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Calculating the speed of city bus trips: The case of Ljubljana, Slovenia

In promoting the use of public transport, an understanding of the passengers' perspective on the provided service plays an important role. A series of factors influence people's selection of transport mode, among which the competitiveness of travel time, or travel speed, is vital. Thanks to the widespread use of electronic payment systems, data collected through user validation can be used to calculate this speed. Thus, the actual trips made can be used to estimate their speed. This study focused on the Ljubljana bus system to analyse all trips made on a typical day. The input and output trip data were used to calculate the distance travelled, and the time and speed of the trips. In addition, an estimate was also made of how quickly the distances travelled by bus could have been travelled by bicycle or on foot. The findings showed that the speed of the bus trips analysed depends on the length of the journey: it increases with longer journeys. Bicycles are generally faster for all distances, but they become a less acceptable choice for longer distances. With regard to distances shorter than 2 km, in terms of speed, walking is competitive on only a few routes. The analyses performed using the data collected through the electronic service payment system provided useful insight into the efficiency of the public transport system from the passenger perspective, which in the future may prove useful in planning system improvements.

Keywords: public transport, travel speed, effective travel speed, electronic payment system, speed comparison

1 Introduction

Understanding the residents' travel habits and reasons for them is an important factor in promoting sustainable mobility. The goals of sustainable mobility measures are often directed towards changing people's travel habits, especially reducing the use of cars and promoting the use of public transport, cycling, and walking as different modes of making daily trips. People's decisions to use public transport are heavily influenced by its quality (Vanhanen & Kurri, 2007). Studies of travel habits examine the factors influencing the choice of travel mode or the indicators defining how a public transport system operates. The quality indicators of a public transport system can be divided into two major categories: the transit capacity and the quality of the actual service provided (KFH Group, 2013). Quality of service is defined using user perceptions or actual numerical measurements (Carreira et al., 2014). If the service is of good quality, then frequency, availability, travel time, price, and staff quality are especially important in deciding to use public transport (Stradling et al., 2007). The key indicators, which are also important factors in selecting the travel mode, are the speed and consequently the time the user spends to make a trip. There are only a few Slovenian studies in this area and the ones that do exist do not provide detailed insight into the conditions that influence the passengers' motivation to use public transport (Statistični urad RS, 2017; Ljubljanski potniški promet, 2019). Travel time is one of the most important elements of public transport quality (KFH Group, 2013) because all the other factors influencing the choice of travel mode only come to the fore when the user is provided with a competitive selection of various travel modes in terms of travel times. Longer travel times (e.g., of commuting to work) are directly connected with reduced user satisfaction (Loong & El-Geneidy, 2016), as well as poorer wellbeing and social inclusion (Morris & Guerra, 2015).

Various methods are used to calculate public transport speed. The speed over a specific stretch, including all stops and delays, is referred to as commercial speed. This indicator is primarily important from the operator's point of view because it makes it possible to calculate a vehicle's travel time on a line, set up timetables and drivers' schedules, and effectively distribute vehicles across the system. From the passengers' point of view, commercial speed is not enough because they compare the travel times of various transport modes from a door-to-door perspective. More important for them are the time and speed that also include the time of reaching the station, waiting, in-vehicle travel, any transfers, and ultimately reaching the destination (Munizaga et al., 2016; Constantinescu et al., 2018). This speed is referred to as the effective total travel speed below.

Data collected through passenger validation enabled by digitalized payment systems provide great potential for acquiring data on and analysing these speeds. Such data allow a much better understanding of passenger travel habits and it also makes sense to use them in improving the public transport systems (Schmöcker, 2016). Smart card data can also be used to calculate the key indicators of a system's operation (Trépanier & Morency, 2016), as well as conduct many other analyses in addition to those focusing on travel speeds (Jang, 2010).

This article presents a method for analysing the speed of public transport trips in Ljubljana using the data on the trips actually made. The study examines the time parameters of trips without the analyses of perceived times. It proceeds from the hypothesis that the available payment system and timetable data can be used to determine the speed of actual public transport trips that is more accurate than the data available to date. The second part of the study compares the public transport travel speeds with the speeds of traveling the same routes by bicycle or on foot. Comparisons of individual travel modes in a city are a frequent research topic (Ellison & Greaves, 2011; Andersen, 2014), but most of these are unsystematic. The literature review revealed no study that would provide a comparison between a public transport mode and cycling based on a sufficiently large sample and comparable routes. Based on the available data on the relatively short distance of an average trip, this study proceeds from the hypothesis that an average public transport trip would take less time by bicycle.

