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Spatial disparities of schedule-based public transport accessibility in coronavirus times: a case study of Riga

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Abstract

The study is devoted to discovering potential spatial disparities of public transport (PT) accessibility during the pandemic times. Following epidemiological restrictions and huge changes in PT demand, the PT operators react by changing PT schedules. These changes are usually made in an accelerated mode and do not always take the aspects of spatial inequalities into account. We apply a methodology, based on travel time matrices, for discovering newly introduced spatial inequalities and provide empirical results for the PT system of Riga, Latvia. The obtained results provide a new dimension for monitoring the efficiency of PT schedules and allow improving the related decision-making process. The conducted analysis allowed discovering spatial disparities in PT accessibility in Riga districts, and provided evidence for practical recommendations for further decision making.

Keywords: mobility; public transport; accessibility; COVID19; big data

1. Introduction

Public transportation plays a crucial role in urban areas by ensuring eco-friendly and socially equal accessibility for citizens. An important step of efficient PT organisation is designing of routes and service scheduling. Forming a city-level efficient schedule is a challenging problem in regular conditions of the stable demand, and it becomes even more complicated in the coronavirus pandemic era (Tirachini and Cats, 2020). Spreading of the virus forces municipalities to introduce new regulations, which directly affect PT demand (e.g., remote work and travel restrictions) and provide additional requirements for PT service (e.g., social distancing and capping of PT loading). Many such restrictions are introduced in short time frames and PT operators have to update their schedules reactively by matching changing demand patterns, fleet availability and own financial statements. At the same time, PT schedules should not only match the demand and governmental restrictions, but also ensure spatially and socially equal PT

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accessibility (Scheurer et al., 2017). Under the pressure of the fast-changing environment, updated PT schedules could create spatial and social disparities in PT accessibility and lead to city management problems in the long-term.

Furthermore, spatial disparities lead to unequal access to opportunities (Van Wee & Geurs, 2011) and, thus, create additional inequalities, e.g., in property price distribution, consequently, pulling poorer parts of society into further poverty (Boisjoly et al., 2017). Since accessibility inequality issue is a problem that has not yet been fully studied, there is still an ongoing search for appropriate methods to measure this. E.g., Lorenz curves and Gini coefficients are already in use. The use of Gini coefficient is justified by the fact that it is widely used to study income distribution (Giannotti et al., 2020). Regression model was used in (Cui et al., 2020), where the authors made separate models for low- and high-income individuals. It should be noted that there exist different variations as to how to define the notion of accessibility. Whilst the majority of publications encountered by the authors dealt with travel time estimation and its comparison, some works, e.g., (El-Geneidy et al., 2016) also considered the financial cost of trips. This study focuses on empirical analysis of spatial disparities of PT accessibility during coronavirus times in Riga, Latvia using travel time estimation.

2. Public Transport during pandemics

Covid-19 has shattered the whole world in every aspect of our lives. Since measures to combat the virus involved severe movement restrictions, this left a huge impact on the PT systems around the world. Gkiotsalitis and Cats (2021) published a comprehensive review mentioning the reductions in passenger flows in different countries and cities worldwide (ranging from 35% to 90% reduction). Nevertheless, the need for transport demand modelling was still persistent during the lockdowns and after them. The reason why it was very important, was to avoid crowding. E.g., there would be no good to reduce the number of buses, s.t., when they finally arrive, people were forced to squeeze in. At the same time driving empty buses incurs financial losses. Different municipalities solved the challenge in multiple ways sometimes incorporating various strategies at different time points. Thus, Riga PT operator at first did not reduce the number of buses even though the passenger flow shrank, but later reduced the amount of operating transport (RS, 2021).

Moving on and starting to get used to the pandemics, Qiu et al. (2020) claim, e.g., that many people in China were still reluctant to use public transport even after the lift of restrictions in the fear of contamination. Such psychological aspects make it even harder to make predictions of the transport demand. Furthermore, the difference in demand is also characterized by the existence of alternative means of transport (Pawar et al., 2020). Although Zheng et al. (2020) proved that there was a significant association between the use of PT and Covid-19 spread, PT as such could not be banned completely since it was not possible to put the whole society on hold. Some members of the society still had to fulfil their professional duty.

