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An urban shared pooled mobility system cuts distance travelled by over 50%

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ABSTRACT

Shared pooled mobility has the potential to reduce both the necessary number of private vehicles and the total driven distance. Here, we use logged car trips in Berlin as input for ride-pooling simulations to analyze the technical potential – assuming a complete switch from private to shared mobility. We measure the share of sharable trips, average vehicle occupancy, relative passenger travel time, and relative driven distance compared to individual driving. In the entire area of Berlin, we observe that a ride-pooling system with 26,500 vehicles could replace all 1,09 million private vehicles and their trips. The travel time is 55% higher, the average vehicle occupancy increases 2.1-fold, and the overall distance traveled is reduced by 61%. Our results demonstrate that system-wide urban efficiency and quality of life benefits – elimination of congestion and gain of public space for people – would come at higher time costs for commuters.

1. Introduction

The implementation of sustainable traffic is one of the key challenges of decarbonization. The transportation sector emits approximately 15 % of the global greenhouse gas, out of which private vehicles and similar mobility options like motorcycles are responsible for 75 % (Jaramillo et al., 2022). In Germany, the transport sector is responsible for 18 % of all emissions, with private vehicles alone responsible for 11 %, which shows that decarbonization requires lowering the emissions from private vehicles (Sachverständigenrat für Umweltfragen, 2017). It would be desirable to reduce both the fleet size required to fulfill all travel needs (as this would speed up electrification) and the total energy demand for individual transport (reducing the total driven distance). Furthermore, a reduction of vehicle miles traveled also reduces pollution, noise, and traffic congestion and helps to improve the quality of life in cities (Bongardt et al., 2013; European Environment Agency, 2023; World Economic Forum, 2023), while a reduction in the number of vehicles frees up space otherwise occupied by parking cars.

In this analysis, we thus focus on pooling similar rides to reduce the overall traffic and the number of private vehicles. Ride-pooling offers a flexible and convenient alternative to line-based public transport. Several studies show that ride-pooling or shared pooled mobility could make a significant contribution to lowering energy demand and increasing transport sustainability (Creutzig et al., 2022; Hu et al., 2024; Wilson et al., 2020; Yu et al., 2017). Furthermore, shared pooled mobility would increase the accessibility of

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line-based public transport (Grubler et al., 2018).

The central idea behind ride-pooling or shared pooled mobility is to bundle similar car trips into the vehicles of a ride-pooling fleet. As a result, the occupancy of the vehicles increases while the total driven distance and the number of necessary vehicles decreases. Generally, ride-pooling is a dynamic pick-up and delivery problem, a subclass of dynamic vehicle routing problems (Berbeglia et al., 2010). Fig. 1 gives a pooling example.

The implementation of ride-pooling services can be realized significantly faster than expanding public transportation systems, especially rail systems. The required hardware – streets and vehicles – are already abundantly available. From the software side, several ride-pooling operators have already developed apps and routing/pooling algorithms (Mitropoulos et al., 2021). In contrast to other public transportation systems, such as bus systems, ride-pooling is flexible and adaptable. Thus, ride-pooling maintains one of the biggest advantages of private mobility.

Despite several promising tests and pilots, shared pooled mobility has not yet emerged as a widely utilized sustainable transport option (Creutzig et al., 2024). Reasons for this include a combination of practical reasons, such as increased travel time, socio-political barriers, and behavioral factors, such an unease to be in a confined space with strangers, enjoyment of driving, or the ease of transporting and storing luggage (Kostiainen & Tuominen, 2019; Marsden, 2022). Shared pooled mobility can only achieve acceptable travel time increases, more specifically delays, in two scenarios. Firstly, it can operate close to a taxi service, where small numbers of rides are occasionally pooled for a small reduction in fares. This scenario is the niche in which Uber Pool and MOIA typically operate, with fares slightly below taxi fares and travel times slightly above direct travel times. It tends to attract customers who don't want to or don't have the option to drive but find public transport too cumbersome. The value of this scenario in the context of sustainability is questionable, with emissions gains from sharing quickly being eaten up by losses due to deadheading (Creutzig, 2021). The other scenario, where acceptable delays are realistic, is as a systemic mobility solution replacing a large fraction of private car travel so that sharing becomes naturally possible with small delays. To achieve such high demands, it becomes necessary to be competitive in price and convenience with personal cars. This is the scenario where shared pooled mobility has the potential to impact sustainability positively. However, studies showing this effect often have to resort to taxi data (Santi et al., 2014; Tachet et al., 2017), data sourced from ride-pooling providers (Chen et al., 2017; Zwick and Axhausen, 2020; Gödde et al., 2023; Kaddoura et al., 2021) or simulation data (International Transport Forum, 2017, 2018). In cases where more complete data is available, often only a small fraction of requests are replaced by a ride-pooling system due to modeling behavioral choices (Kaddoura & Schlenther, 2021), which can underestimate the ride-pooling demand and potential.

In this work, we use the GPS-coded vehicle movement of private car trips in Berlin collected by the private company INRIX as a real-world database. We use the origin and destination points of this dataset as requests for a ride-pooling simulation. As the data contains no information on the occupancies of the tracked vehicles, we make the simplifying assumption that one request is generated per car. This slightly underestimates the required fleet size, as occasionally, group requests might not fit into a single sharing vehicle. However, we also underestimate poolability as group requests would automatically be perfectly poolable, positively impacting occupancy rates.

The main goal of this work is to determine how many shared vehicles would be required to replace all car trips within Berlin. Studies show that with a fleet of around 100,000 taxis, it is possible to replace the whole car fleet in Berlin (Bischoff & Maciejewski, 2016). In 2021, Berlin's residents owned 1.09 million private vehicles. Thus, a taxi fleet of 100,000 vehicles would achieve a reduction of 90 % (Amt für Statistik Berlin-Brandenburg, 2023). We hypothesize that even fewer vehicles are required for ride-pooling. In order to support this hypothesis, we simulate ride-pooling systems with different fleet sizes and measure the fraction of rides poolable within the required service quality parameters. We mainly focus on the rush hours in the morning and the afternoon. The premise is that a system that can replace all car trips at peak times can also replace all trips at any other time. In order to evaluate the system efficiency at different service rates, we also measure the travel time changes for passengers and the total driven distance compared to private

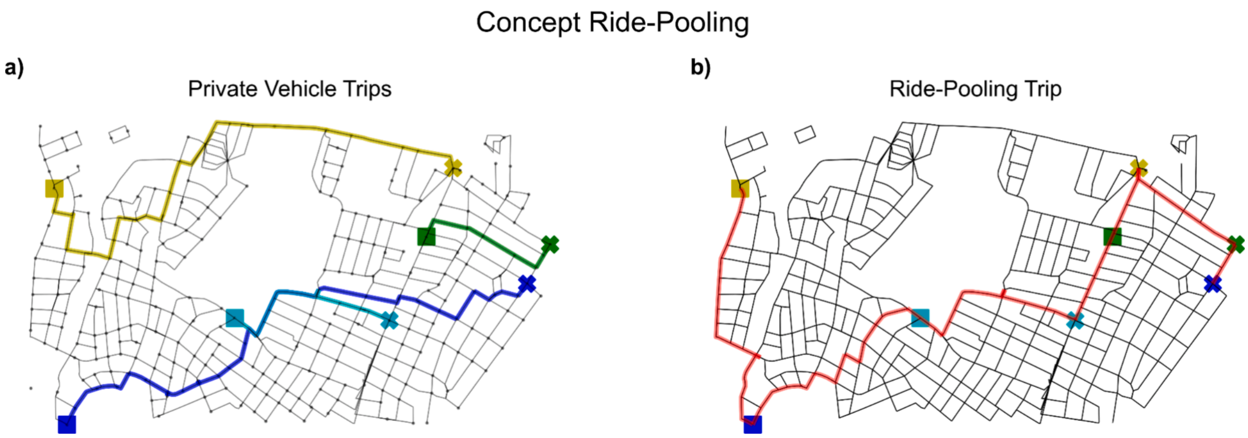

Fig. 1. Concept of ride-pooling. 1a shows four individual car trips in the east of Berlin; the trip starts are marked with a square, and the trip destinations with an X. Four vehicles are required to transport the four passengers using private cars. 1b shows a possible pooling strategy. By this, only a single vehicle is required.

vehicles. Additionally, we measure the number of required cars per capita for specific areas within Berlin.

For the whole area of Berlin, we find that a vehicle fleet of 26,500 can replace all vehicle trips in Berlin. This reduction leads to a relative travel time increase of approximately 55 %, while the driven distance reduces by around 61 %. The central parts of Berlin are already well-served by line-based public transport. To improve convenience in the suburbs while limiting the draw of customers away from traditional public transport, we also studied the suburban area separately. Here, we find that approximately 8,700 vehicles could replace all vehicle trips.

In Chapter 2, we describe the real-world dataset, the ride-pooling simulation, including the parameters and characteristic values, and the simulation scenarios. In Chapter 3, we present the results. Chapter 4 concludes the work.

2. Material and methods

2.1. Real-world dataset

In 2018, around 11.9 million domestic trips were made in Berlin each day, of which 18 %, more specifically 2.14 million, were made by car (Gerike et al., 2020a, 2020b). The temporal distribution of car trips is subject to strong temporal fluctuations, as shown in Fig. 2.

If we consider a ride-pooling system capable of replacing all trips during rush hours, this system could theoretically replace all vehicle trips at all other times of the day. The rush hours are between 7–8 am (8.8 %) and 4–5 pm (9.6 %). The share of trips between 3–4 pm is actually a little higher than between 7–8 am. However, we decided to use the rush hours between 7–8 am and 4–5 pm to cover potential spatial differences between morning and afternoon commutes.

