E-scooter mobility patterns in Zürich

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Contents

1 Introduction

The increased use of electric scooters (e-scooters) in cities worldwide will open up new dimensions in the fields of urban planning, public health and transportation, alongside many others. E-scooters offer possibilities for the electrification of transport and the move away from fossil fuel dependency, as well as convenient solutions for city-dwellers looking to move around quickly. However, they will also present challenges for road safety, pollution, and the overcrowding of urban spaces. Alongside the existing disruptive effects on urban transport, the electric mobility industry is still in an early stage of development (Tuncer & Brown, 2020). Therefore, these effects can be expected to amplify as market size increases. Policymakers will be required to act in the coming years to properly integrate electric mobility into the modern transport system.

To measure the impact of e-scooters in urban spaces, and to identify the relationships of this new means of transport with existing infrastructure, it is critical to have empirical knowledge of their patterns of use. As with other means of transport, it is likely that e-scooter use varies with the time of day, day of the week, (docking stations') locations, and other variables related to the movement of human beings in urban space. Examining the patterns of e-scooter use is important for policymakers reacting to the electric mobility industry, and for operators seeking to innovate. As the electrification of the transport industry offers another means by which to move away from fossil-fuel based transportation, the innovation and integration of electric mobility technologies is highly desirable. In this context the analysis of spatial data regarding e-scooter use is therefore of great importance.

This paper assesses the use of e-scooters in the city of Zürich, Switzerland during three weeks of June 2020 (01.06.-20.06). We examine the patterns of e-scooter micromobility, specifically the journeys taken by users of the firm Tier's scooters. The paper is guided by the following research question: *Which patterns does micromobility follow in the city of Zürich?* Our goals are threefold: 1) We expect a difference in movement patterns between weekends and weekdays. 2) We assume that e-scooters will cluster in the centre and spread from there to the periphery. 3) The e-scooters are used for both intra-district travel and shorter cross-district distances. As a consequence, the goal of this paper is to gain an empirical overview of the patterns of mobility, and then to make some comparisons to existing trends in other studies of e-scooter usage.

2 Literature Review

Although e-scooters are a relatively new feature of urban environments, a body of literature has developed which documents behavioural patterns, new challenges posed by e-scooters, as well as potential solutions. Regarding the relationship with the existing transport network, initial observers of the integration of e-scooters into urban environments remark that electric mobility has served to fill the gaps in transport networks, allowing movement between nodes of larger, less flexible elements of the transport system such as train stations (Tuncer & Brown, 2020). E-scooters also have been observed to cover the final short stages of public transport journeys between residences and transport nodes (Smith & Schwieterman, 2018). This suggests that e-scooters do not exist as an independent means of transport in urban areas, rather as a method of travelling short distances which are not covered by existing transport infrastructure. In serving this function, they challenge the role of the automobile in short distance travel, but not the train or bus network, nor longer distance car journeys. The state of current research shows e-scooters therefore being integrated into existing transport methods, rather than outright replacing elements of the network. Comparisons with other micro-mobility services corroborate this: McKenzie (2020) shows that while bike-share services can be shown to be used by commuters, while e-scooters do not reflect the standard commuting behaviour of high intensity use in the mornings and evenings. E-scooters instead are more likely to be used to support leisure, tourism, or recreational activity. Given these trends, it should be expected that e-scooter use therefore peaks on the weekends, when people have more free time for leisure activities. Additionally, the short distances travelled by e-scooter users observed in the literature can also be expected to play out in Zürich. Concretely, this would be characterised by large numbers of journeys within neighbourhoods, or crossing to the adjacent neighbourhood.

Studies into the patterns of e-scooter movement show that the e-scooter is not used to commute, rather for leisure. A study of e-scooter mobility in Louisville, Kentucky shows that scooter usage peaks on Saturdays (Noland, 2019), and does not reflect the bimodal pattern associated with commuter behaviour. Trips in Louisville averaged approximately 16 minutes in duration, with a mean distance of just over 2km. Furthermore, usage of e-scooters is not universal among the population or geographic areas, and it has been observed that not all stratifications of the population engage in their use equally. Downtown areas and university campuses have been shown to be most frequented by dockless e-scooters (Bai & Jiao, 2020), fitting in with the proposition that they are primarily tools for leisure and tourism. Furthermore, more affluent socio-economic groups are more likely to use e-scooters instead of walking the distances covered (Clewlow et al., 2018; McKenzie, 2019). Thus, we expect that e-scooter use will cluster around the central neighbourhoods of Zürich, given that this is where the majority of shopping, tourism and educational facilities are located. In addition, the neighbourhood of Höngg, containing a large campus of the ETHZ should also see relatively intense e-scooter usage.

