Discrete Choice Modeling of Car Parking Search Behavior

David Kohlrautz[1], Ingmar Seitz*[2], Tobias Kuhnimhof[3]

[1] M. Sc., Institute of Urban and Transport Planning, RWTH Aachen University, Germany
[2] Dipl.-Ing., Institute of Urban and Transport Planning, RWTH Aachen University, Germany
[3] Prof. Dr.-Ing., Institute of Urban and Transport Planning, RWTH Aachen University, Germany

SHORT SUMMARY

An understanding of parking choice and its associated effects is essential for modeling changes in parking supply. This study presents a model that uses a synthetic population and the results of a stated preference experiment to determine where car drivers park. The applied mixed logit regression model simulates the parking behavior of car commuters at RWTH Aachen University, performing an incremental assignment and reassigning drivers who were unable to find a parking space in previous iterations. The resulting model is capable of predicting shares of parking in public spaces, walking distances, and parking search traffic. Consequently, it enables the analysis of the benefits and disadvantages of modifications to the parking supply. The results indicate that a limited number of parking facilities generate the majority of car parking search traffic and that strategies of parking supply centralization are effective in reducing parking search traffic.

Keywords: Car parking, Parking behavior, Parking search traffic, Logit model, University mobility

1. INTRODUCTION

Every morning, many commuters face a decision between two alternatives: 1) try to obtain one of the highly demanded parking spots in very close proximity to the workplace and risk driving around with no success, or 2) play it safe and accept a potentially suboptimal but reliably available spot with a longer walking distance. For estimating the impact of changes in car parking infrastructure, it is crucial to understand this driver behavior when looking for a parking space and incorporate it into models to achieve realistic results.

Parking choice and its parameters have been the subject of research for years, and the most common modeling technique is multinomial logistic regression (Bonsall & Palmer, 2004; Ibeas et al., 2014). Previous studies have provided partially divergent results regarding parameters that influence parking choice. Depending on the model, gender may (Soto et al., 2018) or may not (Ben Hassine et al., 2022; Golias et al., 2002) influence parking choice. Similarly, studies have concluded that trip purpose does (van der Waerden et al., 2015) or does not have an influence (Golias et al., 2002). However, it is widely agreed that parking fees and walking distances or times, respectively, are relevant (Ben Hassine et al., 2022; Golias et al., 2002; Ibeas et al., 2014; Soto et al., 2018). Golias et al. (2002) state that the parameters for parking choice are similar to those for mode choice.

Findings also indicate that the time of day at arrival influences parking choice. Early arrivers tend to prefer park-and-ride systems, while those arriving late accept higher fees to quickly find a parking spot (Rodríguez et al., 2023). A study from Tunisia found that on-street parking is more attractive than off-street or underground, especially in peripheral areas (Ben Hassine et al., 2022). In Colombia, the price of the car and the driver's attitude toward taking care of the car significantly impact parking choices (Soto et al., 2018). Similar findings regarding vehicle age were obtained in Spain by Ibeas et al. (2014).

The familiarity of drivers with the parking infrastructure is another determinant of parking choice (Bonsall & Palmer, 2004). Age, education level, and frequency of car use turned out to be predictors of familiarity (Cools et al., 2013). It is likely that students and employees at a university are usually familiar with the parking conditions and anticipate the risk of overcrowding in advance. However, previous studies did not consider this behavior. Comprehending parking behavior is crucial because the removal of parking spaces often leads to contentious debates. A scientific foundation would enable better predictions of the effects of changes in parking facility supply and objectify discussions. Although previous studies have estimated parking preferences, there is a lack of research predicting demand and measuring accuracy. The study by Waraich and Axhausen (2012) is one of the few that predict parking demand. They considered walking distances and pricing but were unable to compare the occupancy of individual parking lots or garages.

This study presents a model designed to predict the selection of parking facilities at RWTH Aachen University, one of the largest universities in Germany, with 45,000 students and 8,000 employees. The model employs a mixed logit framework based on a stated preference experiment and uses detailed commuting and parking infrastructure data for the campus. In contrast to previous research, the model assumes that drivers attempt to avoid parking lots that are likely to become crowded. The model's primary explanatory variables are walking distance and the drivers' anticipation of parking lot occupancy. The analysis examines the effects of changes in parking infrastructure supply and the impact of parking centralization. According to Shoup (2006), university campuses are comparable to small cities in terms of parking characteristics. Consequently, the results of this study are also relevant beyond the university context.

