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ENHANCING MUNICIPAL ANALYTICS CAPABILITIES TO ENABLE SUSTAINABLE URBAN TRANSPORTATION

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ENHANCING MUNICIPAL ANALYTICS CAPABILITIES TO ENABLE SUSTAINABLE URBAN TRANSPORTATION

Research

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Abstract

Intermodal mobility, the IT-enabled, seamless transition between different modes of transportation to reach one's destination, is a promising approach towards reducing the environmental footprint of urban mobility. We introduce a prototype, a geospatial data analytics system, that allows decision-makers at the municipal level to better understand how different means of transportation interact and interfere with each other within their city. Through a demonstration case, we particularly focus on the relationship between public transportation and private sector carsharing services in the city of Berlin. We outline the methods employed by the prototype to investigate the spatial and temporal dimensions of carsharing usage and how they relate to public transport offers. Our results suggest that carsharing complements public transport in some ways – e.g. by linking parts of the city with an insufficient public transport connection but also low demand – while potentially cannibalizing customers from public transport in the city center due to the increased comfort. We conclude by discussing how stakeholders can transform these insights into actionable advice.

Keywords: Urban Mobility, Urban Planning, Spatial Analytics, Public Transport, Carsharing, Location-Based Services

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1 Introduction

Cities account for an estimated 60 to 80 percent of man-made global CO₂ emissions, substantially driven by energy consumption for lighting, heating, electronics, and mobility (Kamal-Chaoui and Robert, 2009). This share is only expected to increase over the next decades, with 66 percent of the world's population projected to reside in cities by 2050, compared to 54 percent in 2014 (United Nations Department of Economic and Social Affairs, 2014). While being the root of many environmental problems, cities are also powerful levers on the path towards a more sustainable way of living. Information technology and information systems play a critical role in this transition. For instance, data analytics methods enable stakeholders to base their decisions on new insights and robust foundations of evidence while sensitized smart objects enable efficiency gains, as evidenced by the Energy Informatics literature (Jagstaidt, Kossahl, and Kolbe, 2011; Loock, Staake, and Thiesse, 2014; Watson, Boudreau, and Chen, 2010).

In this paper, we focus on the former aspect, introducing an analytics approach that supports decision-makers at the municipal level to plan for sustainable urban mobility, by providing insights into the interaction between different modes of transportation across their city. Besides carbon emissions, a mobility system based on personal gasoline-fueled cars causes excessive noise and other pollutants, leads to higher congestion levels and a shortage of parking spaces, thereby endangering the health of the city's population and their efficient mobility (Loukopoulos et al., 2005). Hence, the concept of intermodal mobility has gained traction in recent years, with smartphone apps and online platforms ideally enabling a seamless transition between different modes of transportation to reach one's destination.

Nevertheless, how different modes of transportation influence and interact with each other is still heavily contested, particularly in terms of public transportation (PT) and privately operated carsharing (CS) systems. On the one hand, CS may take away market share from public transportation. This is particularly relevant for free-floating carsharing (FFCS), which allows users to end their rental anywhere within a predefined business area instead of at fixed stations, thereby providing more flexibility and comfort than public transport alternatives. On the other hand, the flexibility of carsharing may increase overall public transport usage by encouraging vehicle owners to abandon their private cars, switch to PT and use CS only if and when flexibility is needed.

To provide decision-makers with an improved understanding of this interaction between multiple mobility modes, we develop an analytics tool which visualizes and analyzes the spatio-temporal dynamics of carsharing usage and how they relate to public transport alternatives. These dynamics are reflected in the following research questions:

1. How does carsharing usage vary across time and space?
2. How do carsharing trips differ from public transportation alternatives with respect to direct monetary and time-related costs?
3. How can decision-makers use these insights to reduce the environmental impact of urban mobility?

The remainder of this paper is organized as follows. In the next section, we provide an overview of related work. The third section introduces the decision-support-system (DSS) prototype and the data sources on which it is based. In section four, we demonstrate the analytic features of the DSS using the exemplary case of the city of Berlin. The paper concludes with summarizing remarks in section five, a discussion of the managerial implications of our findings and an outlook on further research opportunities.

2 Related Work

Related research on sustainable urban mobility can be divided into the following areas: urbanization and smart cities, carsharing, multi- and intermodality, as well as GIS/geo-analytics.

Smart cities and urbanization: To cope with the challenges of urbanization there has recently been a call for smart solutions in smart cities (see Chourabi et al. (2012) and Hollands (2008) for definition and

classification of smart cities). Neirotti et al. (2014) have identified transportation as a crucial domain of smart cities which should fulfill its role in “providing users with dynamic and multimodal information for traffic and transport efficiency. Assuring sustainable public transportation by means of environmental-friendly fuels and innovative propulsion systems” (Neirotti et al., 2014, p. 27). Mobile technologies and location-based services have become key enablers in achieving this goal (Diamantaki et al., 2015).

