The impact of COVID-19 on day-to-day mobility patterns in the Netherlands. Evidence from smartphone-based travel data.

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Abstract

This study examines the changes in travel behaviour during the first lockdown in the Netherlands. In the analysis, data were used from the NVP, a large-scale smartphone-based panel survey. The NVP allowed constant monitoring of the impacts of the COVID-19 outbreak and taken policy measures on mobility patterns and travel behaviour related to travellers' characteristics. The COVID-19 outbreak and associated measures taken had an enormous impact on society and a disruptive, but not necessarily negative, impact on mobility. The Ministry of Infrastructure and Watermanagement received the most recent insights from the Netherlands Mobility Panel every week. These insights were used to monitor travel behaviour and to analyse behavioural changes and changes in mode use during COVID-19. The analysis shows an enormous decrease in travel at the beginning of the first lockdown in the Netherlands and a gradual increase again towards comparable levels as before the lockdown, although the distribution over time, motives and used modes has changed. It becomes clear that not everyone needs to travel during peak hours, and commuting is not the main reason for the increase in car usage. Furthermore, cycling has shown to be an alternative option for travellers, and public transport is hardly used anymore. If it is possible to sustain the lower level of car usage and integrate public transport as an important alternative for travel again, the COVD-19 impact on mobility could have a substantial remaining positive impact. Moreover, this study shows the added value of actual and continuous GPS tracking data to examine changes in travel and activity patterns, which is not possible with traditional cross-sectional surveys and 1- or 3-day travel diaries.

1. Introduction

Data of any sort are fundamental to research. Different methods are applied to collect reliable and valuable travel data in transport research. The travel data collection process evolved from structured questionnaire surveys to more activity-based travel diaries. Even though travel diaries can reveal travel behaviour and choices, the reliability of the data varies among collection methods (e.g., Ettema et al., 1996). Ettema et al. (1996) pointed out several advantages and disadvantages of collecting travel data using traditional methods such as pen-and-pencil, computer-based, telephone-based and other mixed methods. Since then, several new ways have been developed to increase the reliability of the data. That includes using GPS-logger along with the travel dairy to avoid underreporting (Bricka & Bhat, 2006) or deriving travel data solely from GPS (Wolf, 2000) to prevent non-response and reduce survey burden. With the increasing access to a mobile phone, it has become easier to access the location information of a large number of people continuously, giving rise to the application of big data in mobility.

A targeted GPS-tracking travel survey is the new Netherlands Mobility Panel (in Dutch: Nederlands Verplaatsingspanel, NVP), started in 2019 with an expectation to record continuous travel information of about 10.000 participants, whose household and demographic characteristics are known as well. Its huge added value has become particularly evident during COVID-19. The COVID-19 outbreak and associated measures had a disruptive impact on mobility. As a result, travel behaviour drastically changed, which became visible in the number of traffic jams reported and the use of public transport. However, to understand how travel behaviour changed and evolved during the COVID-19 pandemic and learn from this disruption, more information is needed than traditional traffic data on flows and speeds. Smart card data or floating car data already provides more information on changing mobility patterns. However, to provide explanatory factors for the mobility transition and the impact of policy measures, we need to investigate and monitor people's travel behaviour in much more detail and across modalities. Precisely for this reason, the NVP was introduced. The panel formed by a representative selection of inhabitants allows the daily travel behaviour of thousands of participants to be measured longitudinally using a smartphone app. The omnipresence of smartphones makes it possible to efficiently collect location and travel data for a large number of people. The sensor technology in smartphones automatically tracks people's locations and combines this data with their background characteristics. The measuring technology, data collection method, measuring procedures, and data processing activities are entirely in compliance with the EU's privacy rules (GDPR). The NVP collects far more travel data and more current data than other 'traditional' travel surveys in the Netherlands because the travel behaviour of respondents is measured continuously. Traditional national travel surveys in the Netherlands, such as ODiN (in Dutch: Onderweg in Nederland) and the MPN (in Dutch: Mobiliteitspanel Nederland), use self-reported travel diaries for only one or a few days a year. The NVP allowed constant monitoring of the impacts of the COVID-19 outbreak and taken policy measures on mobility patterns and travel behaviour related to travellers' characteristics.

From March 2020, the start of the COVID-19 pandemic in the Netherlands, the Dutch Ministry of Infrastructure and Water Management receives weekly updates from the NVP on the number of trips, distances travelled, travel times per mode (car, cycling, public transport, pedestrian), and destination choices. The information was sorted by target group (age, income) and geographical area (urbanisation level, regions).