3 Data & Methods

Data

The data used in this investigation is provided by the micro-mobility firm TIER and was collected by a third party via a web scraper.[1] It consists of snapshot measurements of an e-scooter's location every 10 minutes, over a period of three weeks in June 2020 (01.06.-20.06). With each snapshot containing information on the scooter's geographical location using GPS tracking systems, we are able to track the movements of every individual scooters.

Initially, the dataset comprised a little over 2 million data points. Due to connection problems, which arose when accessing the providers' API in the first place, some data points were missing. However, compared to the total data points, these are negligible. Furthermore, we detected several scooters with only a few data points. Reason for this could be a later introduction of the particular vehicle or its removal from the fleet, respectively. Accordingly, we excluded these vehicles from our dataset. To avoid possible bias, we also ensured that the remaining scooters featured data points for each day of the week. Besides, it occurred that distances between 20-80 metres were registered between two timestamps due to localisation inaccuracies. We, therefore, set the threshold of 100 metres to define an actual journey as such. The final dataset contains 1.6 million observations, distributed over 620 scooters.

Methods

To examine trends in terms of distances travelled, we resort to statistical hypothesis tests. More precisely, we use Welch's t-test. This variant of the t-test, unlike the conventional Student's t-test, can handle unequal variances of the two samples and is, therefore, more robust. Further underlying assumptions of the test are discussed in more detail in the corresponding part of the analysis. Thus, we can determine whether the movement patterns at weekends are statistically different from those during the week using a defined threshold.

We examine occurrences of geographical trends such as spatial autocorrelation using the method of global and local Moran's I, respectively. The former serves to detect global autocorrelation. The probabilistic nature of the measure helps us to determine the significance of a potential autocorrelation. The latter allows the same for local clusters but without specifying "the direction" of the respective clusters. However, since we have already determined the values of the individual neighbourhoods, that task remains straightforward. For both tests, we used the Queen procedure to define contiguity.

[1]The data is publicly available here: https://github.com/swiss-bike-data/get-zuerich-bikeshare-data.

That is, neighbourhoods that share an edge or a corner are defined as neighbours. Assuming that the scooters move only over a short distance in most cases, this way of modelling the spatial relationship seems appropriate.

Tier's e-scooters are "dockless" meaning that they can be picked up and dropped off by users anywhere, without being bound to charging stations or depots. In the context of a network, this means that the dataset offers us edges in the form of the duration or distance of journeys taken, but no fixed nodes at which journeys are forced to begin and conclude. At a larger level of aggregation, it is possible to impose nodes onto the network by dividing the city into blocks of space. In this paper we use the centroids of Zürich's thirty-four Quartiere (neighbourhoods) as roughly defined nodes to allow for a network-based analysis of micro-mobility. The advantage of this method is that it allows us to assess patterns of movement between artificially defined points, adding an extra dimension to our analysis. A disadvantage which must be held in mind is that there will likely be results falling on the boundary lines of the neighbourhoods which distort or bias our findings to a certain degree.

4 Results

4.1 Detecting mobility patterns

In Figure 1, binned according to weekdays, we observe several clues to the micro-mobility behaviour.[2] Indicated by the interquartile range of the respective boxplots, it becomes apparent how half of the distances travelled by day fall between 0.5 and 1.5 kilometres. In other words, the journeys are most frequently made in the short-distance range. Nevertheless, there are some outliers, most of which lie between 2.5 and 5 kilometres. Only very few people covered distances of over 5 kilometres with Tier's scooters. The median distance hardly changes during the week – both during the week and on weekends, the median distance varies between 0.8 and 1 kilometre. These initial findings thus follow the literature that most trips with e-scooters fall within the short-distance range.

[2]Despite the three-week period, we only have two values for Sunday because the scraper was deactivated during the day, and thus the data for 21.06.2020 is not complete.