Carsharing: One such location-based service is free-floating carsharing, which, as a relatively novel mode of transportation, has also sparked the interest of researchers, especially since it has been found to contribute to more sustainable urban mobility and reduce the negative environmental impact of transportation (Firnkorff and Müller, 2011), the industry sector with the largest growth in CO₂ emissions (Berrittella et al., 2008). Carsharing provides new access to transportation for low-income households without private cars, who thereby gain in mobility (Costain, Ardron, and Habib, 2012). Interestingly though, the increase in transportation through carsharing does not necessarily translate to more traffic: Carsharing vehicles are being used more efficiently and more considerably, which instead leads to a reduction in driven kilometers by up to 27 % (Martin and Shaheen, 2011), thereby also reducing overall traffic granted that enough people switch (Meijkamp, 1998). Furthermore, private cars are being sold and planned purchases forgone, which further decreases negative environmental impacts (Costain, Ardron, and Habib, 2012; Katzev, 2003).

Multi- and Intermodality: Millard-Ball (2005) envisions that carsharing will become a distinctive part of a more elaborate transportation system, complementing other existing modes and being positively influenced by a well-functioning public transport network. Similarly, Shaheen and Cohen (2007) expect an increasing integration of carsharing into the urban mobility system and a higher degree of cooperation between CS- and PT-providers. But there are also dissenting opinions predicting an increasing degree of competition between the two modes (Stillwater, Mokhtarian, and Shaheen, 2009).

Huwer (2004) shows that a functional and synergistic combination of the two services depends on a strong partnership between their operators and with the government. This partnership should extend to joint pricing and joint infrastructure development. An ideal outcome is then that carsharing users also increase their usage of public transport, thereby reducing their environmental footprint.

But, as described by Schöller-Schwedes (2010), competition between the different transportation modes has been a major cause for why the integrated approach to transport policy aspired to in the European Union has been difficult thus far. Still, whether via integrated planning or not, multi- and intermodal transport are on the rise and will play an integral part in smart cities (Spickermann, Grienitz, and von der Gracht, 2014). These travel modes are not just restricted to carsharing and public transport but also include bikesharing (Jäppinen, Toivonen, and Salonen, 2013) and ridesharing (Teubner and Flath, 2015). Berrittella et al. (2008) map out four desirable outcomes of projects aimed at making the transportation sector more sustainable. The first two focus on an improvement in energy inputs and –efficiency, the other two are described as an “increase in the public and multimodal transport market share” and “improvements due to better mobility management systems” (Berrittella et al., 2008, p. 310). The available policy options for achieving these outcomes are summarized as “tax schemes aiming at promoting environmental-friendly transport modes; better integration between transport planning and land uses; new and better transport infrastructures, [and] development of intelligent transport system (ITS) technologies” (Berrittella et al., 2008, p. 310). The approach laid out in our paper is directly targeted at helping decision-makers in designing these policy options and facilitating their subsequent implementation.

GIS/Geo-Analytics: The underlying methodology of our DSS prototype is grounded in approaches from the location intelligence, geographic information systems (GIS) and geo-analytics disciplines, which are all part of the trend of analyzing and deriving insights from spatial data (De Smith, Goodchild, and Longley, 2013; Levy, 2015). Using easy-to-interpret visualization techniques, geo-analytics is well-suited for providing decision support, and has already been successfully applied in the urban mobility context, by predicting carsharing user demand based on points of interest (Wagner, Brandt, and Neumann, 2016).

So far, however, most research into smart urban mobility has been unidirectional, and there have been only few analyses combining data from different transportation modes (e.g. Jäppinen, Toivonen, and Salonen (2013) for bikesharing and public transport). It is therefore unclear how carsharing and public transport interact and influence each other. The DSS we introduce employs geo-analytics to analyze this interaction on a ride-by-ride basis along spatial and temporal dimensions. From a broader theoretical viewpoint, our approach outlines how ubiquitous data can be employed to derive revealed preferences instead of solely relying on surveys and the associated biases. We demonstrate this in the context of urban mobility, a field which previously largely relied on stated preferences analyses (e.g. Hensher and Rose, 2007).

3 DSS Prototype and Data Sources

3.1 DSS prototype

We follow a design science approach (Hevner et al., 2004) to construct a DSS artifact which can be applied in real life. Figure 1 provides a graphical representation of the DSS prototype for urban transportation planning. CS data is the primary input and is fed into the visualization and reporting interface. For primary analyses, individual CS trips can already be visualized at this step (1) before the data is further transformed by the analytics module (2). Subsequently, in the analytics module, PT data is collected and combined with the corresponding CS rides. The module performs analyses, such as aggregation and filtering, across both spatial and temporal dimensions, thereby transforming the data into understandable information for decision makers. The analyses can be conducted both for the individual datasets, as well as for combinations of CS and PT data. The module relies on methodology from geostatistics, such as areal modeling and kernel density estimation (cf. Banerjee, Carlin, and Gelfand, 2014), which is explained in more detail together with the analysis in section 4. Building on the insights drawn from the analyses, relevant subsets of the consolidated data are returned to the visualization and reporting interface (3) to provide comprehensive graphical and tabular summaries for decision makers (4) in urban planning, for PT authorities, and for CS providers.

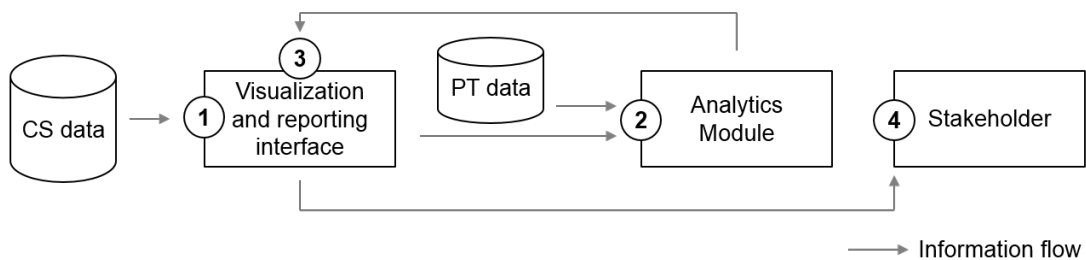


Figure 1. Components of and information flow in the DSS prototype.