1.1 The case of Ljubljana

Public transport in Ljubljana is operated by Ljubljanski Potniški Promet (hereinafter: LPP), which carries nearly 40 million passengers a year. In recent years, the number of passengers has been falling despite many improvements to the service and passenger comfort, such as revamping the bus fleet and the bus arrivals system, improving the quality of bus stops, and introducing separate bus lanes on some arterial roads. The main reason for the falling number of passengers is not entirely clear (Ljubljanski potniški promet, 2019). The accessibility of public transport is good within the city perimeter (Gabrovec & Bole, 2006; Kozina, 2010; Gabrovec & Razpotnik Visković, 2012, 2018; Tiran et al., 2015).

Travel times have been poorly studied to date. Celcer (2009) analysed the travel times on selected lines and compared them to cars, but she did not calculate the travel speeds. She established that travel times for cars were significantly shorter on all the routes studied. Travel times on specific lines were also studied by Šabič (2015), but he only calculated the commercial speed, which does not take into account waiting and walking. Similarly, LPP also only measures the commercial speed (Šmajdek, 2011). Vehicle tracking data were used to calculate the travel speed on line 1, which exceeds 22 km/h throughout the day (Čelan & Lep, 2020). Low travel speed as a key problem in public transport has also been highlighted in strategic documents (Milovanović, 2017; Gojčič, 2018), in which, however, no current or target values are provided, which is most likely the result of this topic being understudied.

The electronic payment system, which Ljubljana introduced in 2010, has good potential for analysis. When entering the bus, every passenger validates their card or uses the Urbana app on their smart phones to pay for the fare. The validation data are sent to the central server together with the information on the bus stop retrieved from the Automatic Vehicle Location (AVL) system (Šmajdek, 2011). Except for keeping records of the total number of passengers for the annual reports, these types of data, except for certain exceptions (Koren, 2016; Koblar, 2017; Koblar & Žebovec, 2018), have not been analysed in detail. However, they proved to be very useful in analysing user travel patterns (Koblar & Žebovec, 2018; Koblar & Mladenovič, 2020) and planning potential changes to the network (Koblar, 2017).

2 Methods

The payment system data were analysed to calculate the travel times. Because only the boarding bus stop is recorded in the payment system, one of the challenges was determining the alighting stops and merging individual trips into a journey. A trip refers to a ride on an individual line validated in the payment system. A journey refers to one or several trips together by taking account the boarding stop of the first trip and the alighting stop of the last trip. These data provided the basis for further analyses.

2.1 Determining the alighting stops and calculating the travel times

Travel times and speeds were analysed based on the trips made and recorded in the payment system used by LPP. The 2015 and 2016 validation data retrieved were first used to select a typical day on which an average number of trips (validations) were made, the weather was nice (no rain) and there were no school holidays, roadblocks or other special events. Wednesday, 18 May 2016, was selected, with 142,181 trips recorded.

Because most public transport payment systems are designed so that they only record the entry into the vehicle, just like this one, a considerable number of authors have so far sought to determine the alighting stops (Cui, 2006; Trépanier et al., 2007; Zhao et al., 2007; Farzin, 2008; Lu, 2008; Wang, 2010; Li et al., 2011; Wang et al., 2011; Alsger et al., 2016; Mosallanejad et al., 2019; Yan et al., 2019; Assemi et al., 2020). To define the alighting stops on individuals' journeys they generally used a simple algorithm that compared two daily trips and took account of two criteria: the alighting stop on the first trip is the same as the boarding stop on the next trip and the alighting stop on the last trip of the day is the same as the boarding stop on the first trip. In addition to determining alighting stops, the reconstruction of journeys also requires merging individual trips into complete journeys. Here, it is vital to accurately determine when a person changes lines and continues their journey and when they end it. This can be determined based on the distance between the alighting stop on the previous line and the boarding stop on the next line and the time between alighting and the next boarding (Alsger et al., 2016). Due to the lack of appropriate data, most researchers did not check the accuracy of their results. Alsger et al. (2016) made an important step toward improving the algorithms and checking the quality of results. They used the smart card data of the South-East Queensland public transport network, in which passengers also validate their cards when alighting, to check the accuracy of results. By modifying established algorithms and including data from the public transport schedules, they managed to additionally improve the quality of origin-destination estimation algorithms. Later additional improvements were introduced, using more complex methods (machine learning) to more successfully determine the alighting stops (Yan et al., 2019; Assemi et al., 2020). Due to its simpler implementation and satisfactory results, we decided to use the algorithm proposed by Alsger et al. (2016).

