Usage Patterns of Free-floating Carsharing Members

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Abstract

Shared vehicles are a building block of sustainable transport systems, because they have the potential to reduce private vehicle ownership rates, vehicle miles travelled and to increase vehicle fleet efficiency. Although both supply and demand of carsharing have increased in recent years, alongside research efforts on the topic, little is known about usage patterns of carsharing members. Yet, we need to consider carsharing usage patterns as a whole to find out who is currently using carsharing and what their usage behavior is, in order to increase demand even further in the future. This paper presents the results of a user-focused cluster analysis which we applied to identify distinctive usage patterns of free-floating carsharing users in Karlsruhe, Germany. The results of a k-means cluster analysis conducted using booking data provided by a free-floating carsharing provider show partitions of members based on their travel patterns. While free-floating and station-based carsharing present an overlap in usage patterns to some extent, the two systems generally supplement each other well, leading to a more comprehensive supply of vehicles, mitigating needs of private vehicle ownership.

1 Introduction

Carsharing services have increased significantly in recent years considering both supply and demand. The number of carsharing users in Germany has increased by a factor of 18 from 2009 to 2019 [11], and between 2011 and 2019, the number of provided carsharing vehicles has increased by a factor of four [10]. Carsharing is a system which enables individuals to share vehicles opposed to owning them. Nowadays, the vehicles are usually provided by a company alongside the contractual, billing, and booking frameworks. The two most common types of operation are station-based and free-floating systems. While users of station-based carsharing have to pick up and drop off the vehicle at the same station, free-floating carsharing users can pick up vehicles at their current location and drop them off at any location within the area of service.

Because they have the potential to reduce private vehicle ownership rates, vehicle miles travelled and to increase vehicle fleet efficiency [7, 12, 13], shared vehicles are a building block of sustainable transport systems [4]. Therefore, municipal policy makers in Germany generally support carsharing systems and were encouraged in their efforts in 2017, when a federal law was passed that states that shared vehicles may be privileged over other vehicles [6].

With an increased demand in carsharing, research activity on the topic has equally risen. However, many studies focus on effects of carsharing on the transport system [1, 5, 12], while little is known about usage patterns of carsharing members. Although Schmöller et al. [16] provide great insights into the determinants of free-floating carsharing demand through analyses of booking data, they do not analyze users' coherent travel patterns. Yet, we need to consider carsharing travel patterns as a whole to find out who is currently using carsharing and what their usage behavior is, in order to increase carsharing demand even further in the future. To form a better view of carsharing usage patterns, we analyzed booking data of a free-floating carsharing service.

This paper presents the results of a user-focused cluster analysis which we applied to identify distinctive usage patterns of free-floating carsharing users in Karlsruhe, Germany. We describe the area of study, the data, and methods in the following sections. We then present the results and discuss them. We compare our results against a similar study presented by Harz [9] and usage patterns of station-based carsharing users which we identified in previous research [15]. In the last section of this paper, we report on our main findings and provide suggestions for future approaches.

2 Materials and Methods

For our analysis, we have used carsharing booking data from Karlsruhe, Germany. Karlsruhe is a city with a population of just over 300,000 inhabitants in the Southwest of Germany. Karlsruhe holds a unique position regarding carsharing as it is the city with the most carsharing vehicles both in absolute terms and relative to the population [2, 3]. The booking data was provided by stadtmobil GmbH, Karlsruhe's largest carsharing provider. As of 2017, they provide 944 carsharing vehicles at 277 stations. Additionally, stadtmobil introduced a free-floating system with an initial number of 50 VW UP in 2017. They later doubled their supply of free-floating vehicles. We describe both the data and the process of preparation below.

Data

The booking data provided by stadtmobil is comprised of trip data and user data. The trip data includes all trip related data: license plate of the shared vehicle, average speed per trip, distance per trip, and the GPS coordinates of both start and end of the trip. stadtmobil provided booking data from a four month period (Aug. 1st - Dec. 1st 2018). The member data includes the type of membership (private/commecial) and, if applicable, age and gender of the users (commercial users do not have an age or gender attribute). Both datasets can be merged such that we can assign each trip to a specific member.

