Modeling the Demand for Bicycle Parking Facilities

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SUMMARY (147 WORDS)

Improving opportunities for bicycle parking is essential for promoting cycling. However, there is a lack of approaches for predicting the demand for bicycle parking based on the facility type and the facility's location. Considering both during planning could help improve bicycle parking according to user needs. This is particularly applicable when cyclists face several parking options, such as on university campuses, as in our case study. The paper presents a stated preference-based model, which was additionally calibrated using bicycle parking count data.
Considering facility types improves the model fit substantially. Furthermore, the stated preference-based, original model underestimates the sensitivity to walking distances between facilities and buildings. When cyclists can choose between multiple parking facilities, it is critical to consider walking distances to realistically predict the demand for bicycle parking facilities. This confirms previous findings, that positioning parking facilities close to destinations is essential for attractive parking infrastructure.

Keywords: Bicycle parking, cycling, cycling behavior, demand modeling

Conference topic: Cycling and walking behavior and design

SHORT PAPER (2,842 WORDS WITHOUT TABLES)

1. INTRODUCTION

Improving bicycle parking infrastructure is, in addition to measures for moving bicycle traffic, essential to promote cycling (Heinen and Buehler, 2019). Even though many previous studies analyzed bicycle parking behavior and preferences, research does not yet cover modeling the demand for single facilities considering facility type and position. We present a model for bicycle parking facility demand at RWTH Aachen University, one of the largest technical universities in Germany (45.000 students, 8.000 employees). We model bicycle parking behavior based on a stated preference experiment among RWTH students and staff, focusing on privately owned bicycles. Specifically, we analyze to which degree the following factors are relevant for the prediction of bicycle parking demand:

1. Type of parking facility
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)

First, we review previous studies regarding bicycle parking before we describe our method, present our results, discuss them, and draw a conclusion.

2. REVIEW

Promoting cycling is one approach to increase the sustainability of mobility, especially in dense urban areas. One way is the improvement of bicycle parking facilities. For a general review of bicycle parking preferences and behavior, particularly at the workplace, we refer to Heinen and Buehler (2019).
Studies show that improving parking facilities increases the probability of commuting by bicycle. Several studies found a strong impact (Bueno et al., 2017; Hunt & Abraham, 2007; Noland & Kunreuther, 1995), while others only estimated a low or even statistically insignificant one (Handy & Xing, 2011; Stinson & Bhat, 2004). Furthermore, research showed that cyclists prefer sheds over parking racks (Lusk et al., 2014; Moskovitz & Wheeler, 2011; Yuan et al., 2017).
Less literature focuses on the influence of parking facility location-related factors. E.g., Molin and Maat (2015) found that the utility of bicycle parking facilities decreases when walking time increases. Papers and guidelines recommend short distances between parking facilities and buildings because users otherwise do 'fly parking' at facilities not intended for bicycle parking (Dufour, 2010; FGSV, 2012; Gamman et al., 2004; Larsen, 2015).

Previous models predicting the parking demand do not focus on single facilities and their attributes as in our paper, e.g.:

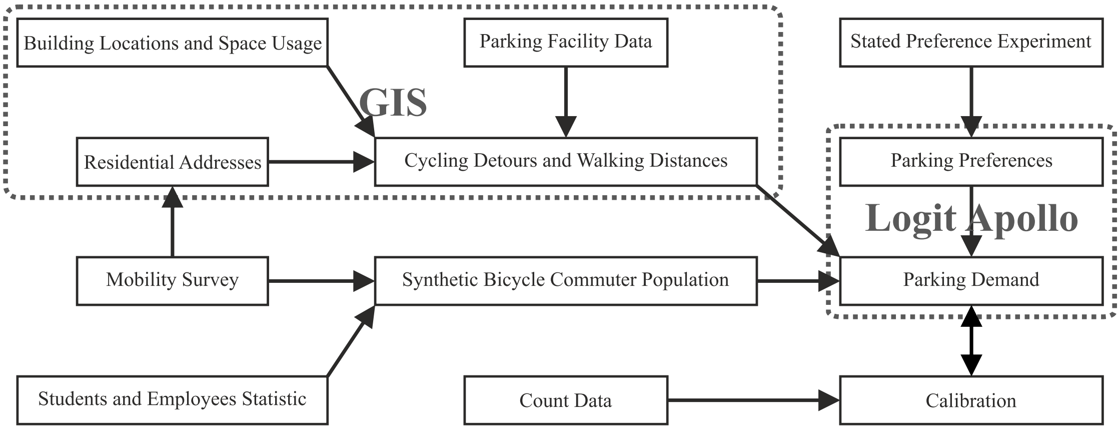
- Xu et al. (2012) developed a model for a university campus based on time series and attraction rates per building.
- Pfaffenbichler and Brezina (2016) analyzed the demand for public bicycle parking facilities in Vienna based on mode share and differentiating city districts, but not single facilities.
- Veillette et al. (2018) modeled the demand for bicycle parking on the grid cell level for Québec city.