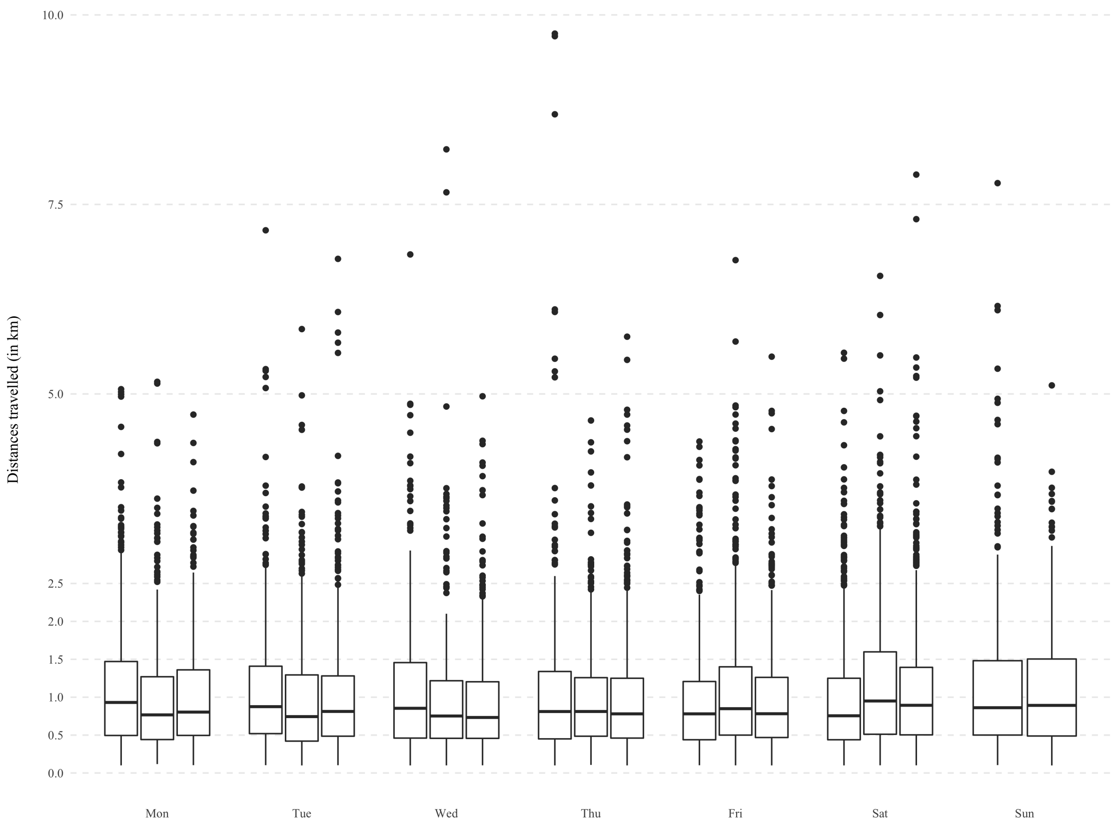

Figure 1: Travels per individual day of the week

In Figure 2, we add the temporal component to examine mobility behaviour at different times of the day. Each row represents a calendar week, from which we can identify several trends. Looking at the weekdays, we see some movements shortly after midnight until 02:00, which reach their minimum until 05:00. After that, the number of journeys increases steadily until it peaks – at times more substantial, at times weaker – in the early evening (between 17:00-19:00). Afterwards, the movements decrease again continuously.

This slightly right-skewed movement pattern during the week contrasts sharply with the weekend. Here, the fitted trend line of the number of trips per hour resembles a sine function. Shortly after midnight the first local maximum forms, which then drops sharply until 06:00. Afterwards, the number of trips rises again significantly until it reaches the second local maximum in the late afternoon. Despite the similar trend line, it must be added that the movement patterns on Saturday differ markedly from those on Sunday in terms of the number of trips. Depending on the time of day, more than twice as many kilometres were travelled on Saturday than on Sunday.

Commuting patterns as observed in the literature (McKenzie, 2019) are less discernible. Although local maxima appear at rush hour times on various days, it is not possible to speak of a general trend. However, the pandemic probably leads to distortion. With recommendations for home offices and cultural venues closed, it is likely that the (commuter) flows would have been more pronounced at normal times.