3. Riga Public Transport system

This study is mainly based on historical PT schedule data, collected for Riga PT system before, during the coronavirus pandemic and during its slowdown. The Riga PT system consists of about 80 bus, tram and trolleybus routes, 1600 stops and served almost 150 million passengers a year in pre-pandemic times. The system is serviced by one PT operator, Riga Satiksme (https://www.rigassatiksme.lv/en/); historical operator schedules are publicly available in general transit feed specification (GTFS) format (OpenMobilityData, 2021).

Similar to almost all other cities over the world, the Riga PT system was dramatically affected by the coronavirus pandemic. Although there are several oppositely directed drivers of PT schedule revisions, the cumulative result of the changes is a significant reduction of PT accessibility. Fig. 1 represents changes of route headways for the first pandemic-related PT schedule update (first-wave lockdown in Latvia, March 2020). As one can see, headways were not changed to the same extent. During the lockdown (Fig. 1a)), routes heading through the city centre were reduced the most, potentially this was meant to discourage passengers from unnecessary trips. Routes heading out of the city centre were also reduced but to a lesser extent with a couple of outskirts routes having been increased. When the schedule was revised during the pandemic slowdown time (February 2022) (Fig. 1b)) many routes were actually not changed, some routes were additionally significantly reduced (again, the ones heading through the centre), some longer routes were also reduced but to a lesser extent than the central ones, furthermore, some routes lying more in the outskirts were actually made more frequent. When comparing directly pre-pandemic and pandemic slowdown times (Fig. 1c)), it can be seen that more than a half of the routes were reduced by approximately 50%, a significant part was not changed, and, a couple of routes were significantly reduced. Overall, it can be concluded that PT in Riga has become less frequent nowadays. One could try to explain this phenomenon with the fact that many people still continue working from home, consequently, Riga PT company does not see the necessity to increase the amount of transport.

Having observed the headway changes through the time, authors admit that the graphs mentioned above rather give a general understanding what was going on with PT in Riga, but, separate changes in routes do not contribute to a better understanding about the accessibility of different city districts.

The main research question, however, is: did the introduced updates (reduction) keep the extent of inequalities in spatial PT accessibility at the same level during pandemics with what it was before? In case of the negative answer, we try to identify Riga districts, which suffered from the reduced PT accessibility at the most extent. Such spatial disparities could be a useful notice for future PT schedule updates and development of mobility-on-demand services.

4. Methodology

To analyse PT accessibility, we used the officially defined Riga districts (https://apkaimes.lv) and defined their coordinates to be located in the centre of the district. The notion "centre of the district" was defined as the place where the majority of shops, PT and other public places is concentrated. Rarely did it happen to be the geographical centre.

For identification dynamics of PT accessibility, we apply the methodology, based on the travel time cubes, proposed by Farber and Fu (2017). The methodology relies on the construction of a three-dimensional data object (travel time cube) that includes information about travel times between a specified set of origin and destination points, calculated for several time frames of the day. Calculation of travel times was conducted using the popular OpenTripPlanner tool (Morgan et al., 2019), configured with open street map data and historical PT schedules in the GTFS format.