To prepare the data for the subsequent cluster analysis, we had to choose variables and summarise them by member. As the aim is to gain insights into travel patterns, we determined trip related variables by member: number of bookings, number of trips for each day of the week, number of trips in 4-hour intervals (starting at 12 a.m.), mean time of usage, share of roundtrips. The last variable is unique to free-floating carsharing as all station-based systems require users to return to the start location of the trip, and, therefore, the share of roundtrips is always at 100%. Although the alternative name of free-floating carsharing - one-way carsharing - suggests that most trips start and end at different locations, nothing prevents users from finishing their trip where they started it. However, as there are generally no reserved parking spots for free-floating carsharing vehicles, users might not return the vehicle to the exact same location. We, therefore, have to define a threshold value for the distance between start and end of the trip at which we determine whether or not a trip counts as a roundtrip. Literature suggests that this threshold value lies between 500 and 650m [9, 17]. As we used the analysis presented by Harz for comparison of our results, we have chosen the threshold value of 500m that he applied in his work as well.

Analysis

To analyse free-floating carsharing usage patterns at a multivariate level, we used cluster analysis. Cluster analysis is a method to assign observations of (large) datasets to identify patterns in the data. There are many different algorithm to partition the data. One of the most commonly used methods is the k-means algorithm. The goal of the algorithm is to optimze the sqaured deviations of a mean. It is, therefore, only applicable when using numeric variables. As our variables are all numeric, this does not pose a problem. However, a disadvantage over other clustering methods is the fact that the number of clusters is needed as an input. An approach to mitigate this problem is to iterate over a given number of clusters and determine the optimal solution. The two most common methods to find the optimal cluster solutions are the elbow-method and gap-statistics. The elbow-method is a graphical heuristic where the number of clusters is plotted against the sum of squares within the clusters. The point at which a visible "elbow" is identified can be considered as an optimal number of clusters. The gap method is a statistical approach to estimate the number of clusters by analyzing the change in dispersion within clusters compared to a null distribution, i.e. a distribution without presence of clusters [18]. We conducted the cluster analysis using the *kmeans* function of the *R* package *stats* [14]. The implemented algorithm is the one proposed by Hartigan and Wong in 1979 [8].

3 Results and Discussion

Figure 1 and figure 2 present the results of the elbow method and gap statistic respectively. The elbow plot reveals several points of optimal solutions, including three and five clusters. The gap statistics reveal five to be the optimal number of clusters. Based on those two results, we have chosen a 5-cluster solution.

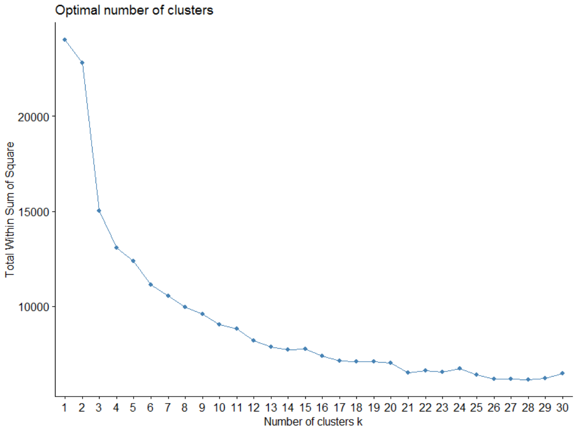

Figure 1: Elbow method

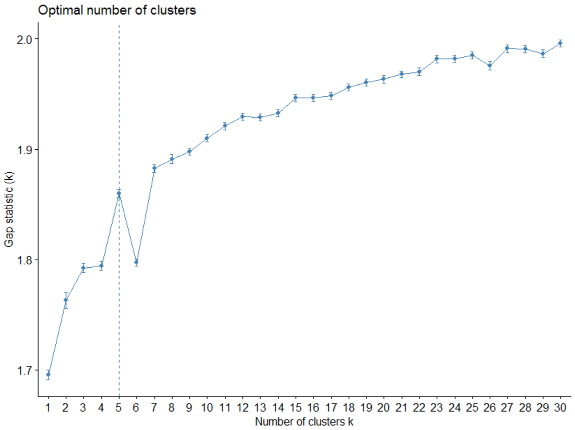

Figure 2: Gap Statistic

Table 1 presents the cluster characteristics assuming a 5-cluster solution. Based on those characteristics we identify five usage patterns of the free-floating carsharing system:

Cluster 1 - *Commuters and commercial users*: The users in this cluster present an increased activity between Monday and Friday. They generally start over 95% of their trips between 05:00 and 18:59, i.e. during regular working hours. They present with a medium percentage share of round trips, indicating that they make both commuting and work-related trips. Compared to other clusters, they reveal the highest number of trips with almost one trip every second day in average.

Cluster 2 - *Supplement of public transport*: This cluster includes users that use the free-floating carsharing system during all days of the week with a slight increase in activity on Saturdays. They have the smallest share of roundtrips, indicating that they do not use the shared vehicles for errands but rather to get to a destination. It is the cluster with the highest share of start of trips between 19:00 and 04:59. These are times during which public transport service is often reduced and shared vehicles can supplememnt those public transport trips.

Cluster 3 - *Errands*: This is the cluster with the highest shares of roundtrips. Members of this clusters show an increased activity during Saturdays and usually start their trips between 10:00 and 18:59, indicating that they use free-floating carsharing for shopping and as a means of transporting their purchases and products using the shared vehicle.

Clusters 4 - *Weekend trips*: The characteristics of this cluster indicate that these members tend to use the shared vehicle on weekend trips. They present the larges mean distances and times of use. They also show an increase in trips during weekends.

Cluster 5 - *Weekend activities*: This cluster also includes members with an increased activity during the weekend, however, their trip distances and times of use indicate that they conduct shorter activities, but more frequent than clusters 2, 3 and 4. They seem to be not as fixed to store opening hours as members of cluster 3, therefore, members of this cluster are less likely to use the vehicles for errands. .

Table 1: Cluster characteristics

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
N [-]	288	37	59	919	199
N [%]	19	2	4	61	13
Trip related variables (means)					
number of trips [-]	53.378378	2.545139	3.220892	4.40678	18.753769
average usage time [min]	192.3783	179.9747	210.7926	2097.5702	213.6271
average trip distances [km]	26.745255	6.519658	14.09215	127.359094	23.660845
share of roundtrips [%]	0.6572295	0.1753734	0.9420045	0.7704619	0.7202351
Share of trips by weekday [%]					
Monday	15.443038	13.3697138	11.89189206	8.461538811	14.20150051
Tuesday	16.30379758	13.09686033	12.36486663	16.15384476	13.6655949
Wednesday	15.84810145	12.82401079	11.5202714	11.92307535	14.76420127
Thursday	17.36708879	15.55252189	14.15540788	14.99999773	13.34405153
Friday	17.31645574	17.59890914	15.13513648	18.07692238	16.66666631
Saturday	9.215189903	16.37107836	21.55405707	17.69230595	15.46087882
Sunday	8.506329098	11.18690178	13.3783809	12.69230595	11.89710612
Share of trips by time interval [%]					
00:00 - 04:59	0.556962034	4.365620502	0.64189206	0.384615297	2.143622703
05:00 - 09:59	35.49367105	18.69031122	18.61486507	21.92307535	23.92818852
10:00 - 14:59	29.51898763	29.87721692	39.32432693	36.53845892	31.45766326
15:00 - 18:59	28.50632929	35.74351735	35.9797317	35.38461189	34.69989259
19:00 - 23:59	5.924050746	11.32332655	5.439188895	5.769230595	7.770632133