3.2 Carsharing data

The DSS prototype is able to process data from different CS providers. For the analyses in this paper, we rely on publicly available data from the booking platforms of CS providers. Customers use the platform to inquire about the location of vehicles available for rental. Similarly, the prototype uses this information and stores ‘snapshots’ of the location of all available vehicles in the city’s business area. By tracking the changes between different snapshots, the prototype extracts information about the CS rides. A CS rental can be expressed as a tuple (1) with the following components:

$$CS_i = (\lambda_{start}, \phi_{start}, \lambda_{end}, \phi_{end}, timestamp, duration, distance, cost, PT_j) \quad (1)$$

- $(\lambda_{start}, \phi_{start}), (\lambda_{end}, \phi_{end})$: Longitudinal (λ) and latitudinal (ϕ) geo-coordinates (in degrees) of the starting and ending points of the rides.
- *timestamp*: A timestamp that records the departure time as well as the day of the ride.
- *duration*: The duration of the CS rides. Since CS providers do not publish the exact driving route of their vehicles, we access publicly available map services (such as Google or Bing Maps) and use the recommended route between the starting and ending coordinates of the rides at the time of the rental as a proxy. Actual routes might differ slightly; however, this approach also allows to record trip duration accounting for potential obstacles or impediments to mobility, such as traffic congestion or necessary detours e.g. due to limited river crossings. Furthermore, it corrects for possible stops during a rental, which would otherwise distort the data.
- *distance*: For trip distances, we also use the data of the routes provided by the public map services.
- *cost*: The cost of the CS ride is the product of trip duration and the provider's fare (0.29 €/min).
- *PT_j*: For each CS ride, the alternative PT ride with index j is determined and recorded. The components of the PT rides are explained in subsection 3.3.

The sample dataset for our analyses in section 4 contains all rentals of a major FFCS provider in Berlin over a period of 7 days in April 2015 (7.4.–14.4.) and comprises in total $n = 24,225$ rides. Its summary statistics are displayed in table 1.

Variable	Unit	Median	Mean	St. deviation	Min	Max
<i>duration</i>	<i>min</i>	15.58	17.00	8.55	1.12	70.80
<i>duration</i> (no traffic)	<i>min</i>	13.27	14.32	6.90	1.00	50.55
<i>distance</i>	<i>m</i>	5,938	7,411	5,219	360	42,090
<i>cost</i>	€	4.64	5.07	2.48	0.58	18.09

Table 1. Descriptive statistics of the CS dataset ($n = 24,225$).

On average, the CS rides took 17 minutes with the shortest ride lasting a little over one minute and the longest about an hour and ten minutes. On average traffic increased CS ride durations by 2.68 minutes. The mean distance of the rides was 7.4 kilometers. There is a large standard deviation of the rides' distance, which is due to some very long rides, the longest one covering about 42 kilometers. The average rental cost for a carsharing ride is 5.07 €.

3.3 Public transport data

For each carsharing ride, we determine the fastest alternative public transport route from the respective start to end coordinates. We obtain the information from Google Maps Transit. Similar to CS rentals, each PT ride is represented by the tuple in (2) and consists of the following components.

$$PT_j = (station_{start}, station_{end}, walk_{start}, walk_{end}, duration, cost) \quad (2)$$

- $station_{start}, station_{end}$: The names and locations of the start and final PT stops.
- $walk_{start}, walk_{end}$: The walking distances from the CS start coordinates to the departing PT station and from the ending PT stop to the destination of the CS trip.
- *duration*: The duration of the PT ride, excluding walking time.
- *cost*: The cost of a one-way ticket. In Berlin, PT stations are assigned to three different fare zones (A–C) which spread radially from the city center. Within and between the zones, flat fares are employed. Additionally, short distance tickets are available for rides between a maximum of three

subway or six tram/bus stops (BVG, 2015). Google Maps Transit does not provide fare information. For simplification, we approximate the fare based on the duration of the ride. The short distance fare of 1.60 € is applied to trips lasting less than 7 *min*. The Zone AB fare is used for all trips with a duration between 7 and 60 *min*, and the Zone ABC fare to those longer than 60 *min*.

The descriptive statistics of the PT rides are displayed in table 2. Walking distances to/from the PT stations are very similar. For the alternative PT ride, CS users would have had to walk about 380 m to get both to the PT station and from the PT station to the end point of the ride. On many occasions, CS rides start or end directly at the PT stop, which explains minimum walking distances of 0 m. The mean of the travel time (excluding walking time) is about 15 minutes. Distances of the rides range between 156 m and 41 km with a mean value of 6.7 km. The average PT fare is 2.48 €.

Variable	Unit	Median	Mean	St. deviation	Min	Max
$walk_{start}$	m	300	382	264	0	3700
$walk_{end}$	m	300	381	270	0	5200
$duration$	min	14.00	15.65	10.30	1.00	85.00
$distance$	m	5,291	6,664	5,156	0,156	41,127
$cost$	€	2.70	2.48	0.44	1.60	3.30

Table 2. Descriptive statistics of the PT dataset ($n = 24,225$).