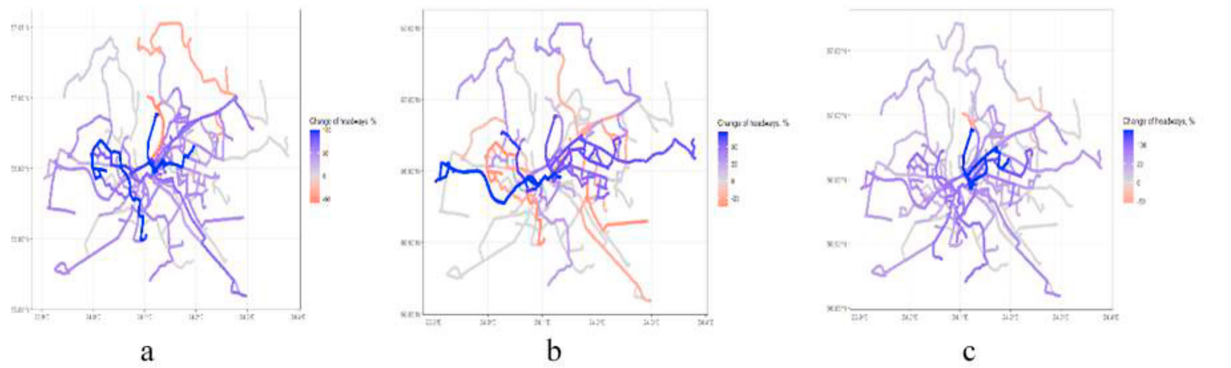


Fig. 1. Changes of route headways from left to right a) during the first pandemic-related PT schedule update; b) revising the schedule towards pandemic slowdown (Feb 2022) c) first-pandemic vs pandemic slowdown

OpenTripPlanner tool offers a number of itineraries to choose from. It indicates the time of the start of the trip (the time of leaving the point of origin), number of mode changes (from walking to PT and vice versa), types of PT used. The proposed options usually consisted of a mix of PT usage and some walking. Itineraries involving the usage of private or rented cars and (rented) bicycles or scooters were not considered since the primary interest of the current research was the accessibility of PT. Since multiple trip options were suggested for a particular time, it had to be decided what to consider as the optional itinerary, i.e., which option to choose. It was acknowledged that the time spent getting from the point of origin to the point of destination was not the most adequate travel time estimation since the waiting time before the start of the trip was not considered. Thus, the authors defined the travel time to be the sum of the actual travel time and the waiting time before the start of the trip.

Travel time cubes were constructed for several critical points – pre-pandemic, lockdown and pandemic slowdown. Both working days' and weekend travel times were obtained to estimate the effect of the PT changes on the accessibility of jobs during weekdays and attraction places or friends and family visits during the weekends. Then, Frobenius norm was used to compare travel time matrices with each other. Frobenius norm $\| \cdot \|_F : C^{m*n} \to R$ is defined for $A \in C^{m*n}$ by

$$\|A\|_F = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{i,j}|^2} \quad (1)$$

The drawback of the Frobenius norm lies, however, in that it only shows the extent of matrix dissimilarity but it does not show whether there has been an improvement or worsening, in other words, it does not depict the direction of the change. For this reason, the average travel time for the whole travel time matrix was also considered, i.e., over all the districts for a particular time point. Thus, for a travel time matrix A^{m*m}, the average travel time is defined as $\sum_{i,j=1}^{m} a_{i,j} / m * m$ .The notion of the average time is very simple, yet it allows to see the direction of the change when comparing two matrices. Having analysed travel matrices on the city level, we turned to exploring district disparities. In order to compare districts with each other, Stepniak and Goliszek (2017) summarize the following formula to calculate district accessibility coefficients:

$$A_i = M_i f(t_{ii}) + \sum_j M_j f\left(t_{ij}\right) \quad (2)$$

The formula has two summands, where the first one is the so-called self-potential and the second summand is called external potential. $f(t_{ii}) = \exp(-\beta * a)$, where a is the approximate time needed to travel by PT the distance that equals to half the radius of the current district; β, in turn, is a parameter that is obtained using "half-life" approach (Östh et al. 2014) and the formula of the exponential median. The exponential distribution rate was chosen to be the average travel time (27 min) in a particular Polish town Szczecin $f\left(t_{ij}\right) = \exp(-\beta * b)$, where b is the travel time between district i and j. M_i is district attractiveness coefficient which is defined by its population size. As one can see, the accessibility of a district increases with its size. Additionally, the faster one can travel to bigger districts from a given one, the more accessible it is considered.

Once all the accessibility coefficients were obtained, Gini coefficients were applied to estimate district disparities. Gini coefficient is a statistical measure used to estimate inequality within a given population. Its values range from 0 to 1, with 0 depicting complete inequality and 1 – perfect equality. Lorenz curve, a visualization of parameter inequality, is needed to calculate Gini coefficient. The formula for the Gini coefficient involves areas under and above the Lorenz curve.

