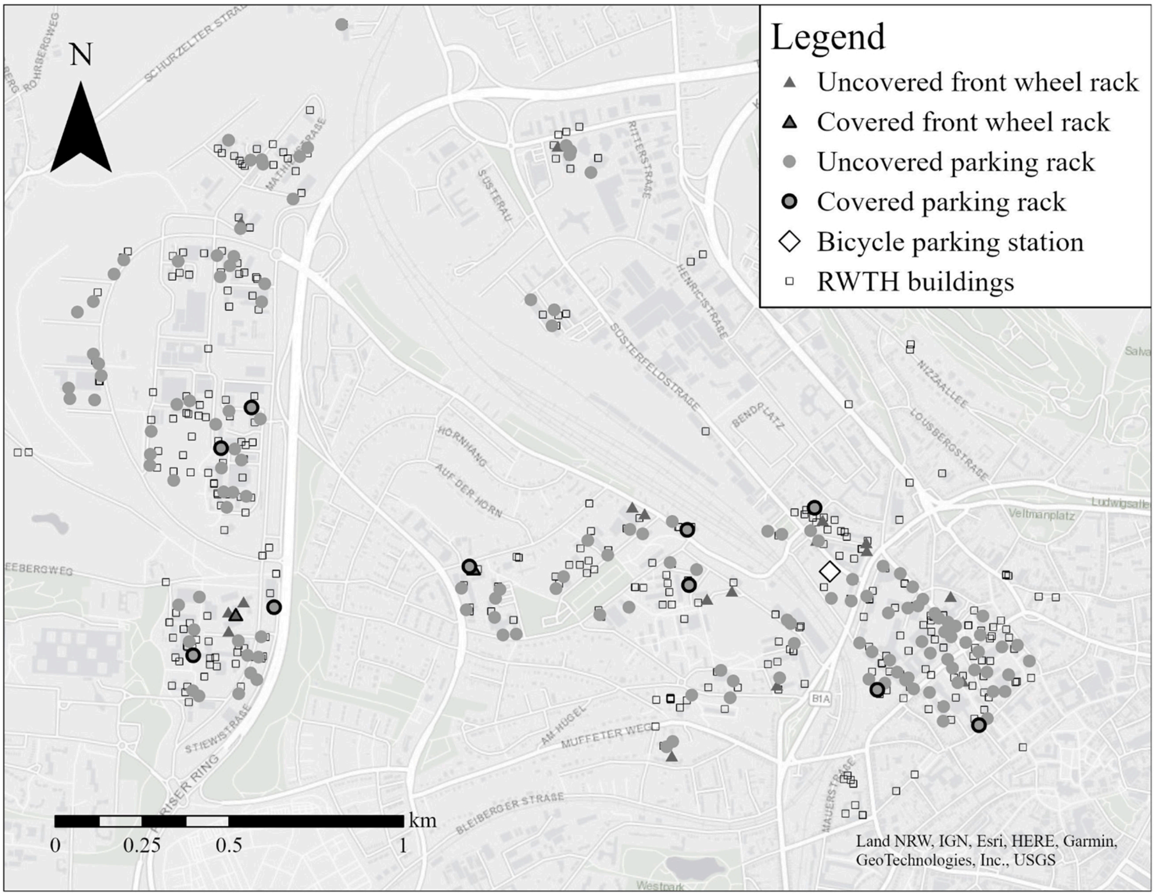
Participants also had the option of parking their bicycles indoors. However, the circumstances of indoor parking (no designated space, prohibited in the building or at the department) were randomly distributed across the population according to their distribution in the stated preference experiment since we did not have data on indoor parking circumstances in offices, etc., per building. In addition, we assumed that each building had poles of traffic signs (i.e., 'fly parking') within a 60 m walking distance. The demand for parking at traffic sign poles and indoors was not examined in the model fit analysis because they are only an opt-out option, as they are not the preferred option for cyclists and are only used when a suitable alternative is lacking (Gamman et al., 2004; Larsen, 2015; Lusk et al., 2014). Therefore, their demand represents the latent demand for bicycle parking that is not directly measurable through counts.