To determine the alighting stops based on this algorithm, the smart card validation data must contain the card identifier, travel time, and the stop and line used. The data obtained include all the necessary information; in addition, a bus schedule database was obtained that was suitably structured for linking with the validation data. Before running the analysis, trips without the required data were eliminated from the database. Some trips were part of long-distance (inter-city) lines and so were not included in the city public transport schedule, and for some the wrong line or stop was recorded. Because the alighting stop can only be determined for passengers that took more than one trip on the same day, data on users with only one trip on a selected day were also eliminated from the database (17,614). The basic conditions for inclusion in the analysis were met by 113,985 or 80.2% of all the trips made. A matrix of distances between the stops is required to determine the alighting stops and transfers. For stops less than 800 m apart, the distances were modelled based on the road network, which resulted in more accurate calculations. For distances between other stops, the Euclidean distance was calculated because the calculation for the 840 × 840 matrix of the stops analysed would have taken too much time.

The alighting stops were determined using our own software, which followed the algorithm applied (Alsger et al., 2016). The software first analyses the consecutive trips of the same person and orders them into journeys. One journey can be composed of several trips with transfers in between. The potential alighting stops were determined based on the bus schedule, from which the potential alighting stop is selected according to the line used. From among the stops selected in the previous step, the stop closest to the next boarding stop is defined as the alighting stop. To determine the alighting time, the travel time between both stops as provided in the bus schedule is added to the boarding time. If the next boarding stop is less than 800 m away and less than 60 min have passed in between, the trip is defined as a transfer; otherwise, it is treated as an independent journey. In the event of a transfer, the software continues to analyse the user's card validations until the last trip in the journey. If this is the last trip of the day, the stop closest to the boarding stop of the first trip of the day is selected as the alighting stop, and the software then continues by analysing the next user's trips. The alighting stops were determined for 110,069 or 96.5% of validations that met the conditions for inclusion in the analysis. The result of the analysis is a consecutively numbered list of trips with additional information on the alighting stop and the alighting time. Trips that continued with a transfer to the next line also contain information on the distance to the next boarding stop. These data were then merged into individual trips, for which the travel times were calculated.

2.2 Calculating the average waiting time

One of the factors affecting the travel time is also the time of waiting for the bus to arrive. Assuming that passengers arrive at the stop randomly, the average waiting time depends on the frequency of bus trips on all lines that are heading in the selected direction and are available at the time of travel. Therefore, the difference in the travel times of the current, previous, and next trips were calculated for the specific line used. If this was the first or last trip of the day, only the difference to the next or previous trip was taken into account. The same method was used to calculate the waiting times for other lines that could have been used between the two selected stops. In this, only the lines on which the nearest scheduled departure was less than 5 min before or after the actual trip made were taken into account. To calculate the average waiting time, the waiting times on individual lines were converted into frequencies and summed up. The sum was then converted into waiting time and divided by 0.5. For journeys in which the waiting time was longer than 4 min, it was assumed that passengers checked the bus schedule before the trip and, therefore, an average waiting time of 4 min was determined for these 16,771 trips. According to the initial estimate, the average waiting time on these trips was 6.1 min.

2.3 Calculating the travel time and speed

Because the calculations and definitions of travel speed vary significantly, to ensure better comparability with research to date, the travel speed was calculated in four different ways, taking into account different distances and travel times, as shown in Table 1.

2.4 Walking and cycling speed

Cycling and walking travel times were modelled in OpenTripPlanner (Morgan et al, 2019). using the transport network created from the OpenStreetMap database (OpenStreetMap contributors, 2015). These data are of sufficiently high quality for Ljubljana to obtain sufficiently accurate results. In the OpenTripPlanner program, the default speed and weighting settings for individual road categories were used. The cycling speed was set at 17.7 km/h. Various estimates of the average speed of urban cyclists are used in the literature, ranging from 15 to 19 km/h (Ellison & Greaves, 2011; Andersen, 2014; Kager et al., 2016). Because no data are available on the average speed of cyclists in Ljubljana, it is assumed that the above speed estimate is suitable. The walking speed was set at 4.8 km/h. Calculations were made for all origin-destination pairs. For walking and cycling, too, another 400 m were added to the distance between stops to calculate the effective travel speed, which added up to 1 min 30 s for cycling and 5 min for walking. We added another two minutes for cycling, as the time required to lock and unlock the bicycle.

2.5 Data merging and quality analysis

After conducting individual analyses, the data were merged into a joint database, in which the data analysed is collected for every journey. Journeys for which it was assumed that there were errors in the calculations were deleted from the database. It turned out that the criterion for merging trips into journeys that allows for less than 60 min for the transfer and a distance of less than 800 m between stops was insufficiently accurate. Thus, to control for the quality of data, the coefficient and difference between $l_{LPP\ line\ distance}$ and $l_{shortest}$ were calculated. Where the $l_{LPP\ line\ distance}$ was significantly greater then $l_{shortest}$, this indicated that a transfer was wrongfully assigned instead of two separate journeys. Thus, all journeys in which $l_{LPP\ line\ distance}/l_{shortest} < 0.8$ or > 4 and $l_{LPP\ line\ distance} - l_{shortest} < -100$ m or > 100 m were eliminated from the database. Additionally,

Table 1: Method of calculating the travel speed.