4 Application of the DSS Prototype

Using data for the city of Berlin, this section provides a real-world demonstration of the functionality of the DSS prototype. First, we investigate the mobility needs of people who use carsharing along spatial and temporal dimensions (section 4.1). Subsequently, we establish the link to public transport (section 4.2) and compare the two travel modes according to travel times, accessibility and cost, in order to get a better understanding of how well the two modes fulfill the above-mentioned mobility needs. Along with the analyses, we provide details on the applied methodology and formulate recommended actions for decision makers.

4.1 Spatial and temporal dimensions of carsharing usage

The spatial dimension of carsharing usage consists of three main components, starting points, destination points and the routes between the two. Consequently, the DSS prototype should provide answers to the following three questions: Where do people start their rides? Where do they end their rides? Which routes are most common?

To identify the hotspots of CS usage in Berlin, we use heatmaps, enabled by kernel density estimation (KDE), which allows aggregating scattered point data of ride origins and destinations, and calculating an estimated probability density of rides at arbitrary points in the business area. We use the standard kernel density estimator (cf. Venables and Ripley, 2002) displayed in eq. (3) together with a two-dimensional Gaussian kernel (4) for the latitudinal and longitudinal coordinates (λ, ϕ) . For each point within the business area, the density estimate \hat{f} is determined by applying the kernel function (4) and calculating the directional distance $(\lambda - \lambda_j$ and $\phi - \phi_j)$ to each rental observations within our dataset and by averaging the resulting values. The distances are adjusted by the directional bandwidth factors h_λ and h_ϕ which control the smoothing of the data. If the chosen factors are too small, the density shows high variations, if they are too large, it remains almost constant over the entire area. We determine the smoothing factors using the rule of thumb defined in Venables and Ripley (2002) since it leads to the satisfactory results in Fig. 2.

$$\hat{f}(\lambda, \phi) = \frac{1}{nh_\lambda h_\phi} \sum_{i=1}^n K\left(\frac{\lambda - \lambda_i}{h_\lambda}, \frac{\phi - \phi_i}{h_\phi}\right) \quad (3)$$

$$K(\lambda, \phi) = \frac{1}{2\pi\sigma_\lambda\sigma_\phi} \exp\left(-\frac{\lambda^2 + \phi^2}{2\sigma_\lambda\sigma_\phi}\right) \quad (4)$$

Figure 2(a) shows the kernel densities for all start and end points on weekdays and clear patterns can already be detected in the overall visualization of point densities. Three areas stick out as hotspots (highlighted) where carsharing users most frequently start and end their rides, all of them located rather centrally. A detailed analysis reveals that 47 % of all rides start or end within these hotspots, despite the fact that they only cover 8% of the overall CS business area. According to this preliminary analysis, the city center can be regarded as the most crucial area for CS in Berlin.

Fig. 2(b) displays temporal patterns in the mobility needs. For this purpose, the data set is divided into six subsets covering four hours each and start and end points are plotted separately. Patterns are clearly visible: In the morning (6-10am) the heatmaps show more rentals starting at the outskirts of the business area, and a very high concentration of destinations in the city center. In the afternoon and early evening (2-6pm) the morning trend reverses and start points are concentrated in the city center while the destination points are more dispersed. This is representative of a typical weekday, commuting to work in the city center in the morning and returning back home in the evening. Interestingly, during the night time (2-6am), there is also a visible hotspot of end points in the west, a district known as Charlottenburg, which is somewhat surprising. While there are some night clubs in this area, more analyses, e.g. of the points of interest in this area (c.f. Wagner, Brandt, and Neumann, 2016) are necessary to explain the activity in this area.

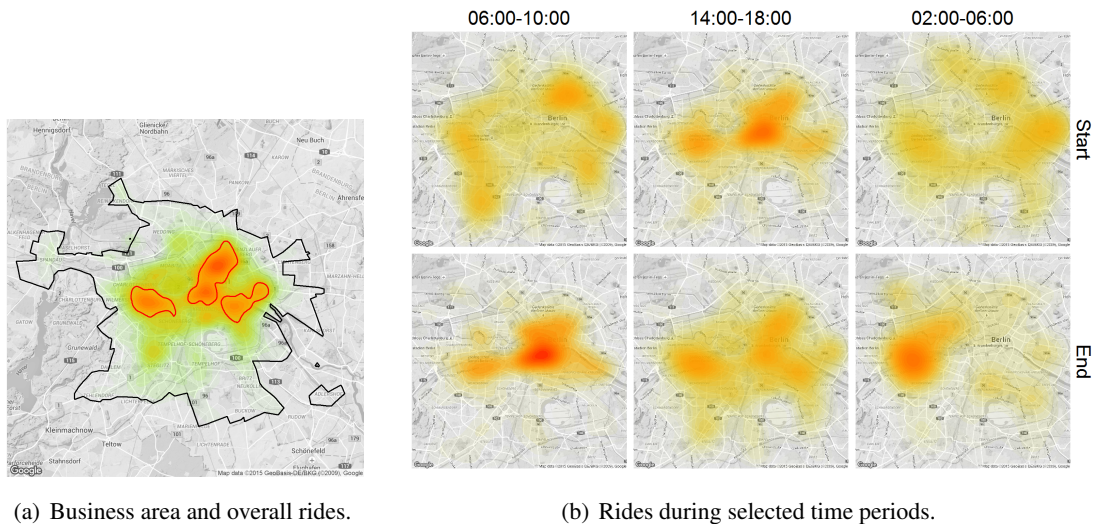


Figure 2. Spatiotemporal patterns of CS in Berlin on weekdays.