In the stated preference experiment, we only included u-racks, also known as Sheffield racks, which allow the bike frame to be locked to the rack. However, several facilities on the campus allow only the front wheel to be locked ('front racks'), also known as butterfly racks. To account for the higher theft risk, we applied the 'pole of a traffic sign' coefficient to these racks; for covered front racks, we additionally used the 'covered bicycle parking rack' coefficients.

We also aggregated the demand for nearby parking facilities of the same type. This reduced the number of facilities analyzed from 163 in 2022 (162 in 2023) to 102 (105 in 2023), as shown in Table 2.

3.4. Cycling detours and walking distances

To calculate the cycling detour to reach a facility, we measured the beeline distance between the quadrant-based geographic centers of the home addresses from the mobility survey (trip origin) and the parking facilities. We then calculated the distance between the trip origin and the building entrance (trip destination). The difference between them defines the (positive or negative) cycling detour. (This simple approach produced unrealistic results for eleven buildings and eight parking facilities, for example, because the parking facilities were located behind the buildings. For these buildings, we manually measured cycling detours using aerial imagery.) We also used the beeline distance between the parking facility and the building entrance to determine the walking distance. Because distances in a built environment are longer than the beeline, we multiplied the beeline-based cycling detour and the walking distance by factors ($F_{Cycling\ detour}$, $F_{Walking\ distance}$).



Land NRW, IGN, Esri, HERE, Garmin, GeoTechnologies, Inc., USGS

Fig. 3. Map of bicycle parking facilities at RWTH Aachen University (2023).

Table 2
Bicycle parking facilities in our analysis.

		Front rack		Bicycle parking rack		Bicycle parking station
		Uncovered	Covered	Uncovered	Covered	
Number of aggregated facilities	2022	14	1	78	8	1
	2023	12	1	81	10	1
Total capacity (bicycle parking spaces)	2022	374	5	4050	452	543
	2023	226	7	4174	504	543

3.5. *Count data*

We counted parking facility occupancy at RWTH on Thursday, 28.04.2022, during a week with changing weather conditions, and on Thursday, 15.06.2023, during a week with good weather. We counted both days in the morning between 10–12 (‘am’) and in the afternoon between 13–15 (‘pm’). The counting phase in 2022 took place after the COVID-19 restrictions had expired, when many employees were still working from home, and many lectures and exercises were still web-based. In 2023, by contrast, the impact of the pandemic appears to be negligible.

3.6. *Model fit analysis*

We used the count data to assess the extent to which our prediction realistically reflects bicycle parking behavior, varying the factors $F_{Cycling\quad detour}$ and $F_{Walking\quad distance}$ as detour factors to represent the difference between beeline and real-world distances in a built environment. While a factor of 1 would imply that the distance is exactly the beeline, we analyzed the correlation, the root mean square error (RMSE), and the scalable quality value (SQV 100) (Friedrich et al., 2019) for values between 0 and 5. The model names represent the factors, e.g., C_1W_4 means that $F_{Cycling\quad detour} = 1$ and $F_{Walking\quad distance} = 4$.

In addition to several models with different $F_{Walking\quad distance}$ and $F_{Cycling\quad detour}$, we evaluated a base model. The base model assigns all demand generated by buildings to the nearest bicycle parking facility.

4. Results

As shown in Table 3, the prediction can explain more than 0.7 of the differences in demand for each parking facility after adjusting for distance weighting. The prediction quality of the models is slightly better for 2022 than for 2023. Furthermore, the base model already explains more than half of the demand differences between facilities.

While the model based on the stated preference experiment using the calculated beelines once (C_1W_1) has a lower correlation than the base model, increasing the $F_{Walking\quad distance}$ substantially improves the correlation with the counts and the SQV 100 and reduces the RMSE. However, the calibration of the $F_{Cycling\quad detour}$ did not show any significant contribution to the prediction quality.