The dataset we use in this work is made available by the commercial data provider INRIX. The data is a representative sample of drivers in Berlin, as shown in (Koch et al., 2023). It contains the GPS waypoints of 34,208,544 trips by private and commercial vehicles that originate, terminate, or pass through Berlin in 2017. The data is sourced from connected cars, mobile devices, and connected commercial fleets. We perform several cleaning and preprocessing steps to create a meaningful and representative dataset of urban mobility in Berlin. First, we exclude all trips originating and/or ending outside Berlin. Second, we only consider private trips during the commute windows (7–8 am and 4–5 pm). Third, we filter out trips with unrealistic average speeds (>60 km/h) and distances considerably beyond the most extended possible direct intra-urban trip in Berlin (>75 km). Fourth, we remove trips that start in the middle of highways. Finally, we want to ensure that the temporal density and trip length distribution are representative. To this end, we downsample it to match the trip distance distribution and hourly trip count according to the representative SrV mobility survey for Berlin. In total, we use 188 thousand trips during the morning rush hour and 205 thousand trips during the afternoon rush hour for our analysis, representing 8.8 % and 9.6 % of all daily trips, respectively (c.f. Fig. 2.).

The average occupancy of private vehicles in Berlin is 1.3 (Gerike et al., 2020b). For the simulations in this study, we have chosen only to request single seats since the occupancy of the vehicles in the data is unknown. In reality, we assume there are 30 % more requests than recorded car trips in the dataset. However, in our simulations, vehicles are rarely full (78 % of the time, two or more seats are free on average); we speculate that the main effect of allowing group requests would be an increased average vehicle occupancy.

Because door-to-door ride-pooling services are inefficient, we use a ride-pooling network that covers the whole area of Berlin (Engelhardt and Bogenberger, 2021). The original network contains around 28,000 stops, which leads to an unfeasible computation time of the ride-pooling simulation. Thus, the stops are pooled, for example, at intersections, which decreases the number of stops to 10,405 (c.f. Fig. 3). Compared to the current public transportation system of Berlin, which uses around 7,600 stations, the ride-pooling network is 33 % denser. In order to use the trips as requests in the ride-pooling simulation, the original origins and destinations are mapped to the nearest stop in the network.

By mapping the original locations to the stops in the network, a walking time for each passenger, calculated as the distance from the original origin and destination points to the stops, is introduced. The resulting average walking distance for passengers is 250 m. For

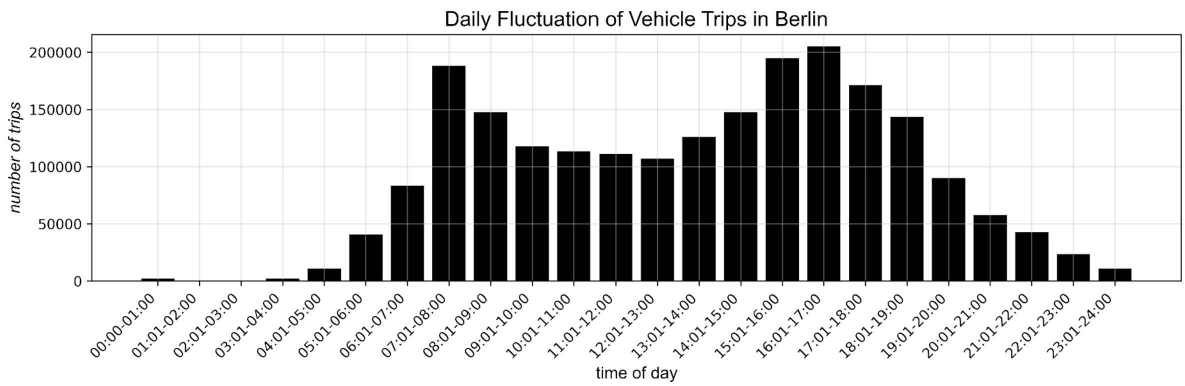

Fig. 2. Daily fluctuation of car trips in Berlin (Gerike et al., 2020b). From 7 to 8 am, 8.8 % and between 4 to 5 pm, 9,6 % of all car trips are made. These high numbers are due to the morning and afternoon rush hour.

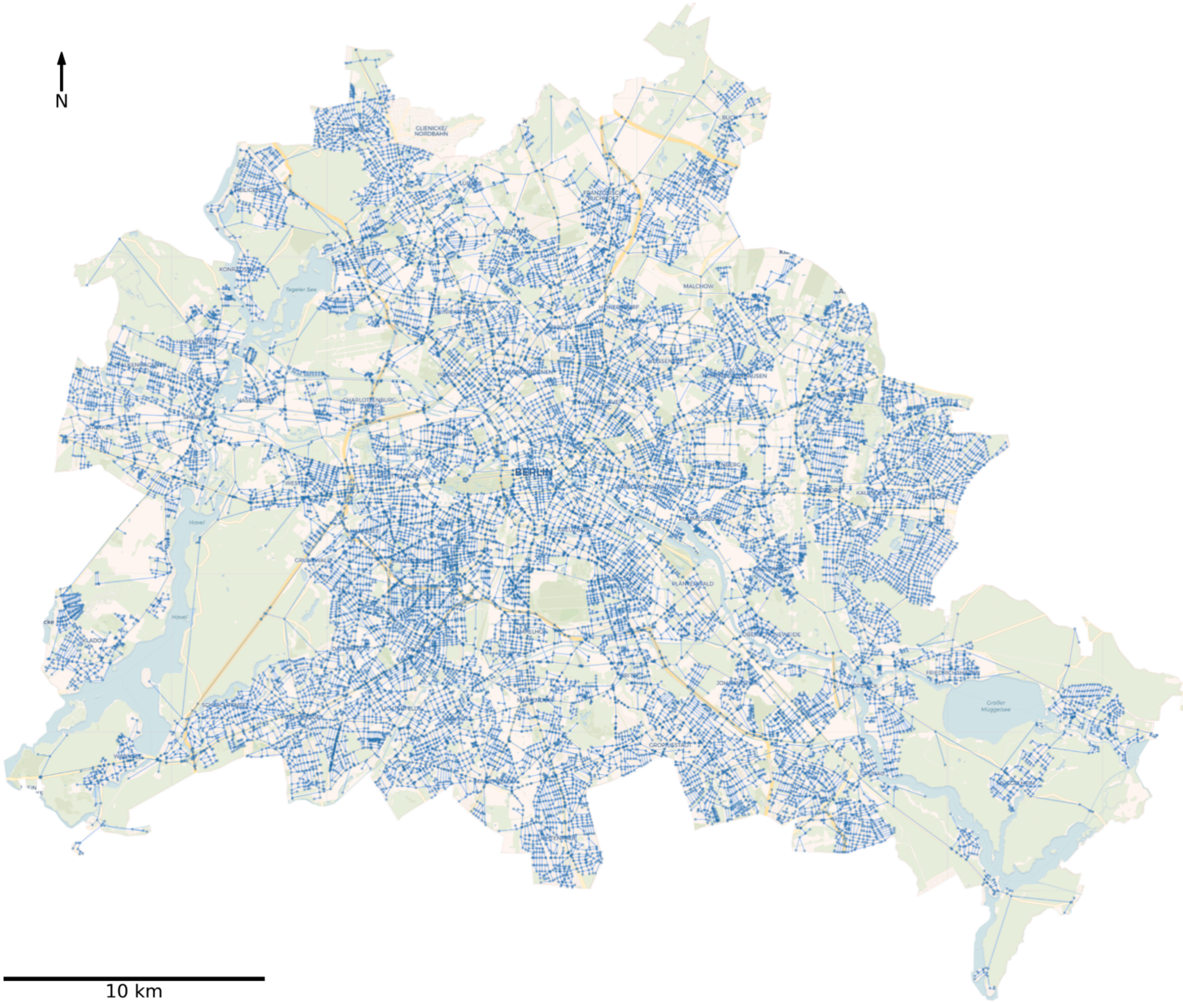

Fig. 3. Ride-pooling stop network with 10,405 stops for Berlin. Every node in the network represents a station of the ride-pooling system, where passengers can hop on or off a vehicle. The original network was downloaded from OpenStreetMap (Boeing, 2017).

some trips, the start and finish are so close together that the origin and destination stop are the same. These trips are not used in the simulation.

For spatial demographic analysis, the administration of Berlin divided the city into 542 community-based areas (LOR, German abbreviation for *lebensweltlich-orientierter Raum*) (Amt für Statistik Berlin-Brandenburg, 2021). Each LOR has a similar population in terms of, for example, social status. Fig. 4 shows the number of trips starting and ending in each LOR during the morning and afternoon rush hour.

2.2. Ride-pooling simulation

To analyze ride-pooling systems, we use an agent-based ride-pooling simulation (Jung & Manik, 2024). As general input, the simulation requires the passenger trips, which we create from the real-world dataset (c.f. section 2.1) and a stop network (c.f. Fig. 3). Additionally, the parameters in Tab 1. are required:

We vary the fleet size to analyze relative replacement effects on private vehicle trips. The vehicle size is chosen to be six, as in real ride-pooling implementations (MOIA, 2024). For the maximum waiting time, we use the ten-minute interval of buses, subways, and metro lines in Berlin as the upper bound. However, the actual waiting times are found to be much lower, implying that the impact of this parameter on the results is likely low. The average vehicle speed and maximum delivery time depend on the used period (morning or afternoon) and scenario (c.f. section 2.3).