Figure 2: Total travels per hour and date

4.2 Corroborating the temporal trends

To determine whether the already mentioned difference in movement patterns between weekends and weekdays is also statistically significant, we apply Welch's t-test. A few remarks on its underlying assumptions. Observations within the sample must be independent. For example, it could be that the length of the distance travelled by a scooter influences the subsequent length of the trip. A low battery level could prompt the customer to switch to another vehicle or travel a shorter distance with the same vehicle. While we cannot refute the first scenario, the battery level information allows us to see if the latter may occur. However, there is virtually no correlation between battery level and distance travelled is virtually non-existent (see .html-file). Therefore, we assume that the independence of the observations within the respective groups is assured. We also assume that the groups are independent of each other for the following reasons. First, as just described, the distance travelled in $t-1$ has no influence on the distance in t. Second, the scooters are regularly recharged. Finally, a normal distribution of the the values is ensured after removing values smaller than the 95% percentile of the respective groups. Since these distances are hardly representative of mobility behaviour anyway, this operation seems justified.

We can reject our first null hypothesis that there is no difference between weekends and weekdays with a statistically significant difference between the two groups (at the 99% significance level). That is, the average distance travelled per hour, according to our expectations, is significantly higher on the weekends than during the week.

The corresponding confidence interval of the estimate lies between 102.8 and 275.3 metres. Important to mention is that this statistic does not give any information about the intensity of the movements. As shown in the second graph in the exploratory part, people move the most on Saturday compared to the other days of the week, while on Sunday they make the fewest trips. Nevertheless, the average distance travelled on weekends is significantly higher than on working days as expected, mostly attributable to the high travelling intensity on Saturdays.

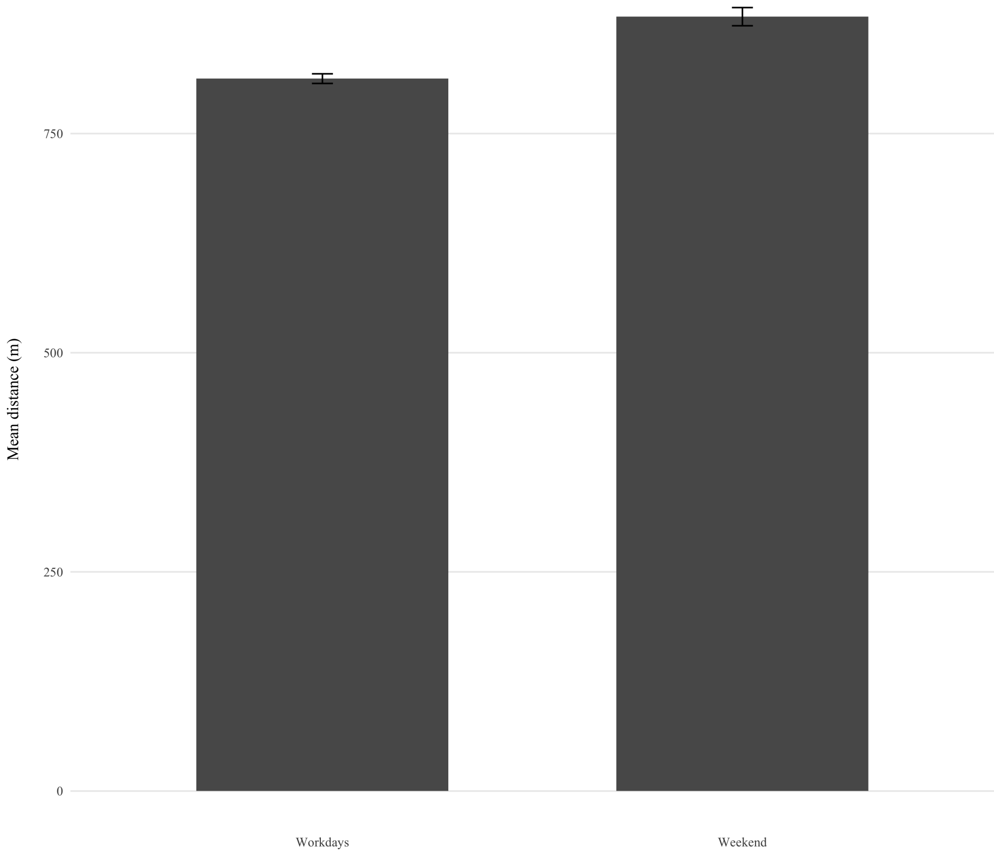

Figure 3: Average distances travelled

4.3 Spatial distribution of the vehicles

In the next step, we add the spatial component. We are interested in where exactly the scooters are located in the city and whether clusters are present. To better visualise the data and combine the individual points into suitable aggregates, we divide the city into its 34 neighbourhoods (Quartiere). First, we assess visually in which neighbourhoods on average the most data points (absolute number and density) per day are located. We then investigate whether spatial autocorrelation is prevalent in the study area. Figure 4 shows that the distinction between the number of scooters and their density is relevant.