In this paper, a parking facility refers to both parking lots and parking garages and includes multiple parking spaces. We begin with a section on the methods applied, then present and discuss our results and draw conclusions.

2. METHODOLOGY

Synthetic population

In order to model car parking behavior, a parking demand is required. To generate this, we first created a synthetic car commuter population based on a mobility survey. We weighted the participants according to the student and employee statistics of RWTH Aachen University. We multiplied the number of students and employees by their respective car mode share to get the number of people who commute to campus by car. In addition, we used reported commute frequency and random numbers to select the final population of 3,846 drivers arriving on one day.

Since the building in which car commuters work or study is unknown, we distribute their activity location based on data on space usage data, including the current use of floor space in university buildings. Using GIS and extensive parking facility data, including all university-owned parking lots on campus, we calculated routed walking distances between parking facilities and building entrances.

Parking facility data

The dataset includes 124 parking lots and three parking garages with a total capacity of over 5,000 parking spaces. The capacities of the individual parking facilities range from two to over a thousand. In total, the parking facilities at RWTH Aachen University are less than half full during peak hours. This is in contrast to other universities, where demand exceeds supply (Daggett & Gutkowski, 2003). However, the occupancy rate varies greatly between the facilities, as displayed in Figure 1, which illustrates data from a count conducted on 21.11.2024.

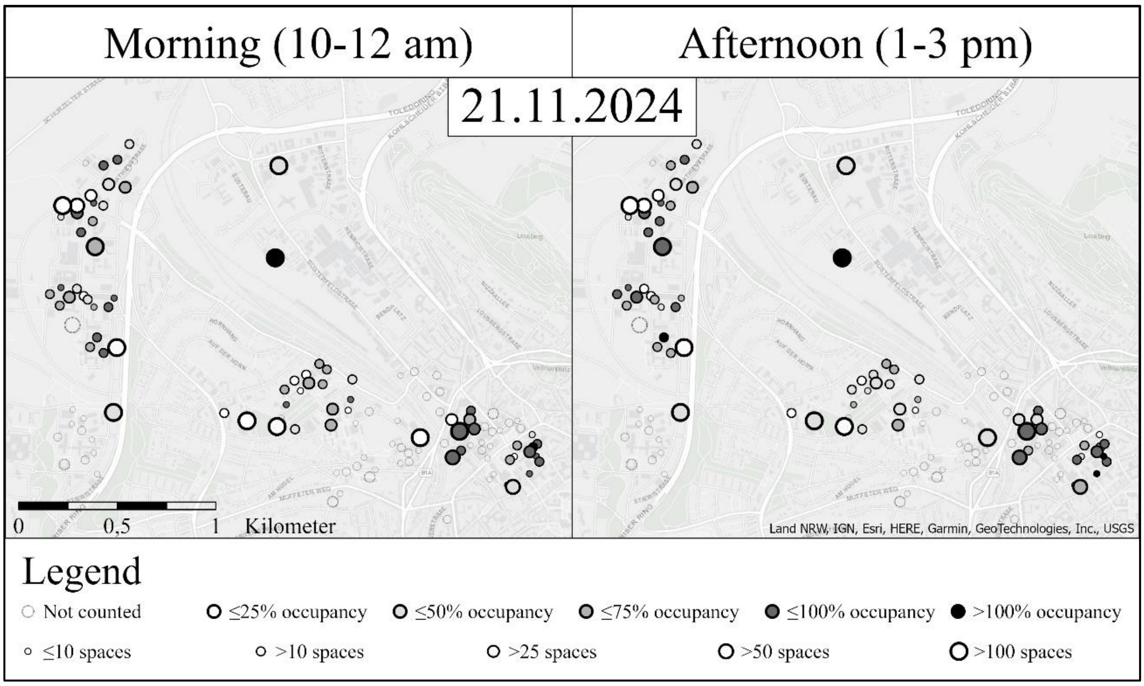

Figure 1: Counted Parking occupancy

For each building, we used ArcGIS Pro to estimate the 50 closest parking facilities, the walking distance to the building entrance, and the driving distance between parking facilities. It has to be noted that university-owned parking facilities are only available to parking permit holders. The parking permit cost 9,50 € per month per person at the time of the count and allows for unlimited parking. However, the conditions of public on-street parking vary, as parking fees are only charged around the central campus part, as displayed in Figure 2.