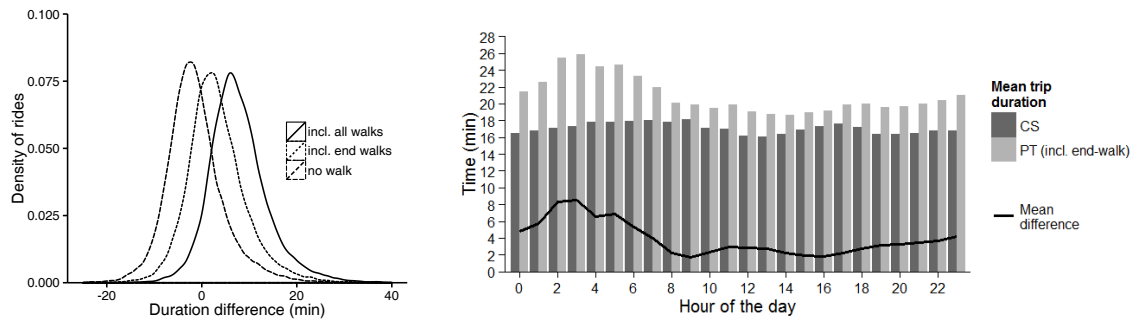
4.2 Comparison of carsharing and public transport

We next address the issue of how well the different travel modes fulfill the mobility needs. Therefore, the public transport data is included into the analytics module of the DSS prototype, which allows us to compare the two modes with regard to trip duration, accessibility and cost.

4.2.1 Overall differences in travel time

Carsharing and public transport can be compared along several dimensions, however, we expect that travel time is a very important factor for individuals' transport mode choice. Therefore, we put particular emphasis on using the DSS to evaluate trip durations.

Figure 3(a) displays global differences in travel time. Differences are measured as public transport travel time (excluding walking, including the end-walk, as well as including both start and end walks) minus carsharing travel (including traffic). The medians of the time differences are $-1:55 \text{ min}$, $2:36 \text{ min}$, and $7:07 \text{ min}$. Without walking time, PT is faster in 65 % of the rides. Including the end walk (both walks), CS is faster in 70 % (93 %) of the rides.



(a) Overall differences in trip duration. (b) Mean trip durations and differences in travel time for each hour of the day.

Figure 3. Differences in travel time.

Disregarding walking times, the majority of CS rentals (64.7%) would have been faster using public transport, which is contrary to our expectations. Comparing net ride times, however, ignores one crucial advantage of carsharing: people can park the car as closely as possible to their desired destination and save the walk from the final public transport stop. Although this advantage is probably more pronounced for residential areas, where parking spaces are readily available and public transport stop density is lower, than for the city center where the opposite is true. Therefore, the actual differences in travel time might be somewhere in between the values of the two curves. For completeness, we also show the difference including walking duration from the carsharing start point to the PT start station. However, assigning the walking times completely to PT likely overestimates the duration advantage of CS. Although we expect that travelers only use carsharing if the next available car is within acceptable walking distance, they still need to walk.

Figure 3(b) displays differences in trip duration between CS and PT (incl. end-walks) over the course of the day. We would expect that traffic affects the duration advantage, which carsharing exhibits over PT, and that the advantage is much lower or even disappears during rush-hour and is higher otherwise. The expected patterns can be observed, however, they are not very pronounced. During the day, the duration advantage of carsharing varies between 2-4 minutes, with minimum values during rush hours at 9 am and 4 pm, where CS travel times peak due to traffic. However, during the night (between 0–6 am) changes in the duration advantage are a lot bigger and CS trips become up to 8:30 minutes faster. This is most likely explained by lower PT service frequencies and lines suspending service (resulting in longer walks).

4.2.2 Spatial differences in travel time

Seeing that there are time periods when carsharing is significantly faster, it is also interesting to investigate whether there is a spatial component to the difference in travel time.

In order to evaluate regional differences between the transport modes, the function (5) is implemented in the analytics module to divide the operating area into tiles. Δx and Δy can be specified by the user and indicate the edge length of the tiles in meters in longitudinal and latitudinal direction. $(\underline{\lambda}, \bar{\lambda})$ and $(\underline{\phi}, \bar{\phi})$

indicate the minimum and maximum values of the longitudinal/latitudinal coordinates of the operating area. G returns $n \times m$ subareas $g_{n,m}$ (tiles), together with the center coordinates $(\lambda_{n,m}, \phi_{n,m})$ of each tile. Each CS ride can then be assigned to the tile with the closest center based on either the starting or ending coordinates.

$$G(\Delta x, \Delta y, \underline{\lambda}, \bar{\lambda}, \underline{\phi}, \bar{\phi}) = \begin{pmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,\bar{m}} \\ g_{2,1} & g_{2,2} & \cdots & g_{2,\bar{m}} \\ \vdots & \vdots & \ddots & \vdots \\ g_{\bar{n},1} & g_{\bar{n},2} & g_{\bar{n},3} & g_{\bar{n},\bar{m}} \end{pmatrix} \quad (5)$$

$$\text{s.t.} \quad \bar{n}, \bar{m} \in \mathbb{N}$$

$$g_{n,m} \mapsto (\lambda_{n,m}, \phi_{n,m}).$$

For the analyses in this paper, we divide the operating area into squared tiles with edge lengths of 1 km. In general, using small tile sizes leads to sparse data and less robust results, whereas large tile sizes average over differences in the data within the tiles. With this in mind, the tile size was chosen as granular as possible under the condition that the sample size remains above 20 observations in the majority of tiles. Fig. 4 displays the geographical distribution of time differences between CS and the net PT duration (a) and PT including end walks (b) for CS rental destinations.