	Presumed distance	Presumed travel time
Effective total travel speed	Effective distance travelled: $l_{shortest} + l_{walking}$	Total travel time: $t_{trip} + t_{waiting} + t_{walking}$
Total travel speed	Distance travelled: $l_{LPP\ line\ distance} + l_{walking}$	Total travel time: $t_{trip} + t_{waiting} + t_{walking}$
Effective travel speed	Effective distance travelled: $l_{shortest}$	Travel time: t_{trip}
Actual travel speed	Actual distance travelled: $l_{LPP\ line\ distance}$	Travel time: t_{trip}

Whereby:

$l_{shortest}$: the shortest distance between the first and last stops calculated as the walking distance along pedestrian routes

$l_{walking}$: 400 m distance – the total walking distance to the first stop and from the last stop to the destination

$l_{LPP\ line\ distance}$: distance travelled by bus; in the event of a transfer, the walking distance between the two transfer stops is taken into account

t_{trip}: time between boarding the bus on the first trip and alighting from the bus on the last trip of the journey; it also includes the time of transferring to the next line

$t_{waiting}$: average time of waiting for the bus to arrive on the first trip in a journey

$t_{walking}$: 5 min – the time required to walk 400 m, which is added as $l_{walking}$. This is an estimate based on how much time people are willing to spend walking to a bus stop (Tiran et al., 2019).

journeys were eliminated in which the actual travel speed was lower than 5 km/h or higher than 50 km/h. This way, errors were eliminated that might have occurred due to mistakes in the bus schedule or mistakes in merging individual trips into a journey where the waiting times were too long. In this situation, in reality a passenger can perform other activities in the meantime, such as go to a bar or shop, and then continue their journey. Such journeys are irrelevant in terms of studying travel speeds. After eliminating these inadequate ones, 70,768 trips remained out of the initial 74,085, based on which further analyses were performed.

3 Results

Based on the data analysed it is possible to conduct a series of analyses. Because the main purpose of this article is to analyse the travel speeds, the main results of analyses related to travel speed are presented below: first, the results of the city bus analyses, followed by a comparison with walking and cycling travel speeds.

3.1 City bus

The main findings of the city public transport analysis are presented in Table 2. Detailed information is presented in the subsections.

Table 2: Key results of the city public transport analysis.

Indicator	Value
Effective total travel speed	10. km/h
Average actual distance travelled	4.8 km
Average effective distance travelled	4.1 km
Average waiting time	2.9 min

3.1.1 Average waiting time

One of the factors affecting the effective travel speed is the average time of waiting for the bus to arrive on the first trip in the journey. The average waiting time is 2.9 min (SD = 1). Figure 1 shows the average waiting times and the share of waiting in the total travel time, depending on the length of the journey. With longer journeys, on average passengers had to wait longer for the bus to arrive. One of the reasons for this is also that longer journeys had to start outside the city centre, where bus arrivals are less frequent. The longer the journey, the smaller the share of time spent waiting compared to the time spent for the entire journey.

3.1.2 Transfers

Users generally dislike transfers. The LPP network originated at a time when tickets were paid each time the passenger boarded the bus and hence one of the goals in designing the network was to reduce the need for transfers (Koblar, 2017).