Before the simulation starts, an initial position is determined for every vehicle of the ride-pooling fleet by uniformly drawing positions from the set of all stops. During the execution, the simulation processes the requests one by one and assigns them to the vehicles according to the dispatcher algorithm. The dispatcher algorithm determines for each request how much additional distance each vehicle must drive to process the request while maintaining the time restrictions. The request is then assigned to that vehicle,

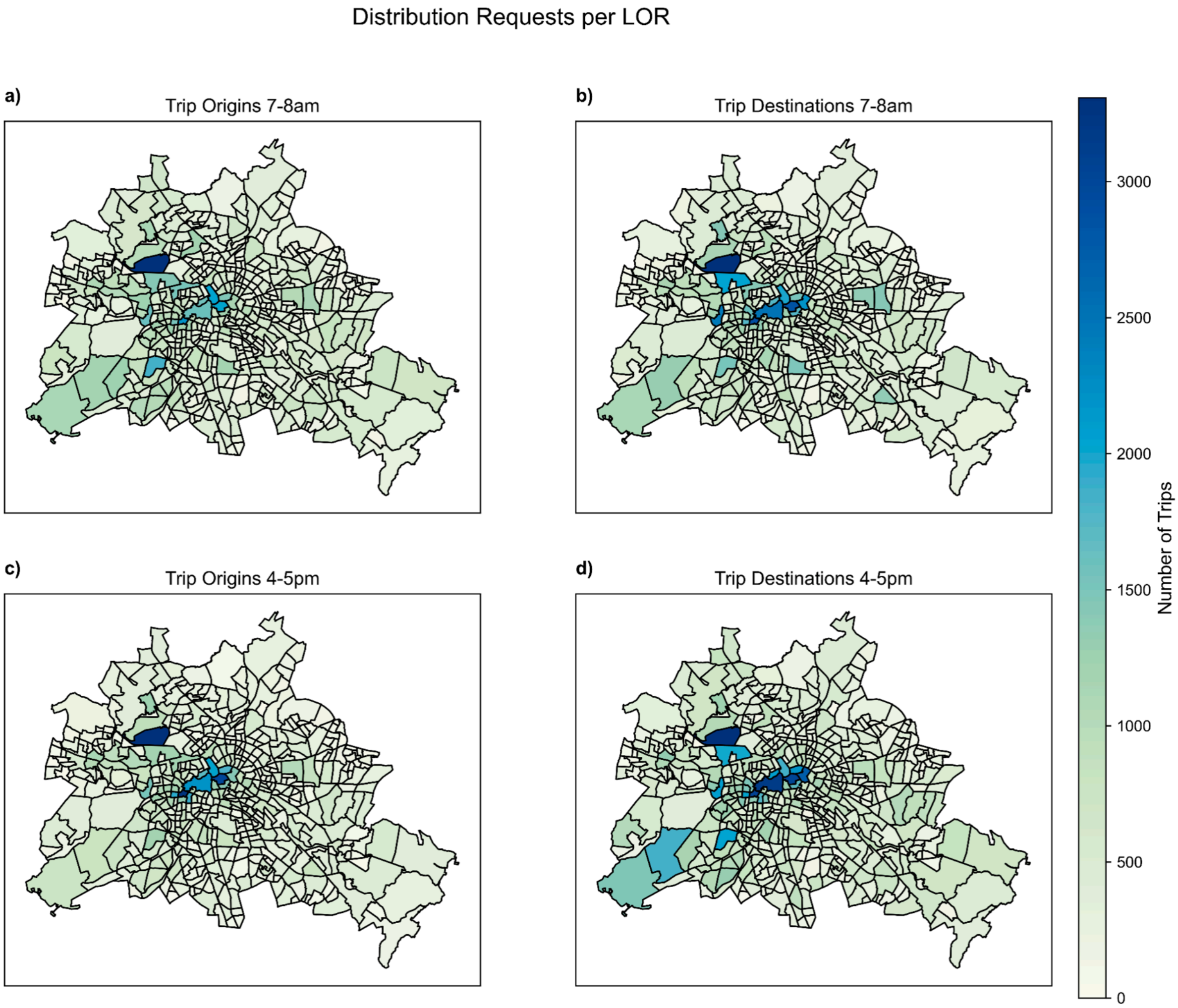

Fig. 4. Origin and destination distribution. 4a and 4c show the origin share for each LOR in the morning and afternoon. 4b and 4d show the destination share for each LOR.

which could serve the requests with respectively minimal additional distance.

To evaluate the efficiency and functionality of a simulated ride-pooling system with a specific fleet size and to make the results comparable to other research, we decided to measure five specific characteristics, which were mainly selected following (Liebchen et al., 2021):

We measure the characteristic values for the scenarios described in more detail in section 2.3.

2.3. Scenarios

In the first scenario, the entire area of Berlin (c.f. Fig. 3) is taken into account. We run simulations for the morning and afternoon rush hour with varying fleet sizes and measure the characteristic values described in Tab 2.

For the second scenario, we identify areas in Berlin with poor access to public transportation where ride-pooling is key to reducing private motorized mobility. These areas are characterized by a combination of low coverage of transit services, resulting in long walks to the nearest stop, and low frequency, further increasing travel time (c.f. Fig. 5). Thus, in these areas, the average vehicle ownership is higher than in areas with high coverage of transit services (Berrill et al., 2024). We refer to these areas as "low-transit areas", modelling the sub-urban areas of Berlin. By analyzing these parts separately, we look for spatial variations compared to the whole area of Berlin.

We calculate transit accessibility based on GTFS data (Verkehrsverbund Berlin-Brandenburg, 2024) according to (Berrill et al., 2024). For 10,000 locations equally distributed across the city, we determine the transit stops within walking distance, including bus, tram, subway, and urban rail stops. We count the number of departures per stop, discount them by the walking distance from the location, and calculate the sum of discounted departures for each location. For discounting, we use a gravity-based model with a Gaussian decay function with $\sigma = 0.5$(see implementation at (Nachtigall, 2024)):

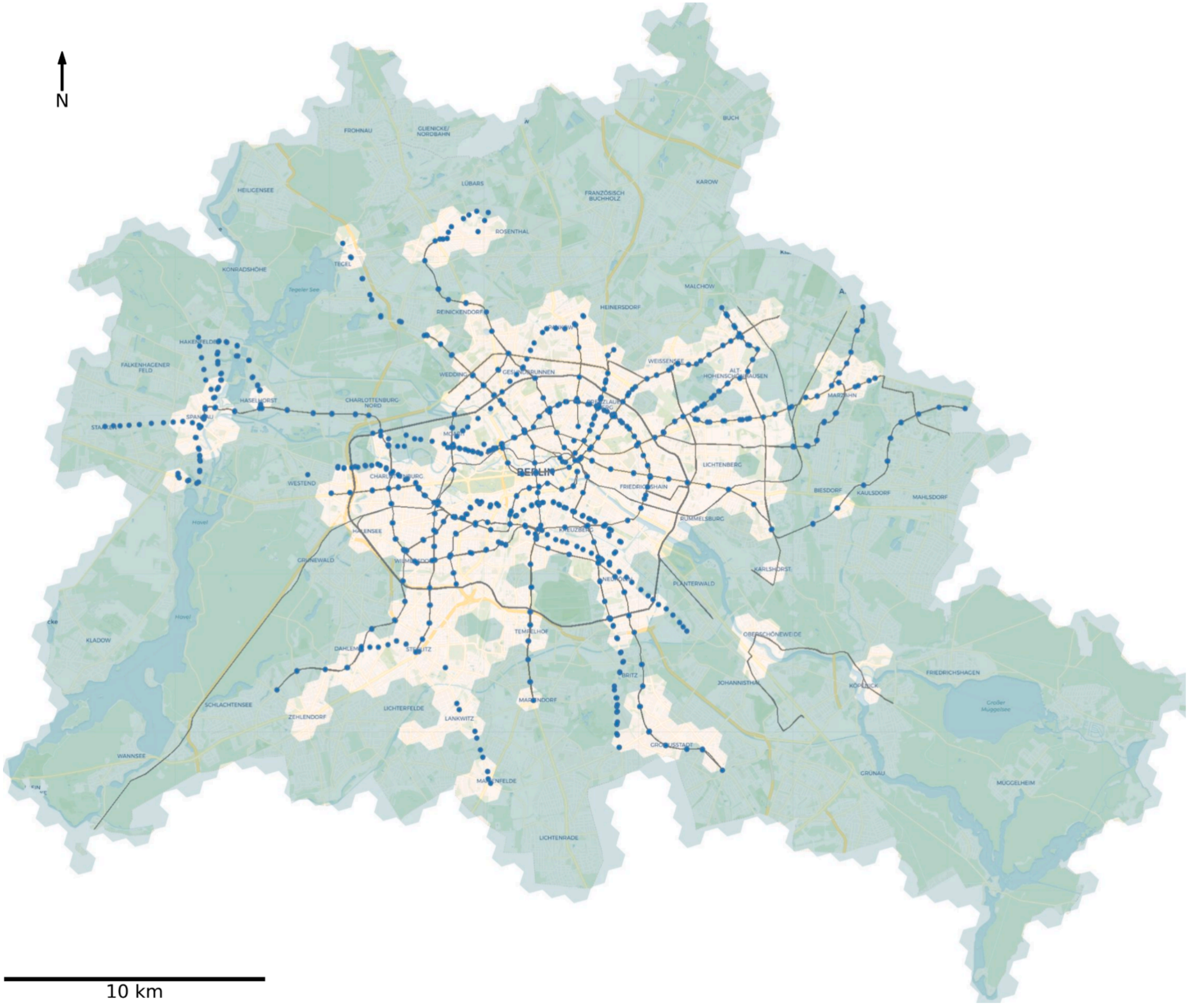

Fig. 5. Low-transit area of Berlin. Areas with low access to transit are highlighted in green. The gray lines are high-frequency metro and subway rail lines (>100 trips/day). The blue nodes mark high-frequency stops (including bus stops) with more than six departures per hour.

$$d = exp(-\frac{dist^2}{2\sigma^2})$$

with *d* as discounting and *dist* as the distance between the locations of interest and the transit access locations. This means, for example, that the transit accessibility for a 500 m walk is 40 % lower than directly at the station. Using the average transit accessibility score, we identify the areas with relatively high accessibility and label the remaining 80 % of Berlin, primarily the suburbs and outskirts, as low-transit areas (c.f. Fig. 5). The areas are defined using Uber's H3 hexagonal grid with a resolution of 9 (0.1 km2 per hexagon). We also use the network from Fig. 3 for the simulations in the low-transit-area, but the initial positions of the vehicles are limited to the nodes

Table 1
Ride-pooling simulation parameters.

Parameter	Description
Fleet Size	Number of vehicles used by the ride-pooling service. This value is one of the central objects of investigation.
Seat Capacity	Number of seats in each vehicle. Here, we use vehicles with six potential seats.
Average vehicle speed [km/h]	Average speed of the vehicles in the simulation.
Maximum waiting time [min]	Maximum permitted waiting time for a passenger. If every vehicle exceeds it, the request gets rejected. Here, we use ten minutes as the maximum waiting time.
Maximum delivery delay [min]	Maximum permitted trip delay after boarding the ride-pooling service compared to direct driving time. The request will be rejected if it's exceeded by every vehicle. The maximum delivery delay applies only to driving time (the passenger's time in the vehicle) and does not include the waiting time. Trip time increase is the sum of the delivery delay and waiting time.

within the low-transit-area. Due to this limitation, we only use the requests starting in the low-transit-area. In the morning rush hour, we get 49,126 requests, and in the afternoon rush hour, 47750. We further created a request set containing requests in the low-transit-area from 6 to 10 am, while all other filter parameters stay the same, which is used to verify our results and test their robustness to off-peak times.