5. Results and Discussion

Fig. 2 visualizes how district centres are located. It can be seen that there are two distinct northern districts (Bolderāja and Vecmilgrāvis) with the rest being approximately equally spaced around the city.

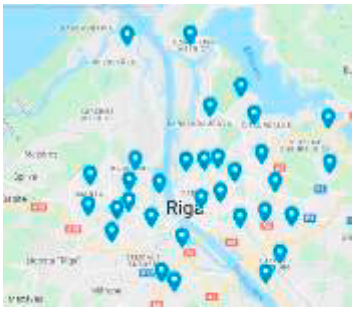


Fig. 2. Riga district map with district centres defined by authors

The minimal Frobenius norm was found for schedules between pre-pandemic and pandemic slowdown working day in the afternoon meaning that schedule differences were the smallest. The maximum, however, was found for the Sunday morning schedule between the lockdown and pandemic slowdown. These could be explained that gradually working day schedules have started to return to their pre-pandemic levels; and that Sunday schedules potentially were reduced dramatically during the lockdown since all the public activities were cancelled. And, in February 2022 the schedule started to gradually get back to normal. Furthermore, we calculated mean travel times over the whole travel matrices to estimate if, on average, travel time increased or decreased and by how much. When comparing pre-pandemic and lockdown schedules, the biggest travel time increase was for a working day evening rush hour. There, travel time was prolonged by 10% during the lockdown. Sunday morning and afternoon followed (with 9% and 8% increase during the lockdown, respectively). It should be noted that some time points were not affected by lockdown, these were workday afternoons and Sunday evenings.

Fig. 3 visualizes average travel times for the years 2019, 2020 and 2022. There, one can see that generally travel times increased substantially during the lockdown, and, that they almost did not change ever since.

When we compare the pandemic slowdown time, i.e., February 2022, when many restrictions were lifted in Riga, with lockdown, we notice that actually there have been only minor improvements in the travel time reductions indicating that potentially PT system has not yet recovered from the pandemics. Only Sunday mornings have experienced a reduction of 3.7% in travel times, other time points have faced almost no changes.

Finally, the comparison of pre- and pandemic slowdown schedules has revealed a substantial increase in travel times. E.g., it takes one 9.6% more time to travel during the workday evening rush hour nowadays than it was in the pre-pandemic times. Morning rush hours and Sunday afternoons follow with 8.3% and 7.6% increase, respectively.