3. METHODOLOGY

Figure 1 shows our approach to model bicycle parking choices. Firstly, we generated a synthetic university student and employee population commuting by bicycle based on mobility data and RWTH statistics. Hence, our total demand for bicycle parking includes the number of relevant students and employees per building.

Secondly, we calculated cycling detours and walking distances from parking facilities to the building entrances of their destination using a GIS. Thirdly, we used a mixed logit model to analyze a stated preference experiment. Fourthly, we applied the model to the synthetic population of bicycle commuters in order to predict their choice of bicycle parking and, thus, the total demand for bicycle parking per facility. Fifthly, we compared the predicted bicycle parking occupancy with bicycle parking count data. Finally, based on discrepancies between predicted and measured occupancy rates, we returned to the model and calibrated model parameters to reflect real bicycle parking behavior more adequately.

Figure 1: Model overview (own illustration)



Synthetic student and employee bicycle commuter population

In order to apply our model to the RWTH campus, we required a synthetic bicycle commuter population including a) group affiliation (students, professors, scientific employees, administrative and technical staff (ATS)), b) geographic direction of residential location (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 = 3,841) mailed out to all students and employees to generate the cycling commuters and assigned them by space usage data to buildings.

Stated preference experiment

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

- indoor parking in the building of their place of work respectively study (if possible in the status quo)
- a traffic sign pole representing 'fly parking'
- uncovered parking rack
- covered parking rack
- bicycle parking station

These alternatives were associated with varying cycling detours, walking distances, and prices, enabling us to analyze the attributes' influence with a mixed logit model using the R package Apollo (Hess & Palma, 2022).
Table 1 shows the models' coefficients for different facility types, taking the interactions with the resale value of the bicycle (RV) and group affiliation (scientific employees (reference category), students, professors, and ATS) into account.

Overall, the results show that – while there are differences between the various groups – the type of parking facility, whether it is covered or not, and the walking distance matter to cyclists. Our later findings in this paper will support these results, where we compare predicted and real 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 will not confirm this finding.

Table 1: Coefficients mixed logit model

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

Parking facilitiy data

In the stated preference experiment, we only included u-racks, also known as Sheffield racks, allowing for locking the bike frame to the stand. However, several facilities on the campus only allow locking the front wheel ('front racks'). To consider a higher theft risk, we applied the

coefficient for 'pole of a traffic sign' to them; for covered front racks, we used the coefficients for 'covered bicycle parking rack' on top.
We also aggregated the demand for close together located parking facilities of the same type. As a result, the number of analyzed facilities decreased from 163 to 99 shown in Table 2.

Table 2: Bicycle parking facilities in our analysis

	Front rack		Bicycle parking rack		Bicycle parking station
	Uncovered	Covered	Uncovered	Covered	
Number of aggregated facilities	15	2	73	8	1
Total capacity (bicycle parking spaces)	650	15	3814	452	543

To calculate the cycling detour to reach each facility, we measured the beeline distance between each geographic center of the residential addresses (trip origin) and parking facilities. Then, we 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 led to unrealistic results for eleven buildings and eight parking facilities, and we manually measured cycling detours with aerial images for these instances.) We used the beeline distance between the parking facility and the building entrance to determine the walking distance. Further, we assumed that poles of traffic signs (i.e., 'fly parking') at a walking distance of 60 m are available at each building.

Count data

We counted the occupancy of parking facilities at RWTH primarily on Thursday, 28.04.2022, in the morning (10-12) and afternoon (13-15), during a week with changing weather conditions. The counting phase took place shortly after the expiration of COVID-19 restrictions when many employees were still working from home, and many lectures and exercises were still web-based. Furthermore, our model does not consider temporal overlap. Therefore, we scaled our predicted demand by the quotient of counted and predicted demand, around one-third. Because the morning and afternoon results are similar, we only show the results for the afternoon.

Calibration

We used the count data to assess to which degree our prediction realistically reflects bicycle parking behavior. In the process, we calibrated the model by multiplying the cycling detour and the walking distance by factors ($F_{Cycling\ detour}$, $F_{Walking\ distance}$). We analyzed values between 0 and 5 regarding the correlation and the root mean square error (RMSE). The model names represent the factors, e.g., C_1W_3 means that $F_{Cycling\ detour} = 1$ and $F_{Walking\ distance} = 3$.