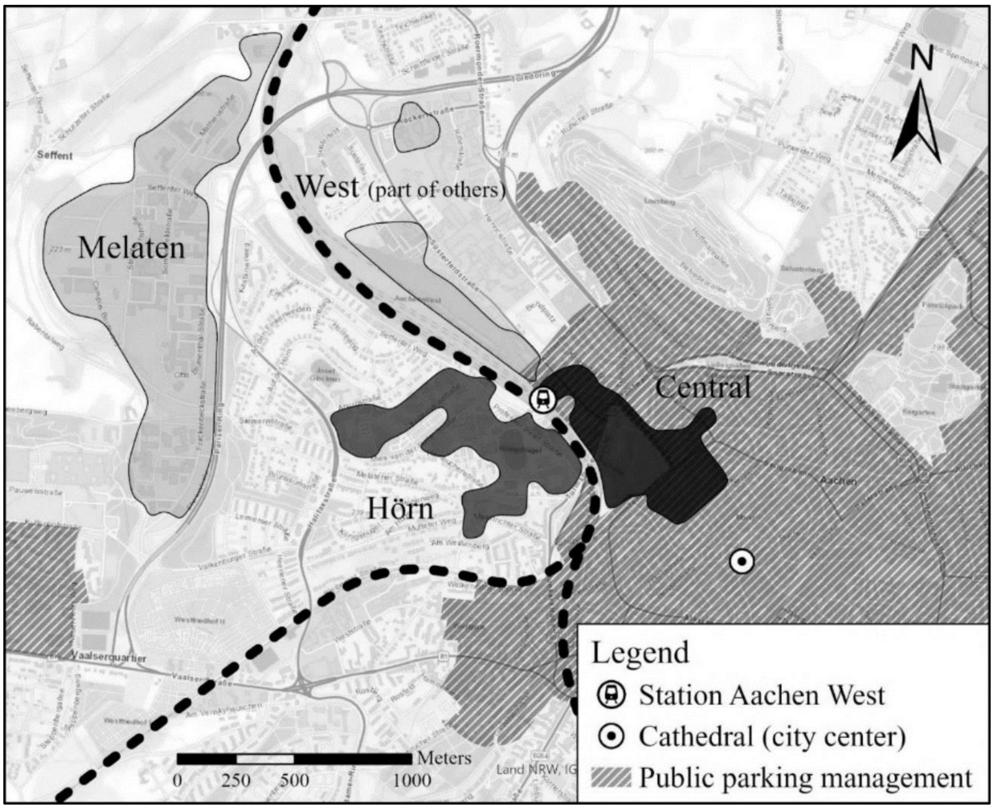

Figure 2: Campus map

Prediction model

We used a mixed logit model from a stated preference experiment that was part of the mobility survey to predict parking behavior. The model takes facility types, parking space sizes, walking distance, and the risk that a facility is crowded, into account. An example choice set is displayed in Figure 3. The coefficients of the model are shown in Table 1.

Which of the following parking facilities would you try first on your way to RWTH?

Parking facility type	Parking facility characteristics
Walking distance	Distance from parking facility to the destination
Size of parking spaces	Size of each individual parking space
P_{full}	Probability that the parking facility will run out of parking spaces and that you will have to drive to another parking facility

Parking facility type:	**On-street**	Parking facility type:	**Gravel lot**	Parking facility type:	**Parking lot**	Parking facility type:	**Park. garage**
Walking distance:	**10 min**	Walking distance:	**2 min**	Walking distance:	**1 min**	Walking distance:	**1 min**
Size of parking spaces:	**large**	Size of parking spaces:	**normal**	Size of parking spaces:	**small**	Size of parking spaces:	**small**
P_{full} :	**0 %**	P_{full} :	**75 %**	P_{full} :	**50 %**	P_{full} :	**75 %**
○		○		○		○	