We start by looking at the average absolute numbers of scooters per day (left plot). The neighbourhoods Altstetten, Langstrasse and Enge contain the most data points, neighbourhoods like Friesenberg, Wollishofen or Saatlen in the periphery the least. However, this graph neglects the size of the respective neighbourhoods. The plot on the right takes this into account, where the average number of data points per square kilometre is shown. A different picture emerges: neighbourhoods such as City, Lindenhof or the university quarter show the highest values. In general, scooter density is highest in the heart of the city with its major traffic junctions. On the other hand, in the periphery, the scooter density tends to be low due to the comparatively large areas of their neighbourhoods. We speculate that the plot on the left rather represents the trips' destinations, while the plot on the right visualises their origins. Without going into this assumption in more detail, it is worth examining the spatial autocorrelation in more detail in a subsequent step to corroborate the visualised trends.

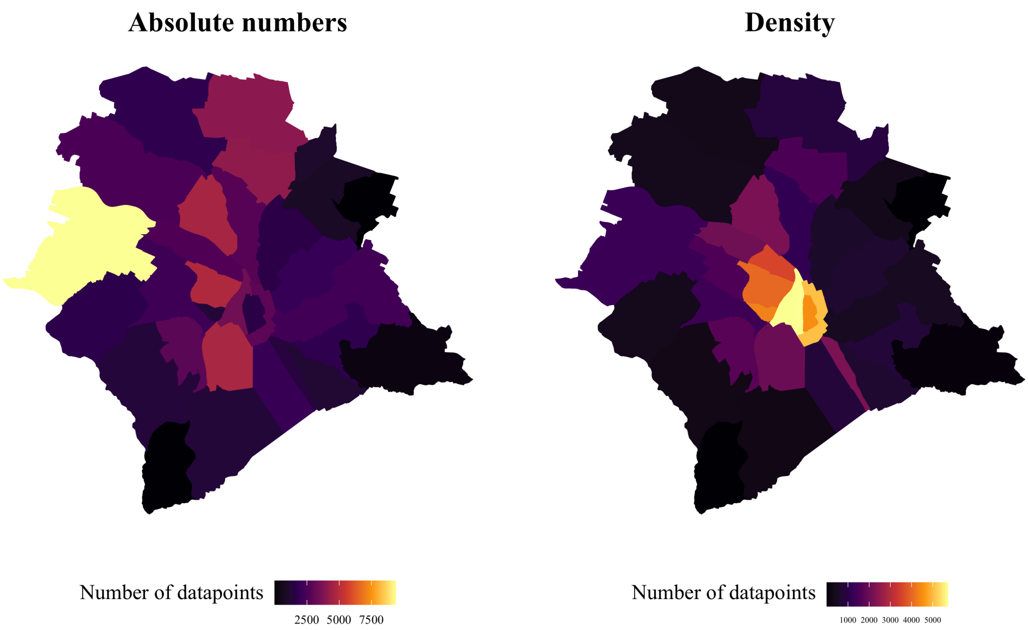

Figure 4: Spatial distribution of e-scooters

To investigate the global autocorrelation, we apply a Moran's I test. The contiguity was determined using the Queen procedure, after which the spatial weights of the neighbour lists were row-standardised. With a p-value of < 0.01 and a statistic of 0.587, we conclude that there is significant global clustering (see plots in the .html-file). With the autocorrelation confirmed, we can then check the data for local autocorrelation using the Local Morans' I statistic.

The plot on the left shows the neighbourhoods with their respective local Moran I statistics. Higher values for a neighbourhood indicate neighbourhoods with similar values. Mostly the neighbourhoods in the centre are surrounded by similar density values. These statistically (at the 5% level) significant local clusters are broken down in the plot on the right. While the Local Moran I statistic itself does not indicate whether the values are similarly negative or positive, we know from the previous plot that the cluster is one with similarly high values. Intuitively, their small area could cause density to appear higher automatically. However, we rather suspect that commuters, especially in these very central neighbourhoods, rely on vehicles to reach the periphery from there. Accordingly, it stands to reason that Tier places a vast number of scooters there, which can explain the high density in these neighbourhoods. Thus, we can also reject our second null hypothesis: Measured by density per square kilometre, we find a statistically significant local cluster in the heart of the centre. How scooters move from there, and around the city in general, is shown in the following network analysis.