Regarding clusters presented by Harz in 2016, our results share some characteristics but also present differences. In his study, Harz also found five clusters after analyzing booking data of DriveNow from Munich, Germany. The first cluster includes members who use the service scarcely and mostly conduct one-way trips. This is the equivalent to cluster 2 of our analysis. The next cluster he found includes members with long times of trips. They make their trips mainly between 12:00 and 18:00 and show an increase in activity on Saturdays. This correspondents well to the cluster which we have characterized by members running errands, although their mileage is not as high as described by Harz. He describes the third cluster he identified as normal users: they conduct many trips on Fridays and Saturdays and show a normal unsage pattern. This can be compared to the cluster which is characterized by members conducting shorter weekend activities in our study. Harz has also identified a commuting cluster in which members show high frequency of trips, especially many trips during weekdays and peak hours. His results show this cluster is relatively small which stands opposed to our results. However, the difference is explained by the fact that our commuting cluster does not only include commuters but members who use carsharing for commercial activities during the day as well. Therefore, the share of roundtrips in this cluster is also higher than in the one presented by Harz. The last cluster Harz identified is characterized by members who conduct many trips and mainly later in the day or at night. This is also comparable to cluster 2, however, our results show a smaller frequency of usage. [9] We have identified one cluster that corresponds to none of the clusters Harz identified: Harz did not characterize members as weekend travellers. This is mainly due to the different pricing schemes: during the time of the study, DriveNow charged between 0.31 and 0.34€/min depending on the vehicly type. Charges for the free-floating carsharing service in Karlsruhe are based on time and distance. Users are charged 0.30€/10 min (maximum of 1.28€/h) and 0.19€/km (maximum of 20.50€/day). The latter price schemes is much less time sensitive and allows users to park the vehicle rather than ending the booking process as costs stay relatively low.

This price scheme is closer to a station-based carsharing system. Therefore, it is not surprising that we found similar clusters in both free-floating and station-based booking data. The cluster analysis of station-based booking data from the same provider revealed five clusters as well, of which three correspond well to the ones found in this study. We also identified commercial users in our previous analysis of station-based booking data that presented with similar characteristics compared to the members of the free-floating commercial cluster: increased activity during the week and relatively short trip distances. Axiomatically, there are no one-way trips in the station-based cluster. Station-based carsharing users also use the service for regular weekly activities which correspond to free-floating carsharing users that use those vehicles for running errands and grocery shopping. Lastly, we also identified travellers in the station-based booking data. This corresponds well to users of free-floating carsharing who use the service for weekend trips. However, station-based users are not limited regarding booking duration, while the maximum booking duration of the free-floating service is limited to 72h. Therefore, travellers using station-based vehicles present with much longer booking durations.

Our results show that there are distinct usage patterns of free-floating carsharing vehicles. The service is currently only offered within city limits. However, in this area public transport supply is already high. As cluster 2 shows, free-floating carsharing could, therefore, be a great asset in the surrounding areas where public transport supply is not as good, especially in off-peak hours. Furthermore, the usage patterns reveal that free-floating carsharing has the potential to replace a privately owned car as they are used by members to run errands, reach places to conduct leisure activities, and destinations of short weekend trips, but frequent trips like commuting trips are conducted by other modes. The free-floating system seems to support the station-based system, as usage patterns are similar in both systems. The customers get a flexible and spontanous option to book a car in hours with a high demand in the station based system.

The question remains, if the service is sufficient for families, especially with younger children as the vehicles are relatively small and do not provide car seats. In these cases, a station-based carsharing service complements free-floating carsharing well. Not being able to answer this question is a limitation of our previous study rather than of this study. We based the analysis of usage patterns of station-based carsharing vehicles on booking data from 2017, when stadtmobil only offered station-based carsharing and there was no other provider of free-floating carsharing. To find out how the two systems co-exist and how users - who can now use both free-floating and station-based carsharing vehicles with the same membership - engage in the two systems, future research needs to focus on data of both services of the same survey periods.

Several extensions would complement this research: considering weather data, conducting user surveys to complement the data with further socio-demographic data, and determining a roundtrip threshould depending on parking pressure. Last, the study should be repeated with updated booking data to evaluate the patterns after a longer period of operation.