Figure 3: Example choice set

Table 1: Coefficients mixed logit model

Coefficient	Reference		Estimate	Rob. s. e.	Rob. t. ratio	p-value	Sig.
Parking lot	Ref.	μ_c	fixed				
		σ_c	0.515	0.382	1.347	0.178	
Parking garage	Ref.	μ_c	-0.695	0.110	-6.315	2.70E-10	***
		σ_c	1.537	0.162	9.464	<1E-16	***
	Students	β_c	1.243	0.360	3.452	5.57E-04	***
On-street parking	Ref.	μ_c	-2.609	0.250	-10.430	<1E-16	***
		σ_c	-1.425	0.285	-5.005	5.60E-07	***
	Students	β_c	1.280	0.498	2.570	0.010	*
Gravel lots	Ref.	μ_c	-1.873	0.157	-11.955	<1E-16	***
		σ_c	1.872	0.192	9.742	<1E-16	***
Small parking space size	Ref.	μ_c	-1.876	0.208	-9.016	<1E-16	***
		σ_c	2.028	0.204	9.927	<1E-16	***
	Small vehicles	β_c	1.452	0.266	5.467	4.58E-08	***
	Woman	β_c	-1.253	0.253	-4.959	7.09E-07	***
Large parking space size	Ref.	μ_c	0.233	0.100	2.328	0.020	*
		σ_c	-0.997	0.174	-5.724	1.04E-08	***
	Large vehicles	β_c	0.564	0.409	1.381	0.167	
Walking distance [min]²	Ref.	μ_l	-2.154	0.175	-12.283	<1E-16	***
		σ_l	1.088	0.098	11.043	<1E-16	***
	Students	β_l	-0.875	0.289	-3.030	2.45E-03	**
	ATS/professors	β_l	-0.751	0.170	-4.414	1.02E-05	***
	Woman	β_l	-0.188	0.131	-1.439	0.150	
Risk that parking facility is occupied [%-points]	Ref.	μ_l	-2.952	0.133	-22.167	<1E-16	***
		σ_l	-0.729	0.087	-8.391	<1E-16	***
	Students	β_l	0.356	0.192	1.852	0.064	.
	ATS/professors	β_l	-0.708	0.138	-5.136	2.81E-07	***

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The following formula shows how the coefficients are applied:

$$U_{it} = \sum_{c=1}^{C}(\mu_c + \sigma_c \cdot \xi_{ci} + \beta_c) \cdot X_t + \sum_{l=1}^{L}\left(-e^{\mu_l+\sigma_l\cdot\xi_{li}+\beta_l}\right) \cdot Y_t + \epsilon_t \quad (1)$$

The normal distributed coefficients are indexed by c, while the negative log-normal distributed coefficients for walking distance and the risk of a facility being full are indexed by l. ξ_{ci} and ξ_{li} are normal distributed error terms with a mean of zero, while ϵ_t is a Gumbel distributed error term. The model had a log-likelihood of -3,358 and an adjusted McFadden pseudo-r² of 0.26. Only parking permit holders were included in the estimation of the model.

In general, the logit model shows a reluctance for on-street parking, parking garages, and small parking spaces, the latter particularly for women. Additionally, when considering the reference category of scientific employees, there are variations in the sensitivity to walking distances and the risk of arriving at an occupied facility. In particular, administrative and technical staff and professors are less willing to walk to a facility and less sensitive to the risk that the facility is full.

Assignment of car drivers

To assign car drivers to parking facilities, we used the approach displayed in Figure 4. First, we randomly divided the population into arrival fractions of similar size so that each fraction arrived at the campus at the same time. Then, for each driver, we calculated the probabilities for each of the 50 closest university-owned facilities and on-street parking. Based on these probabilities, a Monte Carlo simulation selected the chosen alternative. As a result, each driver chose exactly one parking facility. If the number of drivers arriving at a facility exceeded the number of available spaces, the drivers were counted up until the parking facility was full. Unsuccessful drivers were then added to the next arrival fraction. After the assignment of all fractions, additional assignments were made to the few unsuccessful drivers until all found a parking space. To estimate the risk of arriving at a full facility for subsequent iterations, the number of arriving vehicles in the previous iteration was divided by the remaining spaces. E.g., if 10 vehicles arrived in the previous step when 15 spaces were available, the risk in the next step was set to 50 % because only 5 spaces were available. This took into account for the lack of information available to drivers about current occupancy due to daily variations in demand and individual arrival times. If a driver was unsuccessful, we estimated the squared driving time to the other facilities and added it in the utility function to the squared walking time from each parking facility to the destination building to account for the accessibility of alternative parking facilities.