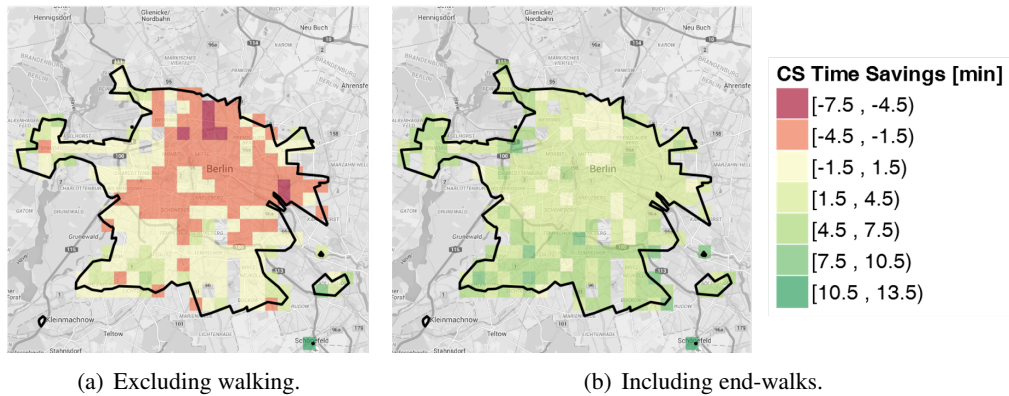


Figure 4. Average time savings of CS over PT in minutes (minimum 20 rides per tile).

Patterns exist, despite the fact that rides which end in one cell can have very different origins. Looking at net travel time difference, carsharing rides are slower for most tiles. In the city center, CS is between 1.5 and 7.5 minutes slower than PT for most locations. Yet, a tendency towards larger time savings with CS towards the outskirts can be detected, especially at the southern and western borders of the business area. Adding the end-walk duration tilts the duration advantage towards CS, the overall pattern however, remains similar.

Recommended action: Since there are major time savings of CS trips towards the outskirts in the southern and western areas of Berlin, PT planners may evaluate overall transportation demand and decide whether to improve the PT service offering in these areas.

4.2.3 Travel duration – differences on the trip level

While the previous analyses allow evaluations on the point level, analyzing travel duration differences on the trip level can provide additional insights. In order to understand where CS customers want to go (the routes they drive), the start and end points of the individual rides have to be connected. Again, some form of aggregation and clustering has to be applied to the routes to interpret the data.

From the heatmaps, hotspots can be extracted as density polygons, which are implicitly defined by the function $\hat{f}(\lambda, \phi) \geq c$; areas where the estimated kernel densities $\hat{f}(\lambda, \phi)$ exceed a predefined threshold c . In fig. 5(a), the hotspot-extraction of the analytics module is illustrated. In order to identify weaknesses in PT service, we choose a subset of our data including only the top 33 % of the CS rides with the largest trip duration advantage. Additionally, the analytics module provides functionality to aggregate trip data between the hotspots. Table 3 illustrates the results for the trips in fig. 5(a).

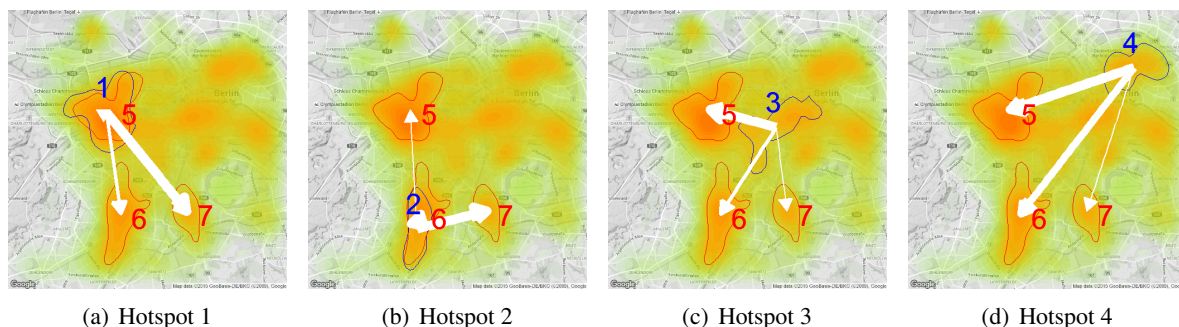


Figure 5. Hotspots of CS rides with a large travel time advantage over PT.

From	To	Outgoing rides [%]	Mean CS duration (min)	Mean PT duration (min)	Mean duration adv. (min)	Mean add. cost (€)	Mean distance adv. (m)
1	5	21 %	10.08	19.09	9.01	0.52	966.33
1	6	29 %	12.91	23.83	10.92	1.17	1358.00
1	7	50 %	16.48	31.04	14.56	2.26	-1400.24

Table 3. Aggregated characteristics of trips leaving hotspot 1, as visualized in Fig. 5(a).