Table 3
Model accuracy (am = 10–12, pm = 13–15).

			Base model	C_1W_0	C_1W_1	C_1W_2	C_1W_3	C_1W_4	C_1W_5	C_0W_3	C_2W_3	C_3W_3	C_4W_3	C_5W_3
$F_{Cycling\ detour}$			-	1	1	1	1	**1**	1	0	2	3	4	5
$F_{Walking\ distance}$			∞	0	1	2	3	**4**	5	4	4	4	4	4
Correlation	2022	am	0.55	0.14	0.50	0.70	0.73	**0.73**	0.72	0.73	0.73	0.72	0.72	0.71
		pm	0.58	0.18	0.52	0.71	0.75	**0.75**	0.73	0.75	0.75	0.74	0.74	0.73
	2023	am	0.53	0.17	0.46	0.65	0.70	**0.70**	0.69	0.71	0.70	0.69	0.69	0.68
		pm	0.52	0.20	0.50	0.69	0.73	**0.73**	0.72	0.74	0.73	0.72	0.71	0.71
RMSE	2022	am	39	72	31	19	16	**15**	15	15	15	15	16	16
		pm	37	71	30	18	16	**15**	16	15	15	15	16	16
	2023	am	38	61	31	21	19	**19**	19	19	19	19	19	19
		pm	38	61	30	21	19	**19**	20	19	19	19	19	20
SQV 100	2022	am	0.61	0.69	0.69	0.71	0.72	**0.73**	0.74	0.73	0.73	0.73	0.73	0.73
		pm	0.64	0.69	0.71	0.73	0.75	**0.76**	0.76	0.76	0.76	0.76	0.76	0.75
	2023	am	0.64	0.70	0.71	0.74	0.75	**0.75**	0.76	0.75	0.75	0.75	0.76	0.76
		pm	0.63	0.67	0.69	0.71	0.72	**0.73**	0.73	0.73	0.73	0.73	0.73	0.73

In the following, we analyze the predictions for the C_1W_4 model because it has one of the best model fit parameters. As shown in Table 4, about half of the demand is predicted to be latent because the bicycles are stored indoors or locked to the pole of a traffic sign (fly parking). The model also overpredicts the demand for covered parking racks and underpredicts the demand for the bicycle parking station. Since the closest facility to the bicycle parking station is a congested uncovered parking rack, this may partially explain why the bicycle parking station is used more than the model predicts and suggests that congestion-related influences on bicycle parking facilities should be considered. Because the model included only one facility with covered front racks, the results for this facility type should not be over-interpreted.

As an example, Fig. 4 shows the counted and predicted demand for the afternoon of the 2022 count day. The figures for the other counting periods are similar. In some cases, no demand was counted, although demand was predicted, and vice versa.

In terms of the geographic location of the facilities, Fig. 5 shows some underpredictions on the left side of the map. Several buildings in this area are not used exclusively for university purposes. Since these buildings, or parts of them, are not included in our dataset, the employees of the companies located there are not part of our prediction. However, they are likely to park in the RWTH parking facilities, which explains the underprediction of demand.

For some locations, an overprediction of demand can also be explained. For example, the users of the RWTH guesthouses have a different mobility behavior than users of other university buildings, resulting in less demand than predicted. In addition, some locations with overpredicted demand have other facilities of the same or a different facility type nearby.