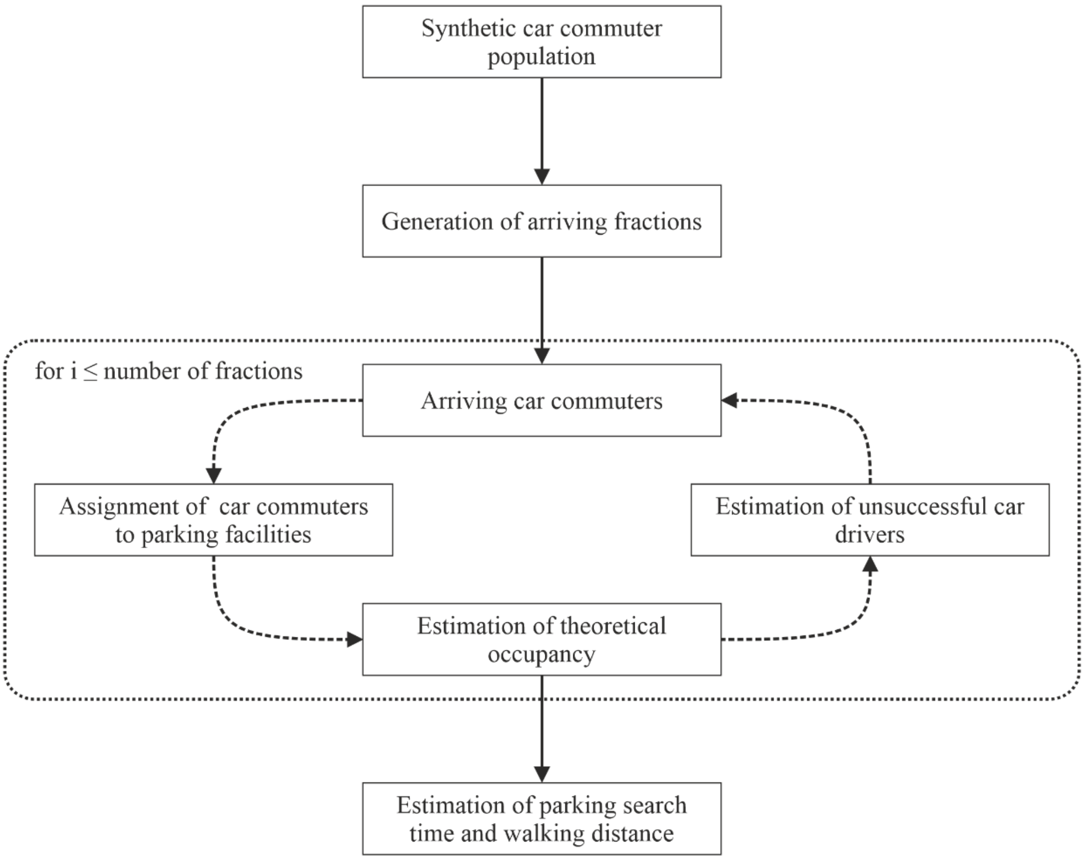

Figure 4: Assignment of car parking demand

To estimate the utility of public on-street parking, the model took into account the average walking distance and the risk of on-street parking being full based on the mobility survey responses by campus part. However, it was assumed that those who chose public on-street parking were always successful. Therefore, they were never reassigned, and it was simplified that drivers do not generate additional parking search traffic after attempting public on-street parking. In addition, university-owned parking facilities were blocked to drivers without parking permits, and the central parking zone was blocked to students according to current parking regulations. Disabled parking spaces were also blocked.

3. RESULTS AND DISCUSSION

Table 2 presents the results of the prediction model with 6 iterations. In general, the model underpredicts the proportion of students and scientific employees parking in public spaces, while it overpredicts the proportion of administrative and technical staff (ATS) parking in public spaces. The values for the mean risks of the first parking facility being full and the mean walking distances refer only to drivers who ended up parking in university-owned parking facilities. With 6 iterations, the model slightly underpredicts the risk of the first parking facility accessed being full. In addition, the prediction model substantially overpredicts the probability of arriving at an occupied facility for students, while underpredicting the same for administrative and technical staff. The stated preference experiment already revealed this variation in risk adversity. However, the prediction model shows that this variation is substantially stronger than estimated. This reinforces the finding that different employee groups vary in their likelihood of generating parking search traffic.