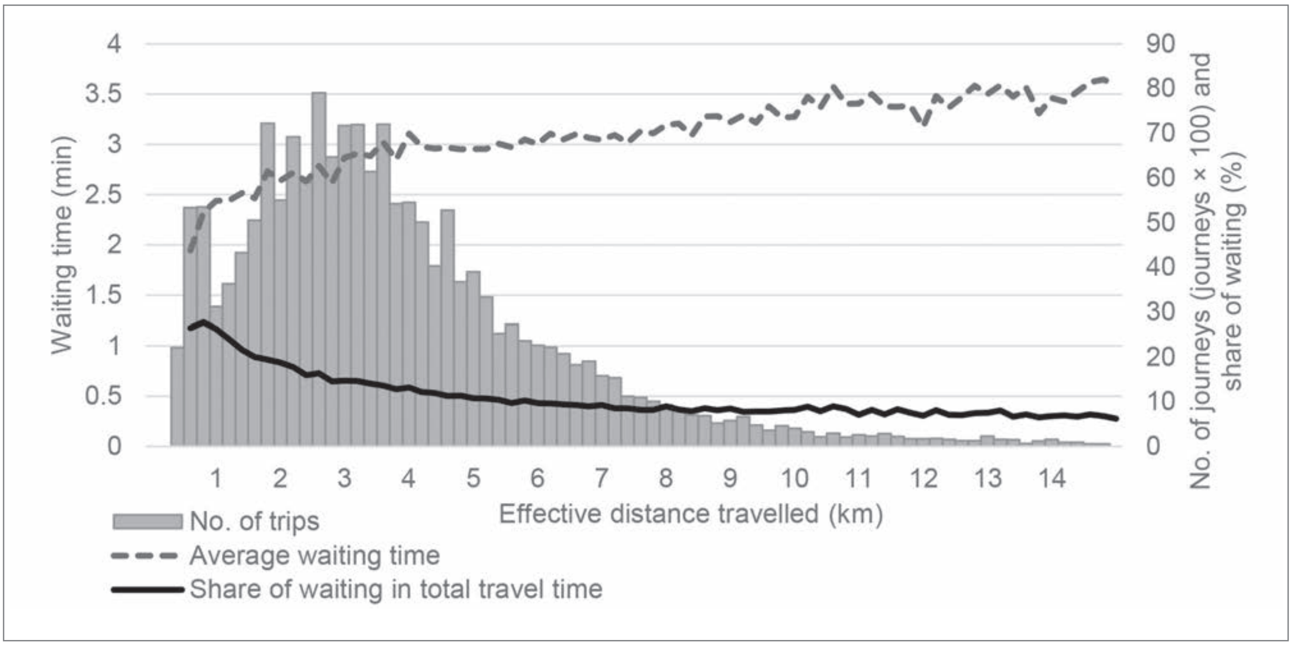

Figure 1: Average waiting time and number of trips, depending on the length of the journey (author: Simon Koblar).

Table 3: Number of journeys based on the number of transfers made.

No. of transfers	No. of journeys	Share of all journeys (in %)
0	70,146	79.1
1	16,459	18.6
2	1,682	1.9
3	311	0.4
4	69	0.1
5	14	0.0
All journeys	88,681	100.0 %

Table 4: Calculated bus travel speeds.

	Average speed (km/h)	SD (km/h)
Effective total travel speed	10.0	3.3
Total travel speed	11.3	3.4
Effective travel speed	15.7	6.2
Actual travel speed	17.6	5.7

In more developed networks, transfers are conceived as an important part of travel routes because they provide a combination of various operators and systems and hence better public transport coverage (Mees, 2010; Dodson et al., 2011). In addition to 70,768 journeys, for which other analyses were also performed, the transfer analysis also included 17,614 user journeys that only made one trip on the day studied and hence their trips were unsuitable for calculating the alighting stops. Table 3 shows the number of journeys based on the number of transfers made.

3.1.3 Travel speeds

Travel speed is one of the factors that determine the quality of the public transport system. Table 4 shows the travel speeds based on the various criteria used and presented in Table 1.

In addition to the average speed, the distribution of the number of journeys shown in Figure 2 is also important. The histogram has a normal distribution shape, with slightly higher values on the right side.

Travel speed also depends on the length of the journey. In longer journeys, the waiting and walking times reduce the impact on travel speed and so the speeds increase with the length of the journey. The effective travel speed curve is interesting: it is very high for short distances, resulting from the fact that the differences between the distance travelled and the shortest distance are smaller with shorter trips. In addition, these calculations do not account for the walking time to the bus stop and the waiting time.

3.2 Comparison with cycling and walking

To have a better idea of public transport travel speeds and to better understand the competitiveness of public transport over other forms of sustainable mobility, a comparison was also made with bicycle and walking travel speeds. In com-