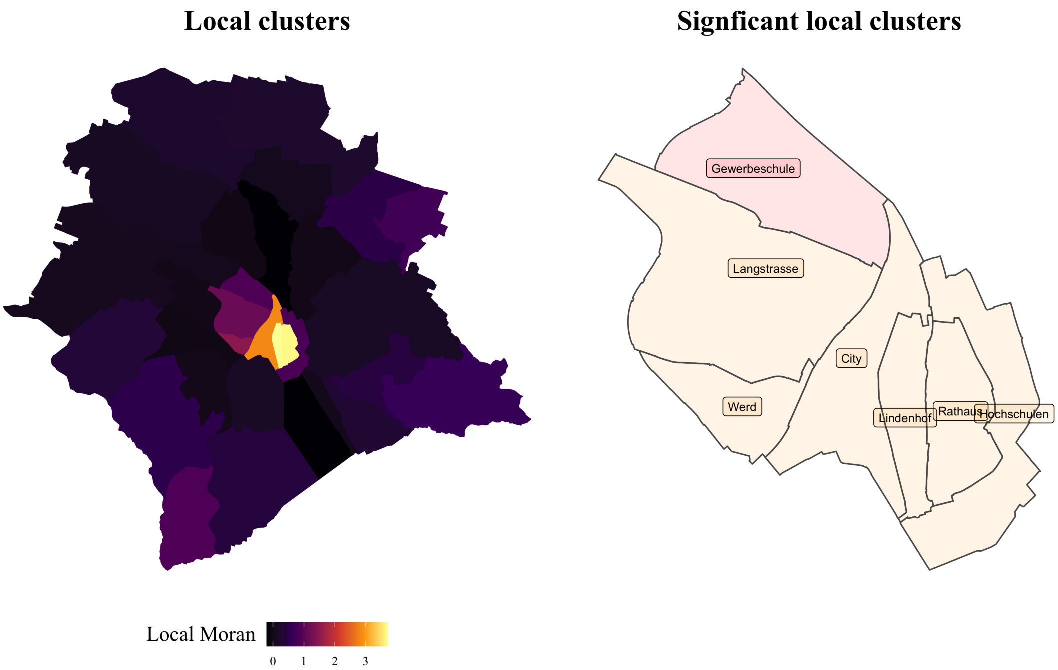

Figure 5: Local clustering of e-scooters

4.4 Mobility patterns across neighbourhoods

The majority of journeys taken using Tier scooters cross between the neighbourhoods of Zürich. 62.2% of all trips in our data cross between neighbourhoods, compared with 37.8% which begin and conclude in the same neighbourhood. Analysis of the most common start and end points of journeys shows that the most frequently taken trip begins and ends in the neighbourhood of Altstetten (891 trips in total). With the exception of the crossing between Oerlikon and Seebach, the rest of the top 14 most common journeys by beginning and end point are also entirely contained within a single neighbourhood.

The following network analysis examines the edges of the network, weighted by the total number of trips taken along the edge. Therefore, patterns of movement in which scooter users frequently cross between two neighbourhoods will appear as more heavily weighted edges in the resulting graphs. Furthermore, we assess the centrality degree of the nodes in the network, to examine the number of edges joined to each node. This allows insight into which neighbourhoods are more frequently arrived in or departed from by e-scooter.

Figure 6 shows the entire network produced with these specifications, with the edges weighted by the total number of trips. We observe that relatively few journeys go further than crossing into the adjacent neighbourhood, and that the majority of such journeys occur in the central neighbourhoods of Zürich. The neighbourhood Hochschulen, City and Enge see a relatively high number of journeys crossing into them from adjacent nodes. Additionally, there is a lot of crossover between Oerlikon and Seebach. Altstetten also shows a large number of journeys crossing to other neighbourhoods. These trends are corroborated by assessing the degree centrality of each node, indicating the number of edges at each vertex, also weighted by trips.