From the request set containing all requests within Berlin, we determine the overall average speed of every time period and scenario (c.f. Table 3).

The acceptable maximum delivery delay (see Table 1 for definition) was set to 50 % of the observed car travel time from the dataset of 16 min in the morning and 15:30 min in the afternoon for all data and 14:30 min in the morning and 14 min in the afternoon for the low-transit area (c.f. Table 3). This selection is in line with (König & Grippenkoven, 2020), which indicates that acceptance decreases slowly with detour factor and travel time if an appropriate fare reduction is offered. For 20-minute trips at a detour factor of 1.5, which, on average, is equivalent to a 50 % maximum delivery delay, (König & Grippenkoven, 2020) observed an acceptance rate of 85 %. However, this analysis compared to taxi trips rather than personal vehicles.

To determine the number of required cars per capita, we use the LORs as the data basis. For each LOR, we know the population and the vehicle densities (Rundfunk Berlin-Brandenburg, 2024; Tagesspiegel, 2023). We form ten LOR clusters with similar population densities. In each LOR cluster, a similar number of trips start during the morning rush hour (c.f. Fig. 6).

For each LOR cluster, we run simulations with the trips starting in the respective LOR as requests and a sufficiently large fleet size to cover all requests.

In summary, we get two scenarios: the entire city of Berlin scenario and the low-transit-area of Berlin scenario. Secondly, we get two additional analyses: one of the rejected requests and one of the car reduction for different population density areas.

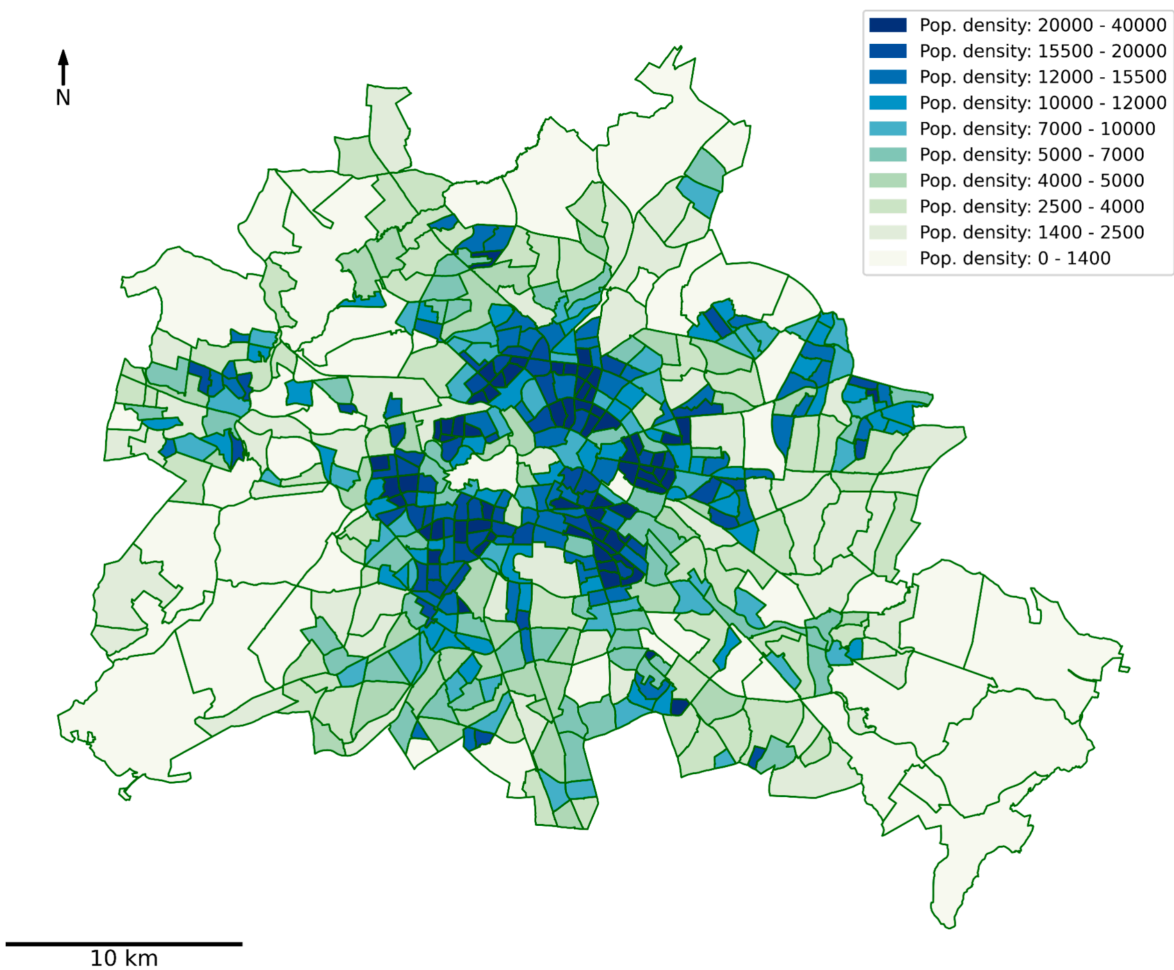

Fig. 6. Ten LOR clusters with different population densities in Berlin.

3. Results and discussion

3.1. Entire area of Berlin scenario

In the first scenario, we run simulations with different fleet sizes for the morning and afternoon rush hour in the whole area of Berlin and measure the characteristic values (c.f. Table 2). The results for coverage, occupancy, relative travel, and driving time are shown in Fig. 7.

The entire car traffic in Berlin can be replaced with around 25,000 ride-pooling vehicles in the morning and around 26,500 vehicles in the afternoon (Fig. 7a). If we compare these values with the 1.09 million vehicles owned by Berlin residents in 2021, ride-pooling achieves a reduction of 97.6 % (Amt für Statistik Berlin-Brandenburg, 2023). Since more requests are accepted, in relative terms, for small fleet sizes (with 5,000 vehicles, 19 % of the 26,500 vehicles, approximately 33 % of the requests could be served in the afternoon), the average occupancy is significantly higher for small fleet sizes with values of around 3.4 than for larger fleet sizes with values of around 2.1 in the morning and afternoon (see Fig. 7b). The average occupancy rate is significantly higher than the current car occupancy rate of 1.3 (Gerike et al., 2020b). Here, for every request, we assume a single passenger; thus, the actual occupancy would probably be even higher.

Fig. 7c shows the relative travel time. For a small fleet size and, therefore, low coverage, the average relative travel time is low, so travel time is only slightly higher compared to the private vehicle trips. The low relative travel time is due to the high rejection rate, implying that a high share of the trips are still taken in private vehicles. At full coverage by the ride-pooling system, the travel time increases by 55 %. For reference, if the sampled trips were done by traditional public transport, the travel time increase would be 95 % (MIB, 2021). If only the serviced requests are considered, we observe that the relative travel time increase is much steeper, exceeding a 50 % travel time increase already at a coverage of around 50 %. However, the curve starts to decrease for a fleet size of approximately 17,500 vehicles, showing the potential to optimize the ride-pooling system regarding travel time.

The increase in travel time by 55 % poses a serious challenge to the willingness of users to switch to ride pooling. A possible solution is fare discounting, which increases the willingness to share even for high travel times (Bujak & Kucharski, 2024; de Ruijter et al., 2023; Li et al., 2022). (König & Grippenkoven, 2020) find that more than 90 % of all users would share a ride for ten minutes; even a 20-minute ride with a 1.5-fold detour would still have an acceptance rate of 85 % (in the afternoon rush hour, a ride-pooling trip lasts on average 24 min including waiting time) if the fare is discounted appropriately. The study doesn't include parking prices, which do not occur for ride-pooling passengers, and thus further lower the relative price.

Fig. 7d shows that the relative driven distance decreases with increasing coverage by 60 % in the morning and 61 % in the afternoon. Thus, CO2 emissions, particulate matter emissions, and traffic congestion are reduced. Empty mileage makes up less than one percent of the driven distance.

3.2. Low-transit-area of Berlin

For the second scenario, the low-transit-area of Berlin, we choose the same approach as in section 3.1. Again, we run simulations with different fleet sizes and measure the characteristic values. The results are shown in Fig. 8.

From Fig. 8a, we derive that with a fleet size of around 8,700 vehicles in the morning and around 8,200 vehicles in the afternoon, the ride-pooling system can replace all traffic in the rush hours in the low-transit-area. The average occupancy at full coverage is approximately 1.5 for both rush hours (c.f. 8b). The relative travel time for all and for serviced requests only is increasing with increasing coverage of the requests (c.f. 8c). However, the relative travel time with ride-pooling stays lower than the relative travel time with current public transportation systems. From Fig. 8d, we derive that the relative driven distance decreases with the increase in

Table 2
Characteristic values for observation.

Characteristic Value	Description
Coverage	Depending on system parameters and fleet configuration, typically a fraction of requests cannot be served within the service quality constraints. Coverage measures how many of the original requests were successfully delivered to their destination within the selected constraints. The rejected requests are assumed to continue to use private vehicles in some further calculations.
Occupancy	We measure the total occupancy of each vehicle over the entire simulation time, including deadheading/empty mileage or idle times, excluding the driver. From the single occupancy measures, we calculate the average occupancy over time.
Relative Travel Time	The relative travel time measures how long it takes passengers to get to the desired location using the ride-pooling service compared to traveling with their own car. It includes the driving time, the waiting time at the station, and walking times from and to the station. To minimize the influence of exceptional data points, for example, with extremely short driving time, we calculate the relative travel time as the average travel time from the ride-pooling simulation divided by the average travel time from the dataset. We use the travel times specified in the dataset as the time measurement for the pure driving time of the private vehicle (thus, walking times to and from the car are omitted). For rejected requests, the original travel time from the dataset is used.
Relative Driven Distance	The relative driven distance measures the proportion of the actual driven distance when using private vehicles (from the dataset) and the distance driven by the ride-pooling vehicles in the simulation. Values smaller than one sometimes occur, as not all car trips in the original data take the shortest routes. As with the relative travel time, we assume that rejected requests drive the distance recorded in the dataset in a private vehicle.
Required Cars per Capita	By replacing private vehicles with a ride-pooling fleet in a specific area, the number of required vehicles is reduced in this area. By calculating the number of required cars per capita, we get a value to compare different areas within Berlin.