Table 2: Comparison of prediction results with data from the mobility survey

		General	Campus part			Student and employee status			
			Central	Hörn	Melaten	Students	Professors	Scientific employees	ATS
Share of public on-street parking [%]	Model	30.0	36.8	23.2	18.5	45.5	9.2	25.0	22.3
	Survey	37.9	30.8	46.0	43.0	56.8	8.3	38.8	9.4
Mean risk that the first facility is occupied [%]	Model	21.5	32.4	14.3	18.7	14.1	11.9	15.2	29.9
	Survey	23.2	29.0	10.1	17.0	14.9	23.6	23.0	27.9
Mean walking distance [min]	Model	3.8	4.8	2.5	3.1	4.6	2.2	3.9	3.3
	Survey	4.7	6.2	2.2	4.1	9.0	3.3	3.0	3.1

Regarding the mean walking distance, the model underpredicts the distances for students. This may be because the time of arrival is not systematically taken into account. Typically, students stay on campus for a shorter period and arrive later than employees. Therefore, they may arrive when nearby facilities are already occupied by vehicles belonging to employees.

Table 3 displays various parameters of the model. The model estimates 0.201 vehicle kilometers (vkm) of parking search traffic per driver. If it is only distributed to those who were unsuccessful at the first attempt, each driver accounts for 0.932 vkm. Unsurprisingly, the results indicate that walking times are much higher than parking search times. The average sum of parking search and walking time is about 4.2 min, which is lower than in Bischoff and Nagel (2017), who estimated about 6.5 min for an inner-city residential area in Berlin focusing only on public on-street parking. The correlation between the number of predicted and counted cars is high.

Table 3: Model metrics

Parking search traffic	Total [vkm]	772
	Per driver [vkm]	0.201
	Per unsuccessful driver at the first facility [vkm]	0.932
	Total [min]	1,426
	Per driver [min]	0.371
	Per unsuccessful driver at the first facility [min]	1.721
Correlation	Morning (10-12 am)	0.877
	Afternoon (1-3 pm)	0.911
Root mean square error	Morning (10-12 am)	25.2
	Afternoon (1-3 pm)	18.6

Eleven of the 124 parking facilities in the base model were visited by more than twice the total available capacity. We therefore applied different scenarios of blockage of parking infrastructure and observed how this affected parking behavior. Table 4 shows that all scenarios hardly affect the average walking distance and moderately influence the share of public on-street parking, leading to small shifts in parking demand from university parking to public parking.

Table 4: Effects of changes in parking infrastructure

	Scenario	Parking spaces blocked	Parking search traffic [vkm]	Average walking distance [min]	Share of public on-street parking [%]
0	Base scenario	-	772	3.8	30.0
1	Blocking of 11 facilities based on access/capacity ratio	173	332	3.8	32.3
2	Blocking of 5 facilities with capacities ≤ 5 based on access/capacity ratio	25	584	3.8	29.4
3	Blocking of 22 facilities based on qualitative selection considering position and capacity	172	325	3.7	32.2

In the first scenario, the 11 facilities with the highest number of drivers visiting divided by capacity were blocked. In this case, the parking search traffic decreased substantially. If only facilities with a capacity of 5 or less are blocked, the total decrease in parking search traffic is smaller, but higher relative to the number of blocked parking spaces. In the third scenario, 22 facilities were blocked based on a qualitative selection considering location and proximity to larger alternative parking facilities. In this case, the parking search traffic decreased more than in the first scenario.

In summary, the results show that the model is able to predict parking occupancy relatively well compared to count values. However, the model has some difficulty in reliably predicting the share of public parking and in accounting for student and employee status. We would have expected a higher number of iterations to be more realistic, but this would have resulted in too low rates of drivers arriving at occupied facilities. Drivers at the university appear to be less aware of actual occupancy in advance, or they would have reported lower rates in the mobility survey. This indicates that we overestimated the familiarity of drivers with the infrastructure. The results indicate that the reduction of decentralized parking facilities is effective in reducing car traffic without causing a large increase in walking distances.