4. RESULTS

Apart from several models with different $F_{Walking\ distance}$ and $F_{Cycling\ detour}$, we evaluated a base model, as shown in Table 3. The base model assigns all demand generated by buildings to the closest bicycle parking facility, already explaining more than half of our demand differences between facilities. While the model based on the stated preference experiment using the calculated beelines once has a lower correlation than the base model, increasing the $F_{Walking\ distance}$ improves the correlation to the counts up to two-thirds and reduces the RMSE. However, the calibration of the $F_{Cycling\ detour}$ showed no significant contribution for the prediction quality of our model.

Table 3: Model accuracy

Model	Base-model	C_1 W_0	C_1 W_1	C_1 W_2	C_1 W_3	C_1 W_4	C_1 W_5	C_0 W_3	C_2 W_3	C_3 W_3	C_4 W_3	C_5 W_3
$F_{Cycling\ detour}$	-	1	1	1	**1**	1	1	0	2	3	4	5
$F_{Walking\ distance}$	∞	0	1	2	**3**	4	5	3	3	3	3	3
Correl.	0.55	0.18	0.51	0.63	**0.66**	0.66	0.65	0.66	0.66	0.65	0.63	0.61
RMSE	22	33	22	19	**18**	19	19	18	19	10	19	20

In the following, we analyze the predictions for the C_1W_3 model. As Table 4 shows, the model overestimates the demand for covered parking racks and, in contrast, substantially underestimates the demand for front racks.

Table 4: Counted and modeled demand after calibration (C_1W_3)

	Indoor parking	Pole of a traffic sign	Front rack		Parking rack		Bicycle parking station
			Uncovered	Covered	Uncovered	Covered	
Predicted	806	747	72	7	1,536	286	32
Counted	-	-	132	11	1,504	201	85
Ratio	-	-	0.55	0.64	1.02	1.42	0.38

Regarding the facilities' geographic locations, Figure 3 shows some underpredictions due to missing demand data for specific buildings based on a lack of space usage data. For some places, an overprediction of the demand is also explainable. For example, the RWTH guest houses have a diverging mobility behavior compared to other university buildings, causing less demand than predicted. Furthermore, some locations with overpredicted demand have other facilities of the same or another facility type nearby. Taking only the closest facility of each type into account might cause prediction inaccuracies, and additional aggregation would be one solution.

Figure 2: Predicted and counted demand per parking facility (C_1W_3)

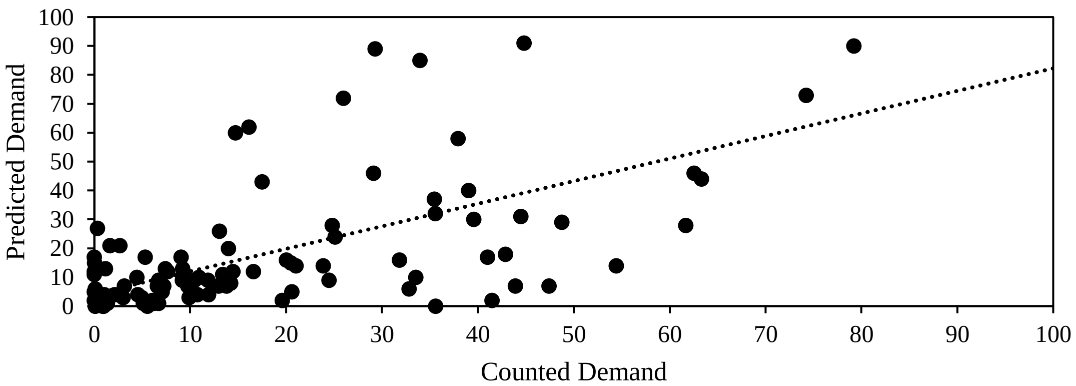
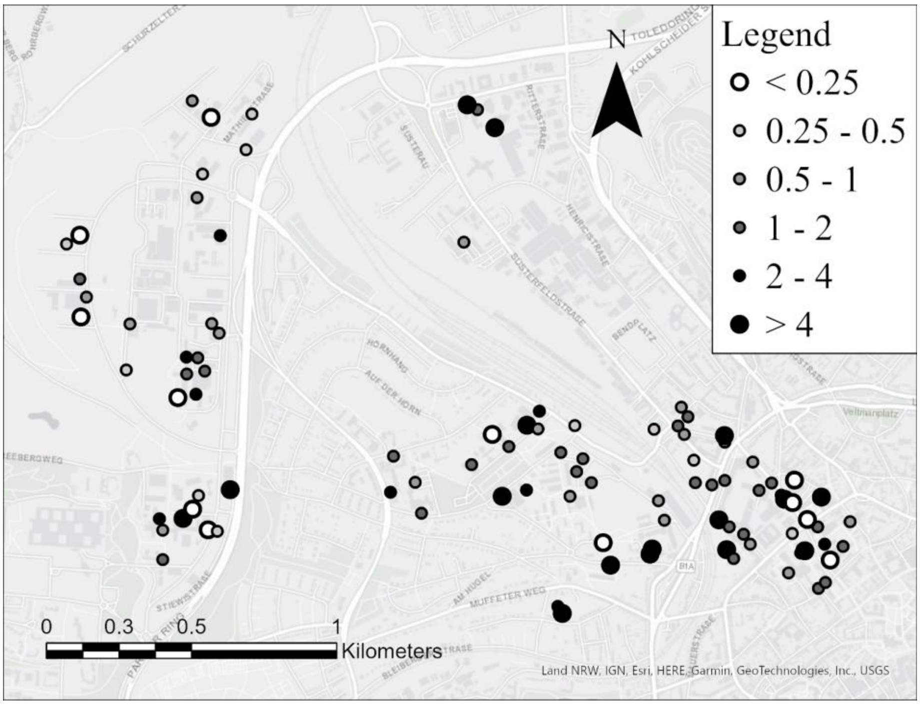