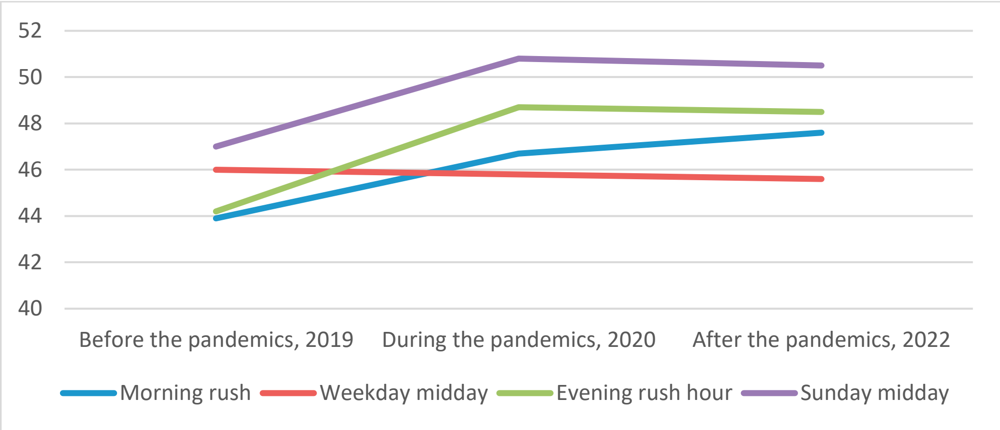


Fig. 3. Average travel times in mins before and during the lockdown

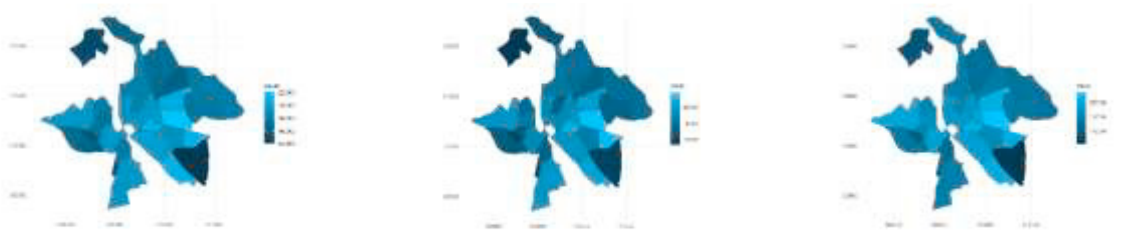
It was also interesting for the authors to compare time disparities within one day. E.g., during pre-pandemic times one could actually travel faster during the rush hours rather than during the day by approximately 4%. And, both morning and evening rush hours were not different in travel time. During the lockdown this trend changed when one could travel during the day faster by almost 2% and the evening rush hour demanded 4.4% longer travel time as compared to morning hours. Nowadays, one travels more than 4% faster during the day than in the morning but evening rush hours demand 6.4% longer travel times than during the day.

As far as Sundays were concerned, it took passengers almost 4% longer to travel on Sunday night during pre-pandemic times whereas travelling in the morning or in the afternoon did not make a difference. During the lockdown the trend, once again, changed in the way that one could travel 5% faster on Sunday evenings than on Sunday mornings and 3.6% faster than on Sunday afternoons. Nowadays, one spends the same amount of time to travel on Sunday mornings and evenings with a minor increase (1%) of the travel time in the afternoon.

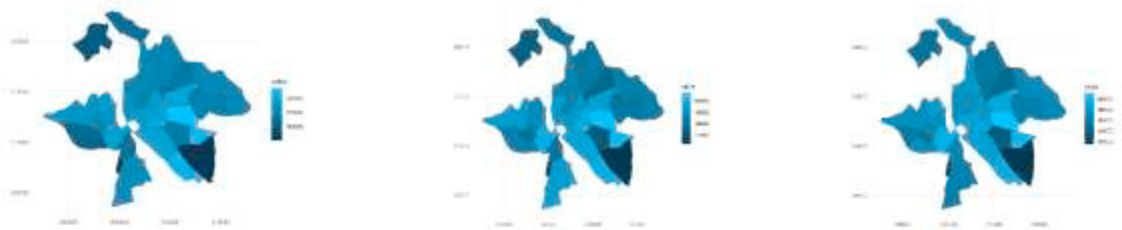
For the district accessibility coefficients' calculation (1), Stepniak and Goliszek (2017) used the approximate time needed to travel on foot to obtain the exponential part of the self-potential summand but since the current article deals solely with PT travel times, the authors felt that they should keep working with PT.

To obtain the radius of districts, we assumed for simplicity that the area of a district is a circle. The parameter 60 (min) was chosen specifically for the Riga city since Stepniak and Goliszek (2017) used a parameter suited for the size of a Polish city Szczecin, consequently, assuming that Riga is approximately twice the size of Szczecin, we doubled the parameter. Thus, the selected parameter value is $\ln(2)/60$. Stepniak and Goliszek (2017) used population size for district attractiveness coefficients, whereas the current article considered both, population size and workplace amount.