Table 3
Overview ride-pooling parameters, which differ for different periods and scenarios.

	Entire Area of Berlin		Area with low public transport options in Berlin	
	7-8am	4–5 pm	7-8am	4–5 pm
Average vehicle speed [km/h]	24.1	24.9	26.6	28.1
Maximum delivery delay [min]	8:02	7:45	7:14	6:54

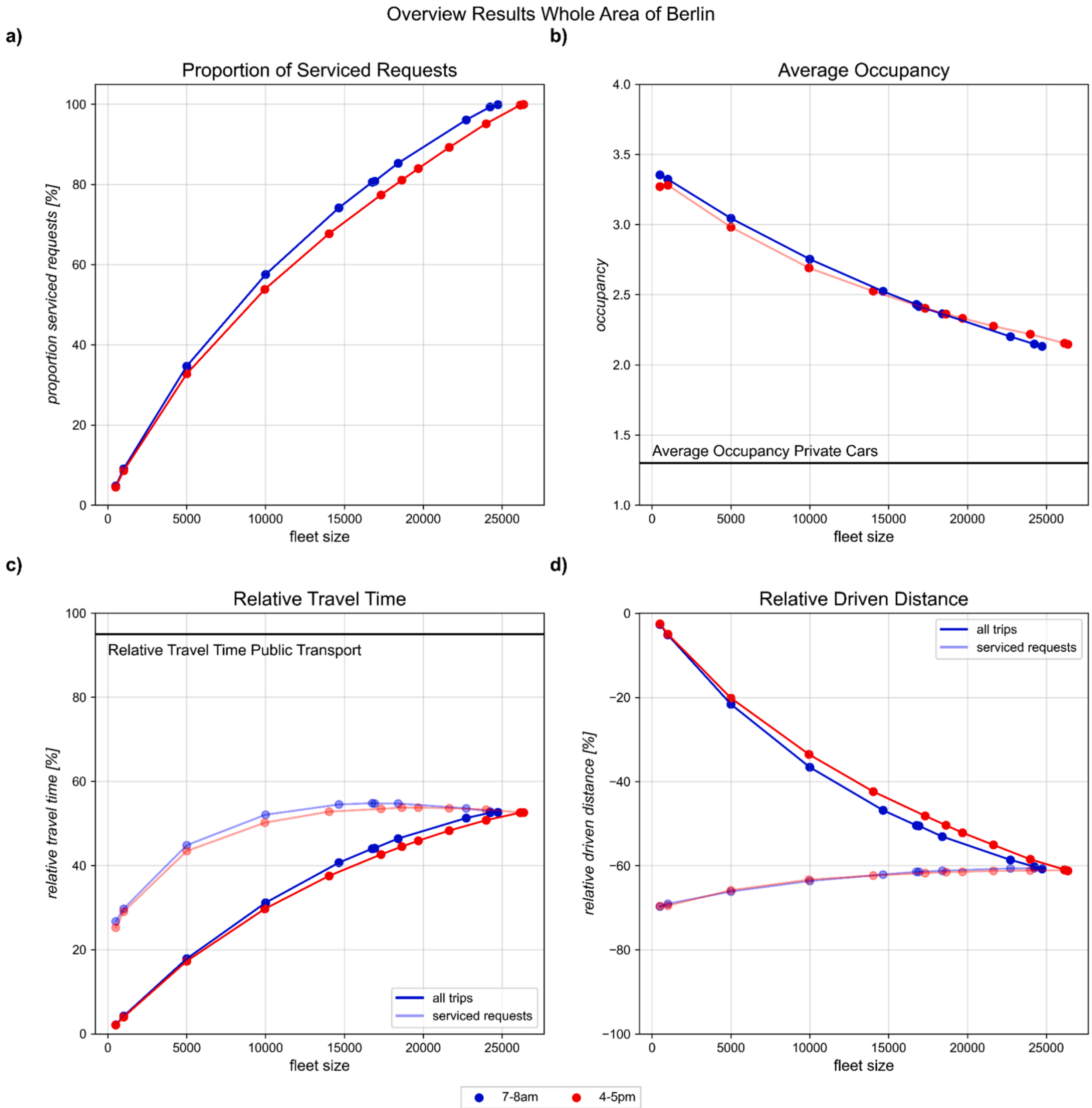

Fig. 7. (a) Proportion of serviced requests, (b) average occupancy, (c) relative travel time averaged over all trips (solid lines) and serviced requests only (faded lines), and (d) relative driven distance for the entire area of Berlin in the morning and afternoon rush hour.

fleet size. In the case of complete coverage, around 48 % less distance is traveled in both periods.

In summary, we get similar results for the low-transit-area as for the whole area of Berlin. However, during the morning rush hour, 24 % of the requests originate from the low-transit-area but 33 % of the vehicles are required compared to the whole area. Thus,

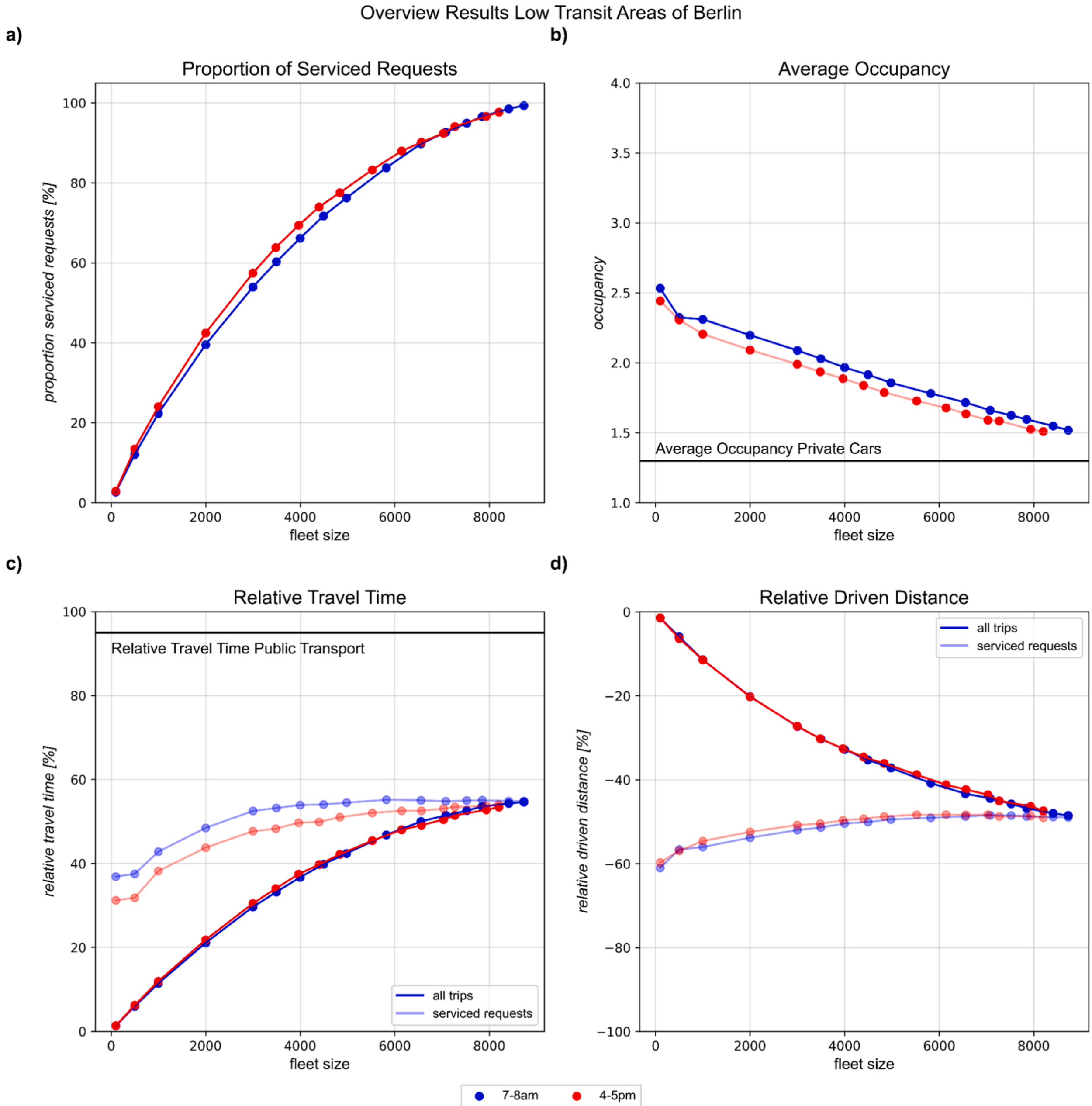

Fig. 8. (a) Proportion of serviced requests, (b) average occupancy, (c) relative travel time averaged over all trips (solid lines) and serviced requests only (faded lines), and (d) relative driven distance for the low-transit area of Berlin in the morning and afternoon rush hour.

relatively more vehicles are required in the less densely populated low-transit-area. The requests are spatially more distributed, which makes them harder to pool for the dispatcher algorithm. This leads to lower occupancy, higher travel times, and lower total travel distance reduction. These spatial variations are shown in more detail in section 3.4.

Simulations running from 6 to 10 am show that the maximum number of vehicles determined within the time frame from 7 to 8 am, is sufficient to serve all requests within the larger time frame. The trips during the off-peak times appear to have a higher variability in origin and destinations, as expected, which surprisingly doesn't affect the relative driving time (62 %, 60 % peak times only) and relative driven distance (49 %, 48 % peak times only) much.