We provide two examples of how these analyses provide insights for PT planning. Firstly, the CS trips exiting hotspot 1 and entering hotspot 6 are on average about 11 minutes faster than PT. One reason for this is that the trips are on average about 1.36 km shorter than the corresponding PT rides. While with CS it is possible to navigate directly from hotspot 1 to hotspot 6, PT most likely has to take a detour through the city center.

Recommended action: Therefore, PT planners may evaluate the introduction of an additional, more direct PT service between hotspots 1 and 6.

On the contrary, CS trips from hotspot 1 to hotspot 7 have a duration advantage although their distance is on average about 1.4 km larger than the corresponding PT rides. CS rides might take a longer, but faster route over the city expressway, whereas the PT route is more direct but slower due to multiple stops or transfers.

Recommended action: In this case, PT service might be improved by introducing express service or the connections in case of transfers.

4.2.4 PT Accessibility

Accessibility is another important determinant of PT service quality. By measuring how close CS users could have gotten to their destination by using PT, we can estimate the convenience of the alternative trip with PT. For this analysis, we assume that the destination of the CS ride is the actual destination of the

trip (as discussed earlier). Figure 6 shows the average walking distance from the final PT stop to the CS destinations. We also display the CS rides per day in fig. 7 as an indicator for the importance of each tile.²

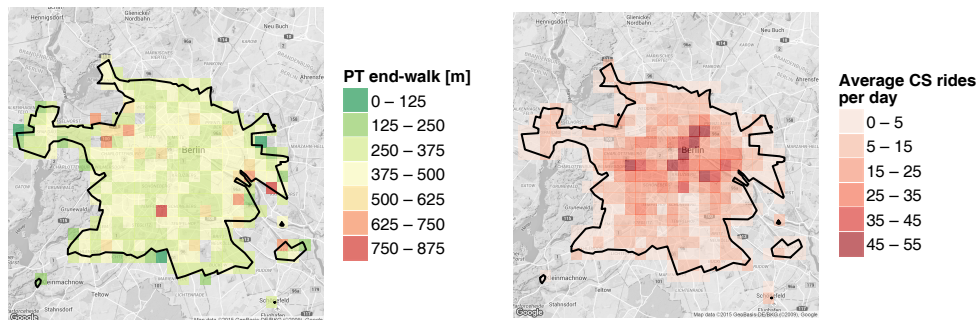


Figure 6. End-walk from PT stop to CS destination. Figure 7. Rides per day within distinct tiles.

In the vast majority of the tiles, the walking distance is between 250 and 500 m. Therefore, accessibility of most destinations via PT seems to be given with a manageable amount of walking. Walks shorter than 250 m or longer than 625 m are rare. Remarkably, some tiles with very short walking distances are located at the borders of the business area. This can be explained by intermodal behavior of commuters ending their rides directly at PT stops to continue the trip via PT to destinations outside the business area.

To improve PT accessibility, urban planners have to focus on the areas with long walking distances. A detailed analysis of the tiles with walking distances larger than 625 m shows, that these areas are indeed badly connected to PT — they generally exhibit a lack of stops or are only served by a few bus stops with infrequent service. The zones are mostly residential areas or contain parks and lakes (reddish tiles in the north west). Interestingly, the observed CS demand in these tiles is almost always below 5 rides per day. In the city center on the other hand, where the observed CS demand is high, walking distances are short and PT would have been an easily accessible alternative.

Recommended actions: Improving accessibility is advisable if long walking distances and a high amount of CS rides occur at the same location. Within our investigated time frame this is not the case. However, for other periods, e.g. during summertime, the analysis might show different results, due to changing mobility needs.

4.2.5 Service Cost

Fig. 8 displays the average additional cost of CS rides ending at the respective tiles. CS has a cost disadvantage compared to PT. To reach destinations within the city center, CS is on average 2 – 3 euros more expensive than PT. Towards the outskirts, cost differences increase, to in between 3 and 6 euros. Since trip length is higher for rides ending at the borders of the business area and — except for short distance rides — the PT fare is almost constant with regards to travel distance, the increasing cost differences must be due to longer CS travel times.

Recommended action: The observed CS demand in the city center is comparatively high (cf. Fig. 7) and the cost differences rather small. In order to encourage customers to substitute CS for PT, the cost advantage of PT would have to be further increased. This could be achieved by reducing the fare for short distance rides in the city center. Towards the outskirts, CS behaves rather complementary to PT. Being more expensive but also offering a faster service (cf. fig. 4). In this respect CS services are a valuable

² However, we highlight that this is the *observed* CS demand of the provider under consideration, due to unavailability of vehicles. The *actual* demand for CS might be higher since some ride requests are served by other providers or cannot be fulfilled.

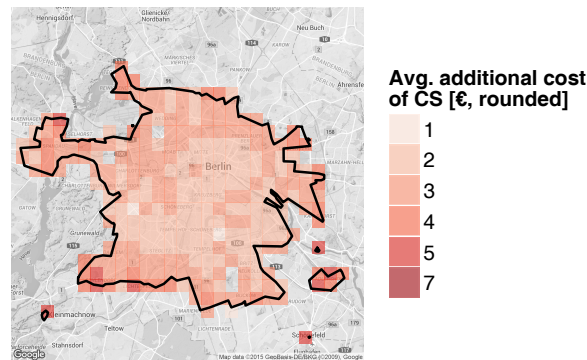


Figure 8. Additional cost of CS rides in comparison to PT.

addition to the city's transportation system.