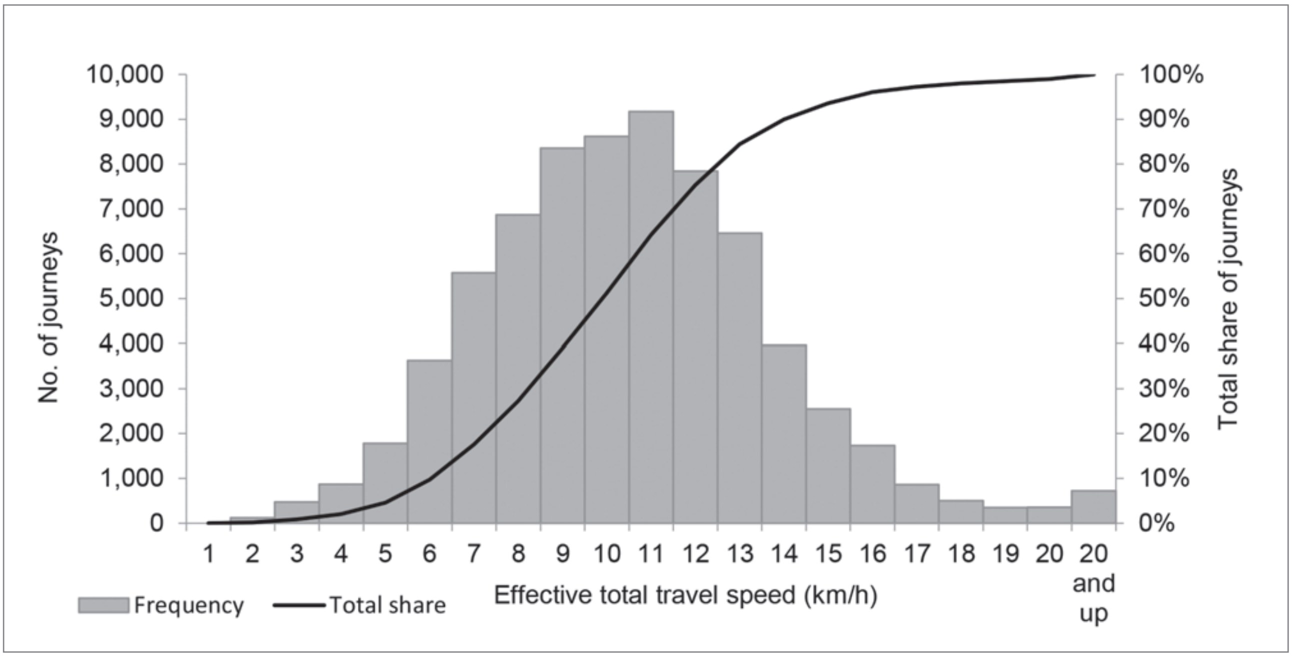

Figure 2: Number of journeys by effective bus travel speed class (author: Simon Koblar).

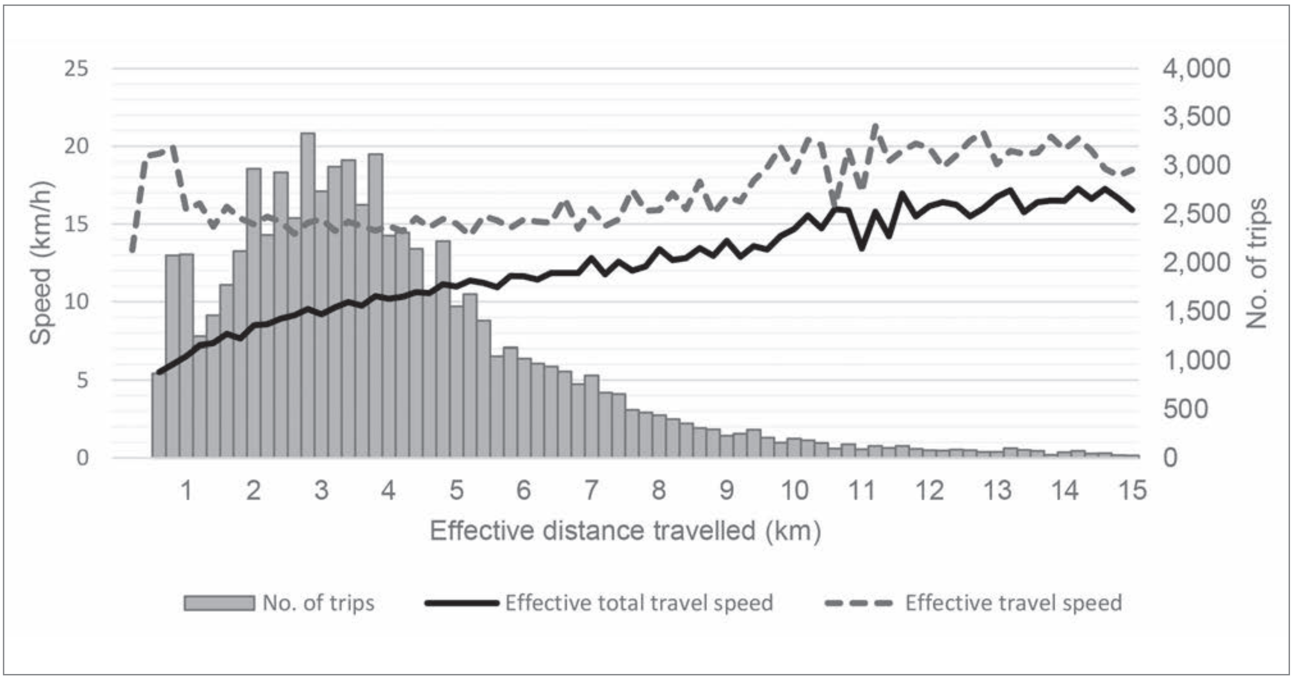

Figure 3: Travel speed in correlation with the length of the journey (author: Simon Koblar).

paring the bus and bicycle travel speeds, effective total travel speeds were taken into account because they best reflect the user experience. Effective total travel speeds increase with the length of the journey, due to a reduced impact of waiting and walking times for buses and a reduced effect of the additional time required to lock and unlock the bicycle. Bicycles are the fastest on all distances, with the difference being the greatest in shorter journeys. On average, a bicycle would be 7.5 min faster than the bus. Only 8% of the journeys would have been faster with the bus and 46% of journeys would have been 5 min faster with the bicycle.