3.3. Rejected requests

From Figs. 7 and 8, we derive that already small fleet sizes can cover a high share of requests. In this section, we analyze the rejected

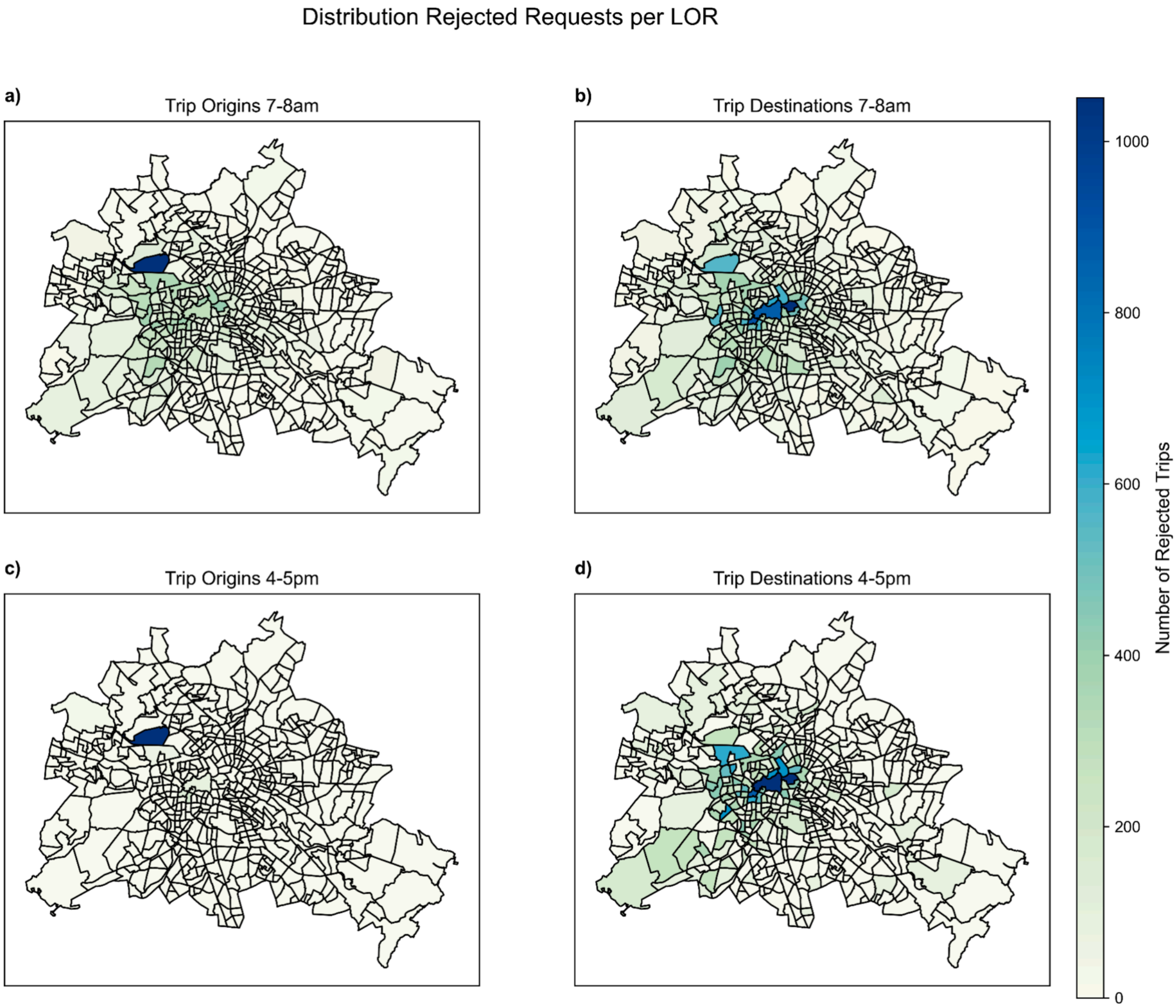

Fig. 9. Origins a) and destinations b) of rejected requests in the 80% coverage phase in the entire area of Berlin and in the low-transit-area c) and d).

requests and their potential implications for further improving the service.

From Fig. 7c, we conclude that in the afternoon rush hour, a fleet size of around 20,000 is capable of replacing around 83 % of all trips (c.f. Fig. 7a). In the afternoon rush hour in the lower transit area, a fleet size of around 5,700 could serve 82 % of the vehicle trips. In both cases, the travel time increase, including all trips, stays below 50 %, but for the serviced requests, it has already reached its maximum of approximately 60 %.

The rejected requests are not distributed evenly across the city but show a few distinct areas that cannot be fully covered, as shown in Fig. 10.

From Fig. 9a and 9c, we derive that for both time periods most of the origins of the rejected requests are located in the same LOR. In this area, the Berlin-Tegel airport was located until 2020, which explains the high number of requests that have started there. Fig. 9b and 9d reveal that the destinations of the rejected requests are also in similar areas but not as centered as the trip origins. The high number of rejected requests hints at the initial distribution of the vehicles as a potential explanation. As mentioned in section 2.2, the vehicles are initially uniformly distributed. This means that probably not enough vehicles are located in the high-demand areas, which indicates the necessity for fleet rebalancing strategies.

3.4. Spatial variations for areas with different population densities

By creating request sets containing only trips starting in areas with similar population densities, as depicted in Fig. 6, we can execute a spatial analysis of how ride-pooling works for differently populated areas. The average waiting and driving time of each area is depicted in Fig. 10.

Fig. 10a shows that the average waiting time is lower in the less populated areas, primarily in the outskirts. Note that even in the areas with the highest average waiting time, the waiting time stays below three minutes despite an allowed maximum of ten. Overall

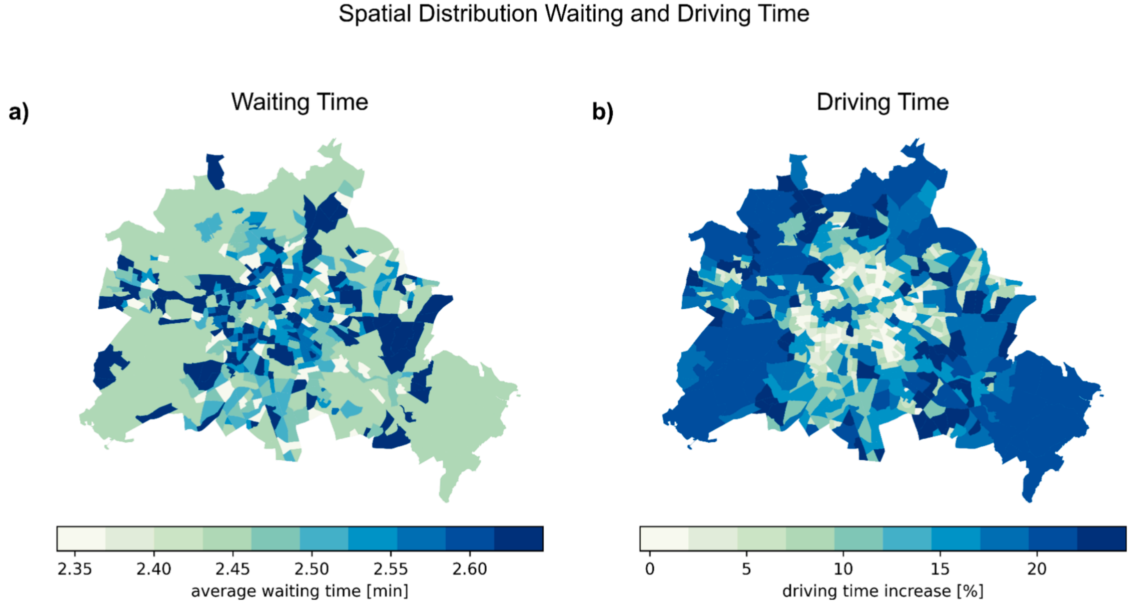

Fig. 10. Spatial variations of ride-pooling performance. a) absolute average waiting for different areas, b) relative increase in driving time in percent. The simulated driving time is compared to the travel time data from the INRIX data set.

differences of about 20 s are unlikely to impact user satisfaction substantially. Fig. 10b shows the relative driving time increase compared to the recorded driving time from the data. Here, we see the opposite effect, with trips originating in the outskirts incurring larger delays than more central requests. However, the maximum recorded average driving delays are about 25 %. The discrepancy between this result and the 55 % observed overall service time increase stems from the fact that this refers to driving time alone, without adding waiting time and walking to and from the pooled stops.

By comparing the required vehicle reduction results for the whole area of Berlin in section 3.1 and the low-transit-area in section 3.2, we observe that more vehicles are required for areas with a lower population density. We investigate these spatial variations in more detail by looking at the average number of required cars per capita for the ten areas defined in Fig. 6. We measure the number of vehicles required to replace all trips and divide this by the number of inhabitants in the respective area. In Fig. 11, the number of private vehicles per capita and the number of required vehicles per capita are displayed.

Fig. 11a shows that areas with a low population density have more cars per capita than areas with a high population density. From Fig. 11b we derive that within areas with a high population density, fewer vehicles are required to replace all vehicle trips, even though the number of requests was similar for every test area.

4. Conclusion

This paper states that a ride-pooling system with approximately 26,500 vehicles could replace all vehicle trips in Berlin if perfect acceptance is assumed. When focusing on the suburban areas, defined as regions with low transit access, around 8,700 vehicles would be required to replace all vehicle trips. This amounts to a fleet size reduction of approximately 97.6 %, with a decrease in the total driven distance by 61 %, while the average travel time for passengers would increase by approximately 55.5 %. In suburban areas, replacing trips with ride-pooling leads to a 48 % reduction in driven distance, while the travel time for passengers increases by around 62 %. Furthermore, we demonstrate that the number of vehicles required for a ride-pooling service is strongly influenced by population density.

The current results focus on analyzing the necessary fleet size on a large stop network with a realistic but static request pattern at a given maximum delivery delay of 50 % (walking time + waiting time + driving time from simulation compared to direct driving time from data). A detailed trade-off analysis between maximum delivery delay and final fleet size is out of scope due to data usage restrictions but would be necessary to optimize user acceptance. In our analysis, we do not distinguish between different types of delay of the pooled journey (walking, waiting, detours). When gauging user experience or acceptance, these might be weighed differently or even be subject to individual preference profiles.

In reality, travel patterns are rarely static but may change with the introduction of new transit options. This is not reflected in this work. Furthermore, we did not include the walking times of private car users to their cars or from their parking lots to their actual destination here, which would probably lead to a smaller overall travel time increase. Importantly, all Berlin car driver's, including drivers of non-domestic traffic, spend on average six minutes to walk from a parking space to their desired destination. This time penalty of private vehicle trips would negate the additional time costs of routing in shared pooled mobility in most cases (Simmons, 2017).