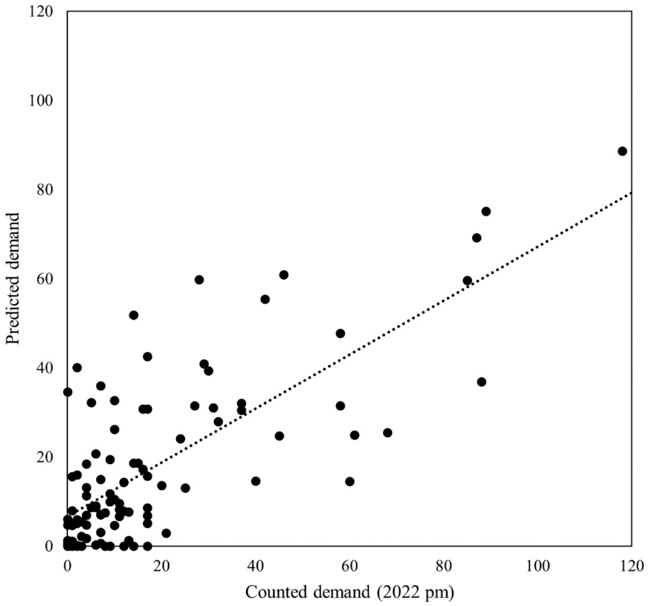


Fig. 4. Predicted and counted demand per parking facility (C_1W_4) 2022 pm.

5. Discussion

Modeling bicycle parking demand at the facility level shows that the facility type is relevant to the quality of the prediction. According to our results, including cycling detours does not improve the parking demand forecast. One explanation is that, according to existing guidelines, most bicycle parking facilities are located between site access points from

Table 4
Counted and predicted demand by parking facility type after calibration (C_1W_4).

		Indoor parking	Pole of a traffic sign	Front rack		Parking rack		Bicycle parking station	Counted facilities
				Uncovered	Covered	Uncovered	Covered		
2022									
Predicted	-	952	892	36	5	1464	207	60	1772
Counted	am	-		31	1	1408	157	96	1693
	pm			25	2	1503	199	85	1814
Ratio	am			1.16	5.00	1.04	1.32	0.63	1.05
	pm			1.44	2.50	0.97	1.04	0.71	0.98
2023									
Predicted	-	943	872	36	2	1481	220	60	1799
Counted	am	-		40	0	1581	200	109	1930
	pm			35	0	1648	197	128	2008
Ratio	am			0.90	∞	0.94	1.10	0.55	1.07
	pm			1.03	∞	0.90	1.12	0.47	1.00