Currently, the model assumes that car drivers only enter parking lots and never exit. This assumption is based on the dominance of destination traffic in the morning period. To improve the accuracy of parking behavior prediction, it is necessary to implement the ability for drivers to exit the parking lot. This could improve the prediction of demand at later times of day. In addition, the current model assumes a random order of arrivals, although the order significantly influences parking behavior (Rodríguez et al., 2023).

A source of inaccuracy in the model is the input data. This is due to the use of floor usage data, and the lack of data on public on-street parking. In addition, the model does not take into account the accessibility of parking facilities by car at the first attempt, which is relevant (Ibeas et al., 2014). Furthermore, we did not include certain case-specific regulations, such as parking spaces designated only for electric vehicles during charging, and neglected disabled drivers. However, we expect this to have a minor impact.

Further research is required to investigate parking behavior in other locations, as this case study is based on a specific university campus. Research should also focus on different trip purposes. It is important to note that in our study, parking permit holders are not subject to parking time restrictions. Therefore, measuring the impact of price differentials is also a relevant topic for further research.

4. CONCLUSIONS

This paper presents a model of car parking demand at a university. The main advantage of the approach is the fusion of an extensive dataset on car parking facilities, space usage in university buildings, a stated preference-based model of parking preferences, and occupancy counts for validation. The estimated models provide quantitative data on the effects of changes in parking supply, allowing for objective discussions about car parking. The results underscore that centralization strategies are effective in reducing parking search traffic.

REFERENCES

Ben Hassine, S., Mraihi, R., Lachiheb, A., & Kooli, E. (2022). Modelling parking type choice behavior. *International Journal of Transportation Science and Technology*, *11*(3), 653–664. https://doi.org/10.1016/j.ijtst.2021.09.002

Bischoff, J., & Nagel, K. (2017). Integrating explicit parking search into a transport simulation. *Procedia Computer Science*, *109*, 881–886. https://doi.org/10.1016/j.procs.2017.05.414

Bonsall, P., & Palmer, I. (2004). Modelling drivers’ car parking behaviour using data from a travel choice simulator. *Transportation Research Part C: Emerging Technologies*, *12*(5), 321–347. https://doi.org/10.1016/j.trc.2004.07.013

Cools, M., van der Waerden, P., & Janssens, D. (2013). Investigation of the Determinants of Travelers’ Mental Knowledge of Public Parking Facilities. In *Proceedings of the 92nd Annual Meeting of the Transportation Research Board (DVD-ROM).* Transportation Research Board of the National Academies.

Daggett, J., & Gutkowski, R. (2003). University Transportation Survey: Transportation in University Communities. *Transportation Research Record: Journal of the Transportation Research Board*, *1835*(1), 42–49. https://doi.org/10.3141/1835-06

Golias, J., Yannis, G., & Harvatis, M. (2002). Off-Street Parking Choice Sensitivity. *Transportation Planning and Technology*, *25*(4), 333–348. https://doi.org/10.1080/0308106022000019620

Ibeas, A., dell'Olio, L., Bordagaray, M., & Ortúzar, J. d. D. (2014). Modelling parking choices considering user heterogeneity. *Transportation Research Part a: Policy and Practice*, *70*, 41–49. https://doi.org/10.1016/j.tra.2014.10.001

Rodríguez, A., dell'Olio, L., Moura, J. L., Alonso, B., & Cordera, R. (2023). Modelling Parking Choice Behaviour Considering Alternative Availability and Systematic and Random Variations in User Tastes. *Sustainability*, *15*(11), 8618. https://doi.org/10.3390/su15118618

Shoup, D. C. (2006). Cruising for parking. *Transport Policy*, *13*. doi:10.1016/j.tranpol.2006.05.005

Soto, J. J., Márquez, L., & Macea, L. F. (2018). Accounting for attitudes on parking choice: An integrated choice and latent variable approach. *Transportation Research Part a: Policy and Practice*, *111*, 65–77. https://doi.org/10.1016/j.tra.2018.03.003

van der Waerden, P., Timmermans, H., & Bruin-Verhoeven, M. de (2015). Car drivers' characteristics and the maximum walking distance between parking facility and final destination. *Journal of Transport and Land Use*. Advance online publication. https://doi.org/10.5198/jtlu.2015.568

Waraich, R. A., & Axhausen, K. W. (2012). Agent-Based Parking Choice Model. *Transportation Research Record: Journal of the Transportation Research Board*, *2319*(1), 39–46. https://doi.org/10.3141/2319-05