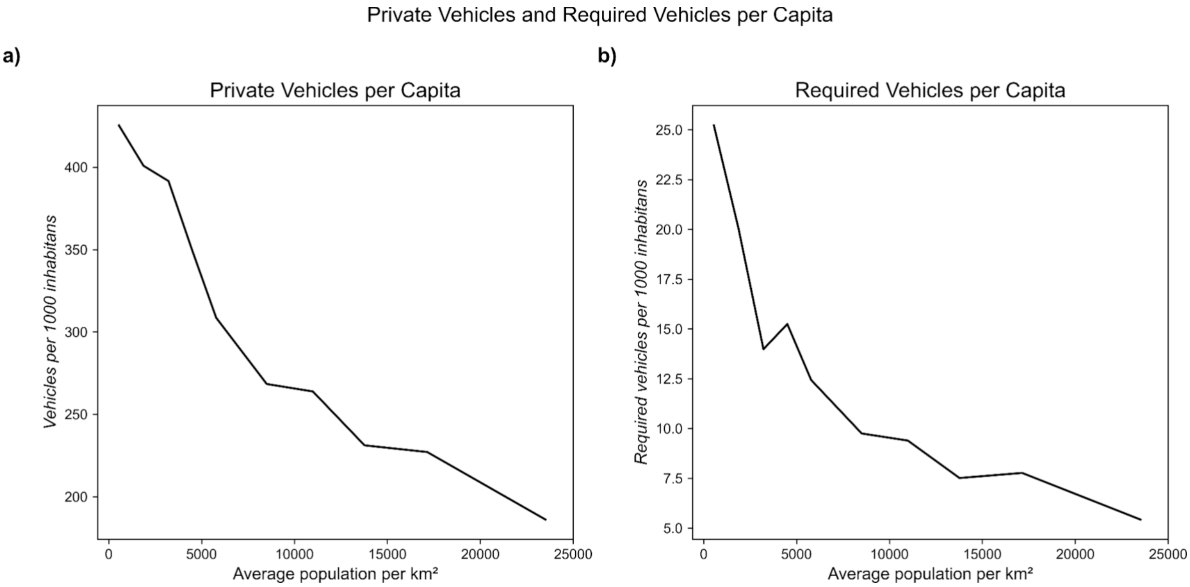

Fig. 11. Private cars per capita and required cars per capita for areas with different population densities.

The technical potentials of ride-pooling could be increased by optimizing the system parameters. Studies indicate that by optimizing ride-pooling parameters, the system efficiency can increase by 20 % (Zwick and Axhausen, 2020). Due to time-limited access to the real-world dataset, a parameter or system optimization was not within the scope of this work. It would further be possible to optimize the used stop network, which heavily influences the efficiency of a ride-pooling system (Manik & Molkenthin, 2020; Molkenthin et al., 2020; Schmaus, 2022; Zech et al., 2022). When optimizing the dispatcher algorithm, the aim is to find a balance between optimization in terms of individual travel time and system-wide distance traveled (Alonso-Mora et al., 2017; Al-Abbasi et al., 2019). Furthermore, optimization regarding the initial vehicle placement, together with vehicle rebalancing, has a high potential of reducing rejections in special points of interest (Schlenther et al., 2023).

Besides the technical potentials, socio-political aspects are the main challenge for implementing ride-pooling. If we assume, for example, that for a vehicle fleet of 26,500, three times as many drivers earning 34,000€ (the average wage of bus drivers in Berlin) are necessary, we get €2.7 billion wage costs per year (Berliner Verkehrsgesellschaft, 2024). To determine whether such a system could be self-sustaining, the results of this paper should be connected to research on ride-pooling and pricing (de Ruijter et al., 2023; Ke et al., 2020). Furthermore, autonomous vehicles could significantly affect prices (Engelhardt et al., 2019).

Further behavioral factors of potential users play a key role in the future success of ride-pooling (Millonig & Haustein, 2020). Various aspects, such as behavioral uncertainty, limited space in the vehicle, negative past experiences, age, gender, and place of residence, can influence user acceptance (Irannezhad & Mahadevan, 2022; Xie et al., 2020). However, these barriers can be partially addressed through effective payment models and system efficiency (Adelé & Dionisio, 2020; Bujak & Kucharski, 2024). In future research, technical potentials and behavioral factors (Hou et al., 2020) should be combined to make accurate predictions.

More broadly speaking, our paper shows that shared pooled mobility systems at the city level can achieve huge system efficiency and quality of life gains — by eliminating congestion and providing public spaces for people instead of parked cars — but at considerable time and convenience costs for traveling individuals. While not fully consistently qualified, the discrepancy between public and private benefits of shared and private mobility indicates that urban transport has characteristics of a tragedy of commons (c.f. (Creutzig, 2023)).

CRediT authorship contribution statement

Alexander Schmaus: Writing – original draft, Software, Investigation, Formal analysis, Conceptualization. **Felix Creutzig:** Writing – review & editing, Formal analysis, Conceptualization. **Nicolas Koch:** Writing – review & editing, Resources. **Florian Nachtigall:** Writing – original draft, Resources, Data curation. **Nora Molkenthin:** Writing – review & editing, Writing – original draft, Formal analysis.

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Data availability

The authors do not have permission to share data.

References

Adelé, S., Dionisio, C., 2020. Learning from the real practices of users of a smart carpooling app. Eur. Transp. Res. Rev. 12 (1), 39. https://doi.org/10.1186/s12544-020-00429-3.

Al-Abbasi, A.O., Ghosh, A., Aggarwal, V., 2019. DeepPool: Distributed Model-Free Algorithm for Ride-Sharing Using Deep Reinforcement Learning. IEEE Trans. Intell. Transp. Syst. 20 (12), 4714–4727. https://doi.org/10.1109/TITS.2019.2931830.

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proc. Natl. Acad. Sci. 114 (3), 462–467. https://doi.org/10.1073/pnas.1611675114.

Amt für Statistik Berlin-Brandenburg. (2021). Lebensweltlich orientierte Räume (LOR) in Berlin. https://www.berlin.de/sen/sbw/stadtdaten/stadtwissen/sozialraumorientierte-planungsgrundlagen/lebensweltlich-orientierte-raeume/.

Amt für Statistik Berlin-Brandenburg. (2023, April 3). Motorisierungsgrad gesunken—Kraftfahrzeugbestand 2022 Berlin. https://www.statistik-berlin-brandenburg.de/076-2023.

Berbeglia, G., Cordeau, J.-F., Laporte, G., 2010. Dynamic pickup and delivery problems. Eur. J. Oper. Res. 202 (1), 8–15. https://doi.org/10.1016/j.ejor.2009.04.024.

Berliner Verkehrsgesellschaft. (2024). Gesucht: Busfahrer*innen. https://karriere.bvg.de/berufserfahrene/fahrdienst/busfahrer/busfahrerin-d95.

Berrill, P., Nachtigall, F., Javaid, A., Milojevic-Dupont, N., Wagner, F., Creutzig, F., 2024. Comparing urban form influences on travel distance, car ownership, and mode choice. Transp. Res. Part D: Transp. Environ. 128, 104087. https://doi.org/10.1016/j.trd.2024.104087.

Bischoff, J., & Maciejewski, M. (2016). Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. The 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016) / The 6th International Conference on Sustainable Energy Information Technology (SEIT-2016) / Affiliated Workshops, 83, 237–244. DOI: 10.1016/j.procs.2016.04.121.

Boeing, G., 2017. OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Comput. Environ. Urban Syst. 65, 126–139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004.

Bongardt, D., Creutzig, F., Hüging, H., Sakamoto, K., Bakker, S., Gota, S., Böhler-Baedeker, S., 2013. Low-carbon land transport. Policy handbook. Routledge.

Bujak, M., & Kucharski, R. (2024). Balancing Profit and Traveller Acceptance in Ride-Pooling Personalised Fares. arXiv Preprint arXiv:2411.03370.

Chen, M.H., Jauhri, A., Shen, J.P., 2017. Data Driven Analysis of the Potentials of Dynamic Ride Pooling. In: Proceedings of the 10th ACM SIGSPATIAL Workshop on Computational Transportation Science, pp. 7–12. https://doi.org/10.1145/3151547.3151549.

Creutzig, F., 2021. Making Smart Mobility Sustainable. Israel Policy Public Institute, Tel Aviv, Israel.

Creutzig, F., 2023. Placed-Based Global Environmental Goods, Local Public Bads? Place- Based Transitions as a Key Contribution to Global Stewardship, Background Paper for the OECD-EC.

Creutzig, F., Roy, J., Devine-Wright, P., Díaz-José, J., Geels, F.W., Grubler, A., Maïzi, N., Masanet, E., Mulugetta, Y., Onyige, C.D., Perkins, P.E., Sanches-Pereira, A., Weber, E.U., 2022. Demand, services and social aspects of mitigation. In: Shukla, P.R., Skea, J., Slade, R., Al Khourdaji, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., Malley, J. (Eds.), Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. https://doi.org/10.1017/9781009157926.007.

Creutzig, F., Schmaus, A., Ayaragarnchanakul, E., Becker, S., Falchetta, G., Hu, J., Goletz, M., Guéret, A., Nagel, K., Schild, J., Schill, W.-P., Schlenther, T., Molkenthin, N., 2024. Shared pooled mobility: Expert review from nine disciplines and implications for an emerging transdisciplinary research agenda. Environ. Res. Lett. 19 (5), 053004. https://doi.org/10.1088/1748-9326/ad3cf5.

de Ruijter, A., Cats, O., Alonso-Mora, J., Hoogendoorn, S., 2023. Ride-pooling adoption, efficiency and level of service under alternative demand, behavioural and pricing settings. Transp. Plan. Technol. 46 (4), 407–436. https://doi.org/10.1080/03081060.2023.2194874.

Engelhardt, R., Dandl, F., Bilali, A., Bogenberger, K., 2019. Quantifying the Benefits of Autonomous On-Demand Ride-Pooling: A Simulation Study for Munich, Germany. IEEE Intelligent Transportation Systems Conference (ITSC) 2019, 2992–2997. https://doi.org/10.1109/ITSC.2019.8916955.