5 Discussion and Conclusion

Due to the ongoing urbanization trend, cities are growing in size and population. Naturally, travel distances within the city increase as well, and the urban mobility system as a whole becomes more complex. Ensuring efficient, comfortable and environmentally friendly urban mobility is a prerequisite to a sustainable way of urban living. Commuters already have access to a wide variety of mobility apps which support them in their decision making. Urban transportation planning can benefit in the same way from such tools and leverage the available data. For this purpose, we develop a prototype DSS for urban transportation planning. Applying it to the city of Berlin, we illustrate the methodology for transforming carsharing data into valuable information for decision makers in urban planning authorities. Thereby, we are able to derive several managerial implications.

5.1 Managerial implications

First, the DSS prototype can be used to identify areas of high carsharing demand. Public transport planners can use this approach to review their existing service offering, for example by evaluating a higher frequency of service. Carsharing providers can also benefit from this information. In our specific example of Berlin, the prototype shows that carsharing rentals are very concentrated in the city center. CS providers could therefore consider limiting their operating area to the high demand areas. While this could prove more economical for CS providers, it would be undesirable for the system as a whole, as travelers to and from the outskirts are being deprived of a mobility option.³

The DSS prototype can also display temporal variations of high-demand areas and routes. This information could prove useful to public transport planners who want to adapt the frequency of rides over the course of the day. Moreover, at the city planning level, very specific recommendations can be deduced from the data. One measure could be changing the direction of single lanes on multi-lane streets for obvious commuter routes which clearly show an imbalance towards one direction in the morning and towards the reverse direction in the early evening.

Next, we have shown how the prototype can integrate data for the different travel modes. To provide meaningful insight, this cannot be done for the two systems as a whole, but needs to be done from the user perspective, comparing carsharing and public transport on an individual ride basis. To the best of our knowledge, we are the first to gather and analyze data in such a way. This approach makes it possible to detect deficits in the system. For instance, the prototype shows that some regions towards the border of the business area can only be reached quickly by carsharing, which means higher mobility costs for people

³ Approximately two months after our data collection period, the CS provider indeed reduced the size of the operating area.

traveling to and from these areas. Within the city center, where public transport accessibility is very high, the price premium for carsharing is much lower. This creates the risk that travelers convert from public transport to carsharing, thereby contributing to traffic congestion and higher emissions, which is clearly an undesirable effect.

Changes to the pricing schemes can certainly reverse undesired incentives (e.g. via decreasing downtown public transport fares, or by imposing a tax on rides by car within the city center (Berritella et al., 2008)). Further measures should be taken to encourage multi- and intermodal behavior, for example providing designated carsharing parking spots at subway stations so that people can easily switch from carsharing to public transport when the car is no longer needed. This is already being done by Metro North in New York, who cooperate with station-based carsharing providers for remote stops and allow travelers to continue their journey by carsharing, a combination that increases sales for both providers (Millard-Ball, 2005). Another insight from our analyses is the identification of areas where walking distances to and from public transport stops are particularly long. While this could hint at necessary new stations, it is also possible that carsharing sufficiently covers mobility needs in these areas and thus complements public transport without the need to adapt the latter.

Finally, our analysis for Berlin has shown that there are some routes on which carsharing exhibits a significant advantage in travel time. Similar to walking distance, urban planners need to investigate these special cases further and evaluate whether the service offering should be improved, e.g. by additional lines or a better coordination of transfers, or whether carsharing (and private cars) should deliberately service these routes.

5.2 Theoretical implications and outlook

The approach we use to analyze mobility behavior also has broader philosophical implications for Information Systems research. We demonstrate how ubiquitous and big data can be used to derive revealed preferences of people — here, preferences on modes of transportation. Behavioral and sociological studies, not just within IS but also in adjacent disciplines, often rely on surveys and the biases associated with stated preferences. Big data provides researchers with a powerful new tool to verify these statements. One focus of our future research will be to further investigate how methods assessing revealed and stated preferences can be combined to provide reliable and robust insights.

Our DSS does however, have some limitations, which we will try to remedy in further research. Going forward we will include additional cities in order to verify the approach and increase the robustness of our results. We expect that seasonal variations have a significant influence on peoples' willingness to walk to and from public transport stations. To account for this effect, we will extend our analyses to a longer observation period. We will also try to obtain more accurate information about the initial walking distance to the carsharing vehicle to make the comparison of public transport and carsharing even more accurate. Finally, adding additional data sources, e.g. socio-economic factors, can further leverage the insights generated by the DSS. Indicators, such as income, education or population density have been shown to affect carsharing demand (Wagner, Brandt, and Neumann, 2016) and visualizing these factors within our DSS can lead to new conclusions, for example a less pressing need to expand public transport into high-income neighborhoods.

Our application of the prototype to the city of Berlin has shown that it might not always tell urban planners exactly what to do and that in some cases additional or complementary analyses, such as commuter surveys, might be needed before implementing changes to the system. The approach can, however, tell decision-makers where to look first, and therefore provides a crucial piece of the puzzle to making urban mobility more sustainable.

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