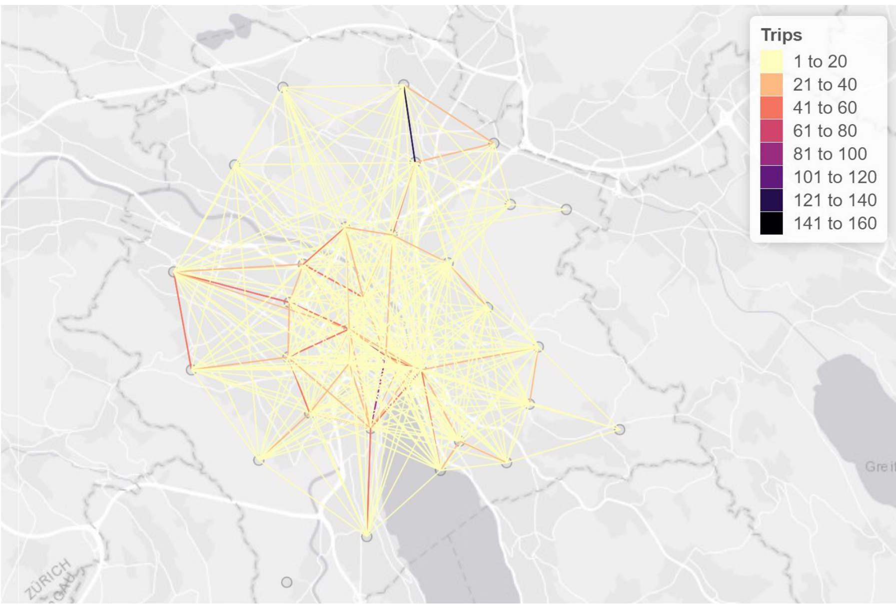

Figure 6: Network of e-scooter mobility patterns in Zürich

Figure 7 shows the degree of centrality of each neighbourhood. As one might expect, the neighbourhoods in the centre of the city have a greater number of edges leading from them. Hochschulen, City and Langstrasse are the neighbourhoods with the highest degree (26). Among the peripheral neighbourhoods, Altstetten stands out as relatively well connected to other neighbourhoods by e-scooter journeys.

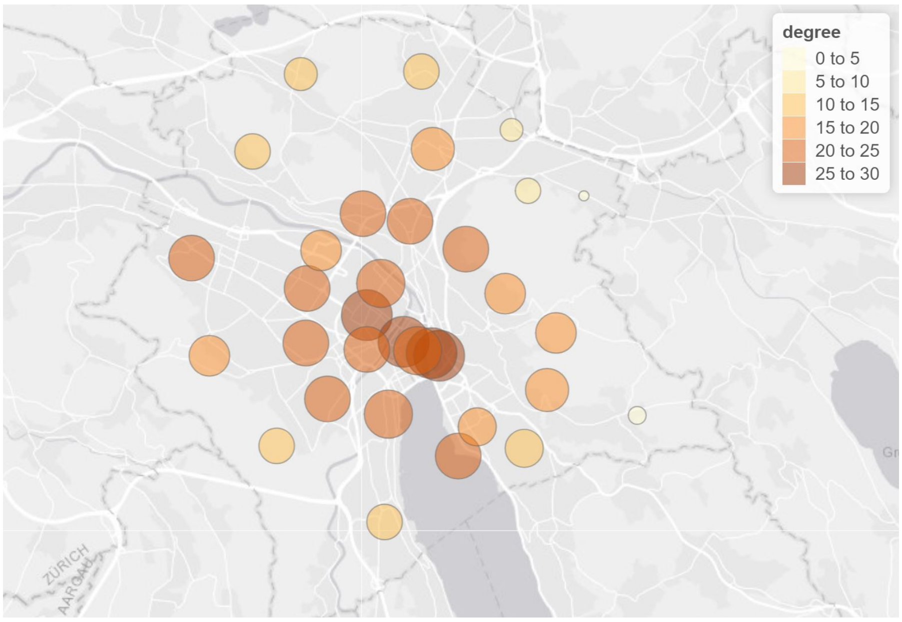

Figure 7: Degree centrality of each neighbourhood

5 Discussion

The network analysis shows that many trends from the literature are observable in the Tier dataset. E-scooters in Zürich are primarily used in the centre of the city, and around college campuses. Interestingly, the Hochschule neighbourhood containing both the University of Zürich and ETHZ main facilities is greatly connected by e-scooter use, while the Hönggerberg campus of the ETH does not see a great deal of scooter traffic to or from other neighbourhoods. However, journeys beginning and ending in Höngg are the 11th most frequent form of journey in the dataset (128 journeys). Therefore, while there is relatively high scooter activity in Höngg, the users do not tend to leave the neighbourhood. The Hönggerberg campus is already excellently connected by other forms of public transport. It is also relatively far away, and an uphill journey, from the other residential neighbourhoods of Zürich. Both of these factors could serve to explain why that while Höngg has relatively high e-scooter use within the neighbourhood, it is not well connected with other neighbourhoods through this means of transport.