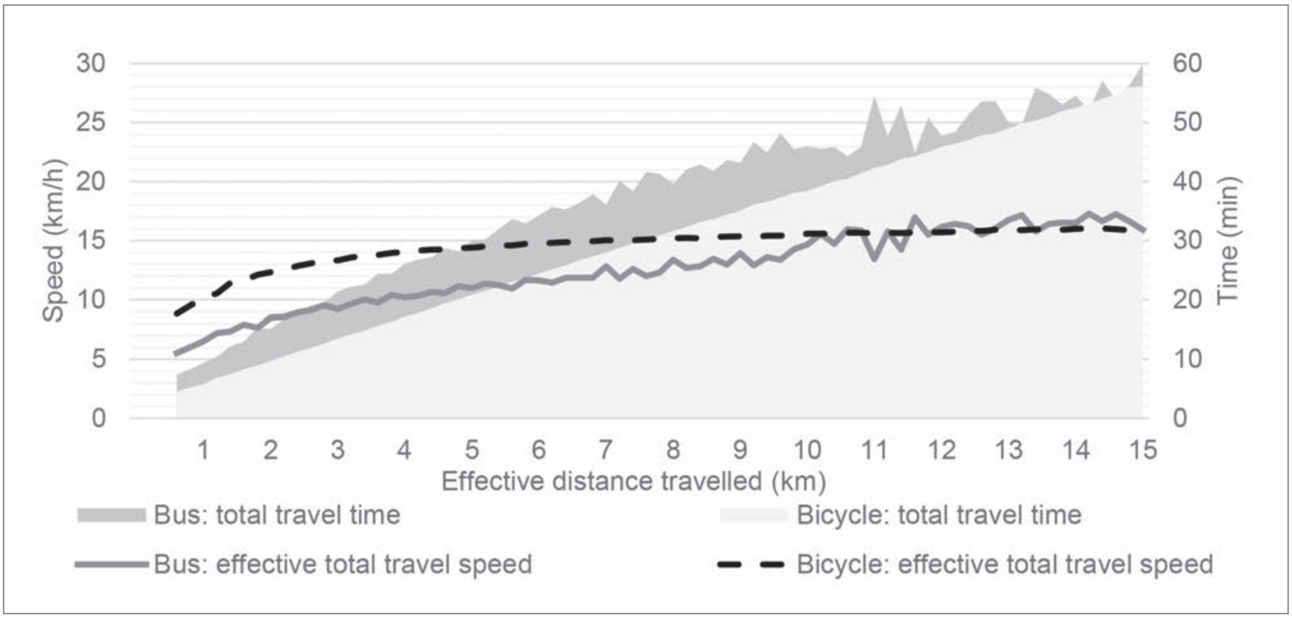

Figure 4: Comparison of bus and bicycle speeds and travel times (author: Simon Koblar).

Due to the low speed of walking, only journeys up to 2 km were taken into account. On stretches shorter than 2 km, 926 journeys (i.e., 7% of the total journeys shorter than 2 km) would have taken less time on foot than by bus. Also taking into account the journeys that are less than 1 minute faster by bus, the total number of these journeys adds up to 1,783 or 13%.

4 Discussion

This article presents new findings related to the measurement of public transport quality and reveals great potential of the electronic payment system data for conducting further analyses. Because analyses are performed based on the trips made, the results are especially interesting from the user perspective because they reflect the user experience and provide insight into passenger behaviour. Because the payment system does not provide information on the alighting stop, determining the alighting stops represented a significant challenge. To this end, available data were applied to a well-tested algorithm (Alsger et al., 2016), whereby the distance between stops was modelled in the GIS environment using pedestrian routes. This resulted in greater accuracy compared to the straight-line distance applied by Alsger et al. (2016). To determine the travel speeds the waiting time at the stop, the travel time, and the distance travelled were also calculated for each trip. The applied method for calculating the waiting time that also takes into account the time of day and relevant lines, yields more realistic results from the passenger perspective than the method of counting arrivals at peak times frequently used in other studies of public transport quality in Ljubljana (Bole, 2004; Tiran et al., 2015).