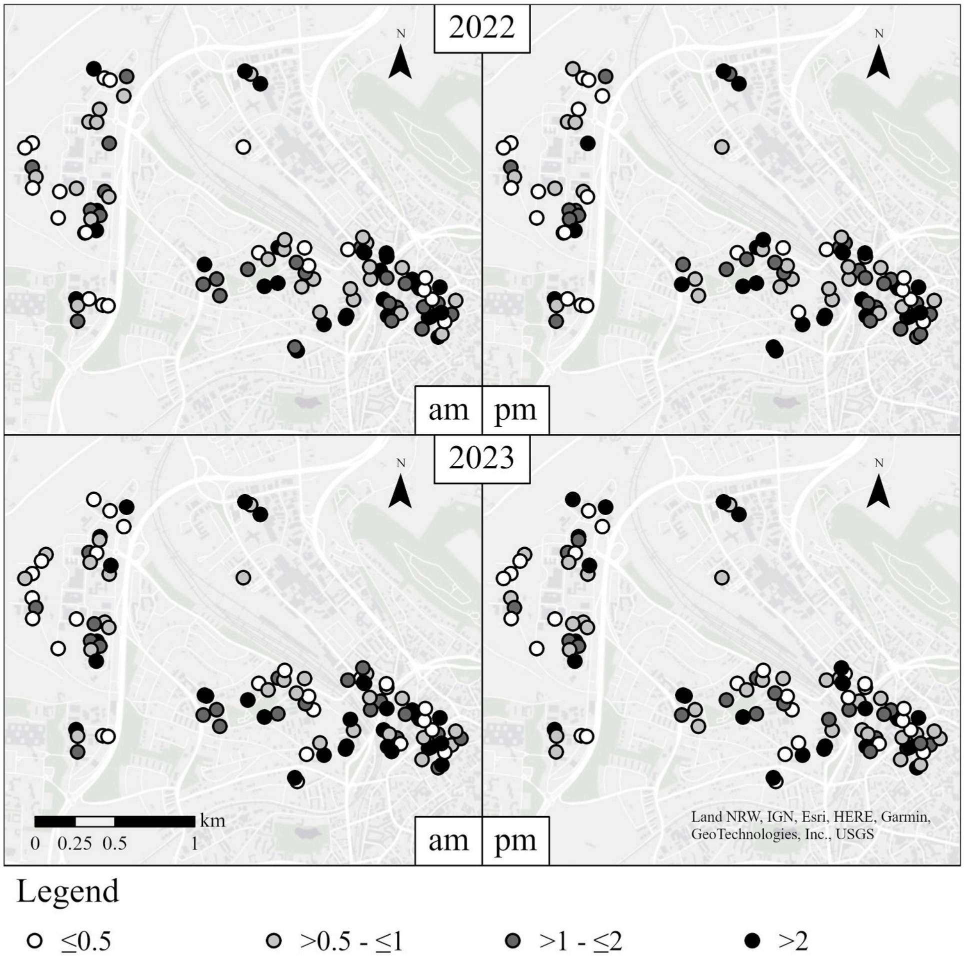


Fig. 5. Ratio of predicted and counted demand per parking facility (C_1W_4).

public streets and building entrances (FGSV, 2012). Consequently, cycling detours carry little weight, as cyclists typically arrive from the direction in which the parking facility is located. A more in-depth analysis of this issue would need to include specific bicycle routing. This would require a detailed network, including all paths that cyclists are allowed or tolerated to use and the exact origins and destinations, even within buildings if cyclists can use side entrances. Although noise may be an issue, GPS-based tracks could be a data source for such an analysis.

Nevertheless, we believe that the modeled assumption that cyclists rely on cycling detours is correct. However, their exact calculation is complex, and their impact is limited compared to other factors such as walking distance and facility type. Finally, the correlation between the length of cycling detours and walking distance explains why accounting for cycling detours does not improve the explanatory power of the prediction.

On the contrary, walking distances between parking facilities and trip destinations turned out to be more influential than our stated preference experiment suggested. Because walking distances in a built environment are longer than the beeline, we expected a detour factor of about 1.5 to optimize our model fit. Surprisingly, we estimated a value of 4 to maximize the correlation with the count data, even though the stated preference-based model already assumed that the utility of a parking facility decreases by about 80% when the walking distance increases by 100 m. Comparing this result with the finding by Arbis et al. (2016) that the actual use of bicycle lockers at train stations decreases by only 20% for the same distance, our results show a substantially different parking behavior than in their study. One reason for this may be a greater willingness to walk to secure bicycle parking at train stations than at work or study locations. It also suggests that stated preference experiments may underestimate cyclists' sensitivity to walking distances. We think that the respondents in our stated preference experiment were probably biased towards people with a higher interest in better parking facilities; one possible reason is an overrepresentation of owners of expensive (e-)bikes in the survey. Therefore, the average cyclist may be more sensitive to walking distances because they benefit less from better parking facilities than the coefficients for facility types from our stated preference experiment suggest, calling into question the validity of the stated preference estimates. In addition, the magnitude of the σ_α coefficients is noteworthy because it suggests that cyclists' perceptions of different facility types vary widely, which is also a source of unexplained differences between predicted and counted demand.

Our approach has some limitations and sources of inaccuracy. The space use data we used is generally imprecise because the density of employees and students per square meter varies between buildings, although we have accounted for categories of space use. In addition, cycling mode share varies between buildings (e.g., due to differences in access to public transit, availability of car parking, and quality of bicycle parking), and demand varies between and within days (e.g., lecture times). If cyclists change buildings during a work or study day without relocating the bicycle, which is common, this is also not captured.