It is important to recognise that the use of neighbourhoods as nodes imposes some artificial results on the network. For example, the strong flow of e-scooter traffic between Seebach and Oerikon appears as an outlier in the network. None of the other periphery neighbourhoods approach this level of traffic. It is possible to explain this outlier by noting that the border between the official neighbourhoods of Seebach and Oerlikon run through the Oerlikon train station, a key transport node in the city where many e-scooters are often deposited and picked up. Therefore, relatively short journeys, or just the random chance of where a scooter is deposited can register as inter-neighbourhood trips. Artificial bias such as this certainly occurs elsewhere in the data as well. We have already remarked how Altstetten is comparatively well connected by e-scooter travel with other neighbourhoods. However, in this individual case it is most noticeable because it only occurs on one edge, whereas in Altstetten there is a pronounced connection with multiple neighbourhoods, which is less likely to be the result of a single anomaly.

One facet of the dataset which cannot be ignored is the fact that the data was collected entirely during the Covid-19 pandemic. Given that the pandemic led to lockdowns, home-working and restrictions on citizens' mobility, it is logical to assume that the figures reported in this study are skewed low compared to pre-pandemic datasets. The aggregate figures of total e-scooter use are therefore likely not generalisable to other studies outside of the pandemic time-period. This pandemic-effect is likely less present in the analysis of mobility patterns, as a great deal of micro-mobility trips were still made in Zürich, however they represent the portion of the population more likely to be mobile during a pandemic.

Specifically, our sample likely over-represents younger people and those less at risk from pulmonary diseases. Future research would benefit from a comparison of e-scooter mobility with the same time-period in 2019 to offer an estimate of the likely depression in e-scooter usage during the pandemic. However, this is beyond the scope of this paper and would have to be investigated in a separate research design.

The quality and availability, respectively, of the data also potentially lessen the findings' external validity. While three weeks is a long enough period to detect general trends, it is not enough to identify seasonal or even more general patterns. Thus, we have to rely on hourly averages to detect differences between weekends and weekdays with enough observations, whereas total distances per day would arguably be more meaningful. However, with only three weeks, this is not possible. Although the scooters are essentially dockless, i.e. have no fixed location, they are always positioned at fixed locations. Hence the city centre's significantly higher density. Unfortunately, we have no knowledge of these "fixed" locations, which would have allowed a more detailed investigation of movement patterns. Finally, we have to acknowledge that we have no information about when and at what intervals Tier returns their vehicles to these locations. Consequently, we have to accept a bias that is small in the optimal case due to the high variance of the values and the high number of observations.

6 Conclusion

Using various methods, we were able to determine e-scooter mobility patterns in the city of Zürich during a three-week period. In line with the literature, we found that the distances travelled on weekends differed significantly from those on weekdays. On average, the scooters travelled longer distances on weekends, with Saturday and Sunday differing again from one another. Furthermore, we showed that the density of scooters in the heart of the city is significantly higher than in the periphery. We then analysed the underlying movement patterns using network analysis. We found that 62.2% of all trips in our data cross between neighbourhoods, compared with 37.8% which begin and conclude in the same neighbourhood. Tier's e-scooters are thus used both for trips within the respective neighbourhoods and to get to neighbouring neighbourhoods.

We already mentioned that further research into the effect of Covid-19 on e-scooter usage would be beneficial. Furthermore, time spent better defining nodes would allow a more fine-grained network analysis of the dockless scooters. In this paper we were able to make preliminary observations about patterns of movement between roughly defined nodes, however it is clear that using the neighbourhoods of Zürich as nodes introduces a significant amount of bias into the equation. Working to improve the vertices of the networks would allow the researcher to avoid the problem of having to divide the city artificially.

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7 Packages used

Data wrangling

- `geojsonio`: Reading geojson files with R
- `tidyverse`: Data wrangling
- `sf`: Spatial data with R
- `lubridate`: Easier workflow with dates
- `data.table`: Data wrangling

Visualizations

- `patchwork`: Assembling plots
- `viridis`: Colour scales
- `tmap`: Interactive plotting

Spatial autocorrelation

- `spdep`: (Global/local) Moran's I
- `sp`: Predecessor of sf

Network Analysis

- `tidygraph`: Creating networks
- `ggraph`: Creating networks
- `sfnetworks`: Adding spatial component to networks