Figure 3: Ratio of predicted and counted demand per parking facility (C_1W_3)



5. DISCUSSION

Our findings show that the facility type is relevant for predicting the demand for bicycle parking because the consideration increases the correlation to 0.66. However, that almost three-fourths were uncovered parking racks might explain this limited increase in the correlation. In many cases, preferences slightly influence the parking choice because cyclists do not have the opportunity to choose between different facility types realistically.

According to our findings, the inclusion of cycling detours does not contribute to improving parking demand prediction. One explanation is that, in line with existing guidelines, most bicycle parking facilities are placed between the points of access to the respective property from public streets and building entrances (FGSV, 2012). Consequently, cycling detours hardly ever carry any weight, as cyclists usually arrive from the direction in which the parking facility is located. Nevertheless, we believe that our stated preference experiment's coefficients are proper. However, calculating exact cycling detours is complex, and their effect is limited compared to other factors such as walking distances and facility type. Finally, as close to the destination-located parking facilities have short cycling detours and walking distances in most cases, the correlation between both factors explains why considering cycling detours does not contribute substantially to 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. One reason is that walking distances in the real-world built environment are longer than the beeline. While we assumed this would lead to a factor with a maximum of 1.5, we estimated a value of 3, optimizing our model. On average, real-world cyclists may not appreciate good parking facilities as much as our experiment participants. We deem it likely that survey participation was biased towards individuals with heightened interest in better parking facilities; one possible reason is that they own expensive (e-)bikes. Therefore, survey participants may have been more willing to walk for better parking. This self-selection bias might also explain why the stated preference experiment overestimates the demand for low-quality front racks. However, our results underline the importance of good positioning of parking facilities. Otherwise, cyclists choose other options as street furniture, initially not designed for that purpose (FGSV, 2012; Gamman et al., 2004).

6. CONCLUSIONS

Our findings show that including the type of parking facility and the walking distances to building entrances improves the prediction of bicycle parking demand relative to a model solely based on the shortest distance to building entrances substantially. In this study, a stated preference experiment provided the user preferences constituting the basis for such an improved model. Bicycle parking counts contributed real-world bicycle parking data, which we used to perform a reality check of our model and to calibrate it to real-world circumstances.

There were some issues in our data that need to be taken into account. Firstly, our RWTH university mobility survey results indicate a higher demand for bicycle parking than counted. Abating COVID lockdown phenomena (e.g., a high proportion of people working and studying from home) and selectivity in our mobility survey may have contributed to this. Secondly, our results indicate a discrepancy between stated preference data-based parking preferences and real-world parking behavior. Hence, for further improvement of the approach presented in this paper, updated data collection and an in-depth investigation of the data discrepancies would be desirable. Another improvement of the approach would be the inclusion of effects induced because of occupancy, i.e., the question of to which degree demand for bicycle parking is diverted to other facilities if the desired facility is (completely) occupied. Due to low occupancy during our data collection period, we could not include these effects.

Nevertheless, we are confident that our model represents a substantial improvement in predicting the demand for bicycle parking compared to preexisting approaches. It is acknowledged that different groups of cyclists have diverging requirements regarding parking infrastructure concerning facility type and proximity to the destination. Simplistic models are not able to take account of that. Moreover, a model such as ours, which accounts for various attributes, may also be used to design a multi-optional bicycle parking facility layout that maximizes user benefit. Therefore, we believe that approaches such as ours will be increasingly needed to assess changes in the bicycle parking infrastructure and optimize extension strategies for bicycle parking in the context of promoting bicycle travel, e.g., regarding growing shares of e-bikes.

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