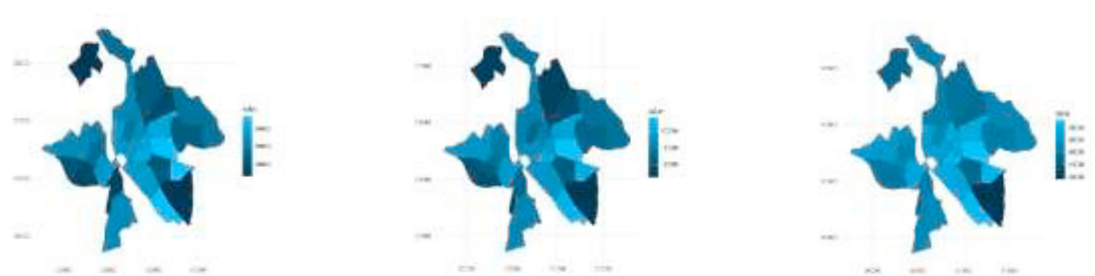
Fig. 4 visualizes accessibility coefficients based on population sizes for different time points. As can be seen, it is quite hard to visually note any differences between different time points. A closer look hints, however, that interestingly, the most distant district in the North-West of Riga (Bolderaja) was more accessible during the lockdown than what it was before the pandemic and during the slowdown. The second visually least accessible district in Riga in the South-East (Šķirotava) did not seem to have changed its accessibility. Moreover, it seems that some distant districts became relatively more accessible during the lockdown, but, their accessibility was again reduced after the lockdown. Visual investigation did not suggest any substantial changes in the relative accessibility, i.e., usually more accessible districts were still more accessible during the lockdown.



a) Pre-pandemic times (left to right) morning, evening rush hours and Sunday afternoon



b) Pandemic times (left to right) morning, evening rush hours and Sunday afternoon



c) Pandemic slowdown times (left to right) morning, evening rush hours and Sunday afternoon

Fig. 4. Accessibility coefficients based on population

Accessibility coefficients based on the workplace amount in the districts were also considered. It was again quite hard to visually note any differences between different time points, however, some interesting phenomena were noticed. A district in the North-East (Mežciems) became less accessible during the pandemics slowdown while its accessibility was not influenced by the lockdown. The distant North-West district Bolderaja slightly improved its accessibility during the lockdown. Generally, the same pattern was seen for workplace coefficients as for the population coefficients. I.e., usually more accessible districts were still more accessible during the lockdown with some districts (usually the more distant ones) improving their accessibility. Nevertheless, relatively, they were still less accessible.

From Table 1 it can be seen that Gini coefficients show good accessibility equality and that this actually did not change substantially during the lockdown. Having said this, almost all the Gini coefficients did marginally increase during the lockdown. Since Gini coefficient is used to estimate income distribution, it was suggested by multiple authors (Delbosc & Currie, 2011) that transport accessibility also influences the wealth of the population. The drawback of the Gini coefficient, which actually is considered its advantage in economics, is its anonymity, i.e., it does not disclose who exactly belongs to low and high income. For our purposes, this is a disadvantage since Gini does not specify which districts were less accessible. The advantage, however, consists of the fact that completely different transport systems with different city sizes may be compared using Gini coefficient.

Table 1. Gini coefficients

Year	Morning rush hour	Weekday afternoon	Evening rush hour	Sunday morning	Sunday afternoon	Sunday evening
2019	0.059	0.054	0.051	0.063	0.060	0.067
2020	0.065	0.055	0.066	0.068	0.065	0.067
2022	0.066	0.056	0.061	0.065	0.0656	0.068

6. Conclusion

Scheduling of PT services in a fast-changing environment is a challenging problem. In this study we propose an easy-to-apply methodology for discovering spatial disparities of city PT services. The conducted analysis provides empirical evidences of minor spatial disparities in Riga PT accessibility that appeared as a result of the PT schedule change due to Covid-19. Travel time matrices were used as a source for accessibility calculations. Further analysis was focused on changes of these matrices, calculated via matrix norms, and their spatial structure via Gini coefficients.

Gini coefficient was used to depict potential spatial disparities that could have arrived due to reduced PT services during the lockdown. To conclude, one observed that travel times increased for almost all days and time points. Even though Gini coefficients increased marginally during the pandemics, a certain trend towards increased accessibility inequality could be noted. It was discovered that some distant regions actually gained in their accessibility suggesting that the PT system of Riga had adequately reacted to the new challenges. The authors suggest that the new time schedule should be revised in order to stay at the improved accessibility level during the pandemic because relatively to other more central districts they were still less accessible. Consequently, more frequent public transport times are advised. A comparative analysis of other cities could be mentioned as a perspective direction of future research.

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