Because the shortest distance between the origin and destination is especially important from the passenger perspective, the shortest distance in the transport network was also modelled in addition to the distance travelled on a public transport line. Various methods are used to calculate the travel speed and hence four different methods were applied, using different distances and times. From the user perspective and compared to other travel modes, the most relevant is the effective total travel speed, which on average amounts to 10.0 km/h; this is significantly lower than the average actual travel speed of 17.6 km/h. Commercial speed is the only information that has been available for the entire network in comparable form to date. According to the LPP data, the commercial speed, which only takes into account the individual trip without transfers to other lines, is 18 km/h (Šmajdek, 2011), demonstrating the accuracy of the analyses conducted. The substantial differences in results indicate the importance of selecting the travel speed calculation method.

By calculating the travel speeds, the first hypothesis was also confirmed. Based on the electronic payment system data and bus schedules it is possible to determine the travel speed of bus trips. A comparison of bus travel speeds with walking and cycling showed that the bus is poorly competitive with bicycles. On average, equivalent trips took 7.5 min longer by bus than by bicycle. This also confirmed the second hypothesis. An average bus trip would have taken less time if made by bicycle. Some shorter routes would even have been travelled faster on foot, which points to frequently irrational passenger decisions. Most of these shorter trips are made in the city centre, where buses are very full as it is. The ratio between the bus and cycling travel speeds is most likely one of the reasons for the increase in cycling (Klemenčič et al., 2014) and the decline in the number of bus passengers in recent years (Ljubljanski potniški promet, 2019). In addition to travel speeds, insight was also provided into passenger behaviour in terms of transfers. It turned out that despite changes to the payment system, which allows free transfers within 90 min after the first validation, only 20.9% of journeys include transfers. This probably results from the network's design, which is supposed to reduce the number of required transfers as much as possible, and partly also from the fact that (predominantly elderly) users tend to only accept change and change their habits slowly.

The method applied also has certain deficiencies and some could be eliminated through further research and more complex methods. Due to the large quantity of the electronic payment system data, complete control over their quality cannot be guaranteed. Certain errors can already arise in determining the alighting stops, whereby additional parts of the trips for which there are not suitable data are eliminated. In terms of data quality, what is especially problematic is merging several trips into a journey, which could be improved through more complex methods (Assemi et al., 2020). The key step in this study was the elimination of outliers from further calculations. Unfortunately, the accuracy of the alighting stops determined cannot be estimated, which, modelling on Wang et al. (2011), could have been done through field research and by comparing the results. In addition, using different presumptions about the random passenger arrival at the bus stop would have yielded somewhat different results in calculating the average waiting time (Amin-Naseri & Baradaran, 2015). In determining the walking distance, a uniform value of 400 m was used because no data are available on what distance the users of the Ljubljana public transport system actually walk. The cycling speed applied in the study was a mere estimate, too. Due to many elements that affect it (e.g., the quality of the cycling infrastructure, waiting at traffic lights, and ultimately the type of cyclist and bicycle used), the results could have been different if a different assumed speed have been used. By improving the quality of the cycling infrastructure and increasing the share of electric bicycles the average cycling speeds can be expected to rise. A certain degree of error also occurs in calculating the bus speed, which was determined based on the available bus schedules. The actual speeds always deviate from these, especially at the stops close to the end of the lines. A solution would be to use the data from the vehicle tracking system, based on which the bus speeds could be determined more accurately (Wang et al., 2011).

The public transport payment system data also make it possible to conduct a series of other analyses (Pelletier et al., 2011; Ali et al., 2016; Trépanier & Morency, 2017), which would be prudent in the future. Good familiarity with the public transport system and passenger behaviour may be of great help in introducing improvements to the system, which are vital for Ljubljana due to the poor competitiveness of its public transport and the inappropriate design of its network (Koblar et al., 2018). Specifically, it is vital to reverse the decreasing trend in the number of passengers because only this way the targeted share of public transport trips can be achieved (Milovanović, 2017), which would contribute to a reduced environmental impact. On the other hand, improvements in the public transport system alone are not enough; a better integration of spatial and transport planning is also required (Plevnik, 1997), which especially applies to the well-served public transport corridors (Šašek Divjak, 2004).

5 Conclusion

The method of analysing the public transport payment system and measuring the travel speed presented and applied to Ljubljana is one of the few attempts to measure the quality of the public transport network based on trips actually made. The effective total travel speed reflects the user experience significantly better than the more widely used commercial speed measurements. In turn, comparing the bus trips to cycling and walking suitably contextualizes these speeds. Calculating the speeds also yielded other important information, such as the travel time, the distance travelled, the average waiting time, and the number of transfers. In the future, the actual distance walked to the bus stop should be taken into account, the bus speed should be calculated from the vehicle tracking system, and greater attention should be dedicated to quality control, especially in determining the alighting stops and merging trips into journeys. In addition, analysis should cover a longer period. The method applied is very useful for monitoring the use of the public transport system and improving it, which could reverse the falling trend in the number of passengers. The current findings for Ljubljana alone can be used by transport planners and LPP to introduce changes that would increase the competitiveness of the public transport systems.

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