Furthermore, about three-quarters of the facilities in our example were uncovered parking racks. Cyclists' preferences have little effect on parking choices when they cannot realistically choose between facility types. This is the case when only one suitable alternative is available around a building, such as only uncovered parking racks, and could explain the limited increase in the correlation compared to the base model, which assigns each cyclist to the closest facility regardless of facility type. Moreover, considering only the closest facility of each type could have led to prediction inaccuracies, which likely explains why there are facilities for which no demand is predicted at all. Approaches to address this would be using a nested logit model that considers multiple facilities of each type or additional aggregation during the analysis.

The models predict that half of the bicycles are parked indoors or at the post of traffic signs. We believe that the actual proportion of bicycles parked there is lower. There are several possible reasons for this. For example, our approach does not include public bicycle parking spaces in the wider area. If a cyclist parked there, the bicycle was not counted. Since this is most often done in the absence of a proper facility, it is likely that the cyclist is predicted to park at a traffic sign post or indoors. In addition, the lack of consideration of occupancy may lead to an overestimation of the attractiveness of fly parking options, as options such as posts of traffic signs are limited. As mentioned above, we believe that the ownership of expensive bicycles in the stated preference experiment was probably higher than in reality, making indoor parking more attractive than it actually is. One approach to addressing this issue would be to collect data on the types of facilities cyclists currently use to park their bikes.

Overall, our results underscore the importance of good positioning of parking facilities. Otherwise, cyclists will choose other options, such as street furniture, that was not originally designed for this purpose (FGSV, 2012; Gamman et al., 2004), as shown by the high proportion of bicycles predicted to be parked indoors and at traffic sign posts. Therefore, when designing bicycle parking facilities, it is recommended to consider both the location and the type of facility. Only by taking both into account is it possible to correctly predict demand, which is necessary to promote cycling effectively and to avoid fly parking of bicycles.

6. Conclusions

Our results show that including parking facility type, combined with a strong weighting of walking distance to building entrances, substantially improves the prediction of bicycle parking demand compared to a model based solely on the shortest distance to building entrances.

In this study, a stated preference experiment provided the user preferences that form the basis of such an improved model. Bicycle parking counts provided real-world bicycle parking data that we used to perform a reality check on our model and calibrate it to real-world conditions.

Our results indicate discrepancies between parking behavior modeled with the results of stated preference experiments and real-world parking behavior, as our stated preference experiment-based prediction substantially underestimates the influence of walking distances relative to facility preferences. Reasons for this include an incorrect self-assessment of the participants' actual willingness to walk to bicycle parking facilities and a bias in the recruitment of experimental participants (via email to the entire target population of university members), although different groups of university members were weighted.

An improvement to our approach would be to include occupancy-induced effects, i.e., the extent to which demand for bicycle parking is diverted to other facilities when the desired facility is (fully) occupied. However, this affects not only designated bicycle parking facilities but also fly parking options such as street furniture, which are difficult to quantify. Further research should address this issue.

Nevertheless, we are confident that our approach represents a substantial improvement in predicting bicycle parking demand over existing approaches. It recognizes that different groups of cyclists have different needs for parking infrastructure in terms of facility type and proximity to destinations. Simplistic models cannot account for this. Moreover, a multi-attribute model such as ours can also be used to design a multi-optional bicycle parking facility layout that maximizes user benefits. This includes aspects such as incorporating different preferences for bicycle parking facilities according to the resale value of the bicycle and the willingness to cycle and walk, which varies among user groups, such as students or employees, short-term or long-term users, and those with short or long commutes.

We believe that approaches such as ours will be increasingly needed to evaluate bicycle parking infrastructure changes and optimize bicycle parking expansion strategies in the context of promoting bicycle travel, e.g., in light of growing shares of e-bikes. Further research is needed to analyze parking preferences and predict parking demand in other locations and for different trip purposes, including other circumstances such as parking duration and user composition.

Ethical declaration

Informed consent was obtained from all participants in the survey.

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CRediT authorship contribution statement

Kohlrautz David: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Kuhnimhof Tobias:** Funding acquisition, Resources, Supervision.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: David Kohlrautz reports financial support was provided by RWTH Aachen University.

Data availability

Data will be made available on request.

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