European Environment Agency, 2023. October 18). How Air Pollution Affects Our Health. https://www.eea.europa.eu/en/topics/in-depth/air-pollution/eow-it-affects-our-health.

Zwick, F., Axhausen, K.W., 2020. Impact of Service Design on Urban Ridepooling Systems. In: 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), pp. 1–6. https://doi.org/10.1109/ITSC45102.2020.9294289.

Gerike, R., Hubrich, S., Ließke, F., Wittig, S., Wittwer, R., 2020a. Sonderauswertung zum Forschungsprojekt „Mobilität in Städten–SrV 2018 " (Fakultät Verkehrswissenschaften "Friedrich List" Institut für Verkehrsplanung und Straßenverkehr). Städtevergleich, Dresden https://tu-dresden.de/bu/verkehr/ivs/srv/ressourcen/dateien/SrV2018_Staedtevergleich.pdf?lang=de.

Gerike, R., Hubrich, S., Ließke, F., Wittig, S., Wittwer, R., 2020b. Tabellenbericht zum Forschungsprojekt "Mobilität in Städten-SrV 2018" in Berlin. TU-Dresden, Dresden.

Gödde, J., Ruhrort, L., Allert, V., Scheiner, J., 2023. User characteristics and spatial correlates of ride-pooling demand – Evidence from Berlin and Munich. J. Transp. Geogr. 109, 103596. https://doi.org/10.1016/j.jtrangeo.2023.103596.

Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D.L., Rao, N.D., Riahi, K., Rogelj, J., De Stercke, S., Cullen, J., Frank, S., Fricko, O., Guo, F., Gidden, M., Havlík, P., Huppmann, D., Kiesewetter, G., Rafaj, P., Valin, H., 2018. A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. Nat. Energy 3 (6), 515–527. https://doi.org/10.1038/s41560-018-0172-6.

Hou, Y., Garikapati, V., Weigl, D., Henao, A., Moniot, M., Sperling, J., 2020. Factors Influencing Willingness to Pool in Ride-Hailing Trips. In Transportation Research Record (vol. 2674 (5), 419–429.

Hu, J., Ayaragarnchanakul, E., Yang, Z., Creutzig, F., 2024. Shared pooled mobility essential complement to decarbonize China's transport sector until 2060. Mitig. Adapt. Strat. Glob. Chang. 29 (5), 37. https://doi.org/10.1007/s11027-024-10135-3.

International Transport Forum. (2017). Shared mobility simulations for Auckland. OECD Publishing, 41.

International Transport Forum. (2018). Shared Mobility Simulations for Dublin. OECD Publishing, 58.

Irannezhad, E., Mahadevan, R., 2022. Examining factors influencing the adoption of solo, pooling and autonomous ride-hailing services in Australia. Transp. Res. Part C Emerging Technol. 136, 103524. https://doi.org/10.1016/j.trc.2021.103524.

Jaramillo, P., Kahn Ribeiro, S., Newman, P., Dhar, S., Diemuodeke, O. E., Kajino, T., Lee, D. S., Nugroho, S. B., Ou, X., Hammer Strømman, A., & Whitehead, J. (2022). Transport. In P. R. Shukla, J. Skea, R. Slade, A. Al Khourdaji, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. DOI: 10.1017/9781009157926.012.

Jung, F., Manik, D., 2024. RidePy: A Fast and Modular Framework for Simulating Ridepooling Systems. 9 (97), 6241.
Kaddoura, I., Leich, G., Neumann, A., Nagel, K., 2021. From today's ride-sharing services to future mobility concepts: A simulation study for urban and rural areas. Technische Universität Berlin. https://doi.org/10.14279/depositonce-12055.
Kaddoura, I., & Schlenther, T. (2021). The impact of trip density on the fleet size and pooling rate of ride-hailing services: A simulation study. The 12th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 4th International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops, 184, 674–679. DOI: 10.1016/j.procs.2021.03.084.
Ke, J., Yang, H., Li, X., Wang, H., Ye, J., 2020. Pricing and equilibrium in on-demand ride-pooling markets. Transp. Res. B Methodol. 139, 411–431. https://doi.org/10.1016/j.trb.2020.07.001.
Koch, N., Ritter, N., Rohlf, A., Thies, B., 2023. Machine Learning from Big GPS Data about the Heterogeneous Costs of Congestion. Available at SSRN 4526796. https://doi.org/10.2139/ssrn.4526796.
König, A., Grippenkoven, J., 2020. Travellers' willingness to share rides in autonomous mobility on demand systems depending on travel distance and detour. Travel Behav. Soc. 21, 188–202. https://doi.org/10.1016/j.tbs.2020.06.010.
Kostiainen, J., Tuominen, A., 2019. Mobility as a service—Stakeholders' challenges and potential implications. Towards User-Centric Transport in Europe: Challenges, Solutions and Collaborations 239–254.
Li, M., Jiang, G., Lo, H.K., 2022. Pricing strategy of ride-sourcing services under travel time variability. Transportation Research Part e: Logistics and Transportation Review 159, 102631. https://doi.org/10.1016/j.tre.2022.102631.
Liebchen, C., Lehnert, M., Mehlert, C., & Schiefelbusch, M. (2021). Betriebliche Effizienzgrößen für Ridepooling-Systeme. In Making Connected Mobility Work. Springer Gabler. DOI: 10.1007/978-3-658-32266-3_7.
Manik, D., Molkenthin, N., 2020. Topology dependence of on-demand ride-sharing. Applied Network Science 5 (1), 49. https://doi.org/10.1007/s41109-020-00290-2.
Marsden, G., 2022. Social benefits of shared mobility: Metrics and methodologies. 26th ACEA European Automobile Manufacturers' Association. Scientific Advisory Group report.
MIB. (2021). Travel Time Index—Mib | Mobility Institute Berlin. https://mobilityinstitute.com/publikationen/travel-time-index.
Millonig, A., Haustein, S., 2020. Human factors of digitalized mobility forms and services. Eur. Transp. Res. Rev. 12(1), 46, s12544–020-00435–5. https://doi.org/10.1186/s12544-020-00435-5.
Mitropoulos, L., Kortsari, A., Ayfantopoulou, G., 2021. A systematic literature review of ride-sharing platforms, user factors and barriers. Eur. Transp. Res. Rev. 13 (1), 61. https://doi.org/10.1186/s12544-021-00522-1.
MOIA. (2024). Unser MOIA-Fahrzeug im Spotlight. https://www.moia.io/de-DE/blog/moia-6-das-fahrzeug-im-spotlight.
Molkenthin, N., Schröder, M., Timme, M., 2020. Scaling Laws of Collective Ride-Sharing Dynamics. Phys. Rev. Lett. 125 (24), 248302. https://doi.org/10.1103/PhysRevLett.125.248302.
Nachtigall, F. (2024). Transit-access [Computer software]. https://github.com/ai4up/transit-access.
Engelhardt, R., Bogenberger, K., 2021. Benefits of Flexible Boarding Locations in On-Demand Ride-Pooling Systems. In: 2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems. https://doi.org/10.1109/MT-ITS49943.2021.9529284.
Berlin-Brandenburg, R., 2024a. January 18). In Diesen Bezirken Und Kiezen Ist Es Voller Geworden. https://www.rbb24.de/panorama/beitrag/2024/01/berlin-bevoelkerung-einwohnerdichte-entwicklung.html.
Sachverständigenrat für Umweltfragen. (2017). Umsteuern erforderlich: Klimaschutz im Verkehrssektor (1. Auflage, digitale Originalausgabe).
Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S.H., Ratti, C., 2014. Quantifying the benefits of vehicle pooling with shareability networks. Proc. Natl. Acad. Sci. 111 (37), 13290–13294. https://doi.org/10.1073/pnas.1403657111.
Schlenther, T., Leich, G., Maciejewski, M., Nagel, K., 2023. Addressing spatial service provision equity for pooled ride-hailing services through rebalancing. IET Intel. Transport Syst. 17 (3), 547–556.
Schmaus, A., 2022. A Markov Chain Monte Carlo Approach for Stop Pooling in On-Demand Ride-Pooling Services [Master's Thesis]. Technische Universität München.
Simmons, M.. Germans Waste 41 Hours a Year Searching for Parking. https://www.parking.net/parking-news/inrix/germans-41-hours-searching-parking.
Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S.H., Ratti, C., 2017. Scaling Law of Urban Ride Sharing. Sci. Rep. 7 (1), 42868. https://doi.org/10.1038/srep42868.
Tagesspiegel. (2023, July 4). In diesen Kiezen gibt es die meisten Autos. https://interaktiv.tagesspiegel.de/lab/autokarte-berlin-in-diesen-kiezen-gibt-es-die-meisten-autos/.
Berlin-Brandenburg, V., 2024b. Datensätze. GTFS, Haltestellen, Linienfarben https://www.vbb.de/vbb-services/api-open-data/datensaetze/.
Wilson, C., Kerr, L., Sprei, F., Vrain, E., Wilson, M., 2020. Potential Climate Benefits of Digital Consumer Innovations. Annu. Rev. Env. Resour. 45 (1), 113–144. https://doi.org/10.1146/annurev-environ-012320-082424.
World Economic Forum. (2023, March 7). Traffic congestion cost the US economy nearly $87 billion in 2018. https://www.weforum.org/agenda/2019/03/traffic-congestion-cost-the-us-economy-nearly-87-billion-in-2018/.
Xie, Y., Xiao, H., Shen, T., & Han, T. (2020). Investigating the Influencing Factors of User Experience in Car-Sharing Services: An Application of DEMATEL Method. In H. Krömker (Ed.), HCI in Mobility, Transport, and Automotive Systems. Driving Behavior, Urban and Smart Mobility (pp. 359–375). Springer International Publishing. DOI: 10.1007/978-3-030-50537-0_26.
Yu, B., Ma, Y., Xue, M., Tang, B., Wang, B., Yan, J., Wei, Y.-M., 2017. Environmental benefits from ridesharing: A case of Beijing. Appl. Energy 191, 141–152. https://doi.org/10.1016/j.apenergy.2017.01.052.
Zech, R.M., Molkenthin, N., Timme, M., Schröder, M., 2022. Collective dynamics of capacity-constrained ride-pooling fleets. Sci. Rep. 12 (1), 10880. https://doi.org/10.1038/s41598-022-14960-x.