4 Conclusion

This study examines usage patterns of free-floating carsharing users. The results of a k-means cluster analysis conducted using booking data provided by a free-floating carsharing provider show that members can be grouped depending on their travel patterns. While free-floating and station-based carsharing present some overlap in usage patterns, the two systems generally supplement each other well, leading to a more comprehensive supply of vehicles, mitigating needs of private vehicle ownership.

The work presented here is based on data from the period of initial start of the operation. Since then, the carsharing provider doubled the number of available free-floating carsharing vehicles. As our results correspond well to work based data from other cities gathered over longer periods of time, we expect that usage patterns have not significantly changed. However, further studies need to confirm this assumption.

These findings are of interest to policy makers, carsharing and public transport providers. It is in the public interest that especially public transport and sharing services complement each other to increase significance of sharing services as a building block of sustainable transport systems.

References

[1] Milos Balac, Francesco Ciari, and Kay W. Axhausen. Carsharing demand estimation. *Transportation Research Record: Journal of the Transportation Research Board*, 2563(1):10–18, 2016.

[2] Bundesverband CarSharing. Anzahl der carsharing-fahrzeuge* je 1.000 einwohner in ausgewählten deutschen städten, 2017.

[3] Bundesverband CarSharing. Anzahl der carsharing-fahrzeuge von stationsbasierten anbietern in ausgewählten deutschen städten, 2017.

[4] Lawrence D. Burns. A vision of our transport future. *Nature*, 497(ulm):181–182, 2013.

[5] Robert Cervero, Aaron Golub, and Brendan Nee. City carshare: long-term travel demand and car ownership impacts. *Transportation Research Record: Journal of the Transportation Research Board*, 1992(1):70–80, 2007.

[6] Deutscher Bundestag. Gesetz zur bevorrechtigung des carsharing: Csgg, 05.07.2017.

[7] Jörg Firnkorn and Martin Müller. What will be the environmental effects of new free-floating car-sharing systems? the case of car2go in ulm. *Ecological Economics*, 70(8):1519–1528, 2011.

[8] John A. Hartigan and Manchek A. Wong. Algorithm as 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 28(1):100–108, 1979.

[9] Jonas Harz. Variablen-verdichtung und clustern von big data: Wie lassen sich die free-floating-carsharing-nutzer typisieren?

[10] Horizont and Bundesverband CarSharing. Anzahl der carsharing-fahrzeuge in deutschland in den jahren 2011 bis 2019 [graph], 2019.

[11] Horizont and Bundesverband CarSharing. Anzahl registrierter carsharing-nutzer in deutschland in den jahren 2008 bis 2019 [graph], 2019.

[12] Clayton Lane. Phillycarshare. *Transportation Research Record: Journal of the Transportation Research Board*, 1927(1):158–166, 2005.

[13] Elliot W. Martin and Susan A. Shaheen. Greenhouse gas emission impacts of carsharing in north america. *IEEE Transactions on Intelligent Transportation Systems*, 12(4):1074–1086, 2011.

[14] R Core Team. R: a language and environment for statistical computing, 2018.

[15] Anna Reiffer, Tim Wörle, Lars Briem, Tamer Soylu, Martin Kagerbauer, and Peter Vortisch. Identifiying usage profiles of station-based car-sharing members using cluster analyses. *In Transportation Research Board (Ed.), TRB 98th Annual Meeting Compendium of Papers*, 2019.

[16] Stefan Schmöller, Simone Weikl, Johannes Müller, and Klaus Bogenberger. Empirical analysis of free-floating carsharing usage: The munich and berlin case. *Transportation Research Part C: Emerging Technologies*, 56:34–51, 2015.

[17] Frances Sprei, Shiva Habibi, Cristofer Englund, Stefan Pettersson, Alex Voronov, and Johan Wedlin. Free-floating car-sharing electrification and mode displacement: Travel time and usage patterns from 12 cities in europe and the united states. *Transportation Research Part D: Transport and Environment*, 71:127–140, 2019.

[18] Robert Tibshirani, Guenther Walther, and Trevor Hastie. Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 63(2):411–423, 2001.