In this paper, we present the results of the analysis with the NVP-data during the first period of the COVID-19 pandemic in the Netherlands and show how it was used by the Ministry of Infrastructure and Water Management to monitor and evaluate the changes in travel patterns and transport mode choice during COVID019 and the impact of different policy measures. Section 2 provides further background on related work, focusing on the use of smartphone apps in travel behaviour research. In Section 3, the NVP data is further described. Section 4 describes the methodology and analysis done. The results are described in Section 5, and the conclusions and discussion can be found in Section 6.

2. Background

Smartphone apps have been acknowledged to have the potential to replace traditional travel surveys to monitor the travel behaviour of participants. Traditional travel surveys, in which respondents are asked to self-report their travel behaviour, are associated with underreporting of short trips and inaccuracy (Thomas et al., 2018). At the beginning of 2000, GPS data loggers were tested and seen as a solution for these problems (e.g., Schönfelder et al., 2002). Although the results were promising and used in practice in some countries as an additional means of data collection, the smartphone's rise reduced the disadvantages of using a GPS data logger in terms of money. Not only because the device costs money but also the labour of distributing, retrieving and reading the devices (Wolf et al., 2004). Because almost everyone owns a smartphone nowadays and even provides the opportunity to use and combine several sensors of the phone to provide the location (i.e. hybrid localisation techniques), there have been numerous developments to use these phones to derive travel data using specific apps. Furthermore, several intelligent algorithms have been developed to reduce the battery drain using additional sensors within the phone (Patterson and Fitzsimmons, 2016; Prelipcean and Yamamoto, 2018).

Over the past years, collecting travel survey information using a smartphone app has become more common (e.g., Allström, Kristofferson and Susilo, 2017; Geurs et al., 2015; Thomas et al., 2018). However, in most cases, the survey is on a regional basis and for a short period. In the Netherlands, the companies Kantar, Mobidot and DAT.Mobility started the NVP in 2019. Over 6,000 people, who already participated in the broader Kantar panel of over 200,000 participants, were randomly selected and recruited, providing a proper distribution in terms of sociodemographics as well as spatial characteristics (residential location). All participants voluntarily installed a smartphone app developed by Mobidot, which automatically tracks and analyses their travel behaviour, allowing us to explore the changing mobility patterns and travel behaviour during the COVID-19 pandemic. This commercial smartphone app, the first version already has been launched in 2013 and further improved ever since, has been used and showed its value in various studies non-scientific as well as scientific (e.g. Geurs et al. 2015; Thomas et al. 2018).

At the same time, there are some challenges and possible errors when using smartphone apps. These challenges are mainly related to the correct detection of trips (missing trips and non-trips) and detection of the accurate modality. The magnitude of these errors depends, for example, on the setting of the gap between trip legs, with higher gaps leading to more missing trips but fewer non-trips detection, as well as the challenge of minimising the battery drainage versus the accuracy of detection (Thomas et al., 2018; Harding et al., 2020).

3. Data

In the analysis, data were used from the NVP. Travel information of the participants (e.g., number of trips, distance travelled, travel mode, origin and destination) was collected entirely GDPR prove 24/7 through the smartphones of about 6,000 participants, including background knowledge which is comparable with traditional repetitive household surveys (e.g. income, age, household size, residential location, gender, car ownership). The setup of the NVP even allows us to do an additional survey among participants, see, for example, Olde Kalter et al. (2021). However, we did not use survey information in the analysis provided in this research.

The methodologies used to detect and classify trips using the smartphone app has extensively been described in Thomas et al. (2018). To summarise this, the automatic trip detection process consists of two stages and four main components. The first stage has one main component comprising the sensing module and battery management. This component uses an array of available sensors in the smartphone to automatically sense the beginning of a trip, movement and trip end. This results in a coherent trace of GPS locations on a raw trip. Combining the sensing techniques with information of, for example, historical travel patterns of the same user and detection of mode during travel resulted in an optimised learning strategy, balancing measurement accuracy and battery consumption. After a trip-end is detected, the raw trip information is uploaded to the backend when communication is possible.

Then the second stage begins, comprising three main components. The first component is the cleaning and map matching. This component filters, cleans and enriches the raw trip data to produce complete map matched trips. The filtering and cleaning are needed to remove outliers. The enrichment is necessary to fill gaps resulting from missing the actual start of the trip or parts in which the location data are missing (e.g. as a result of fast-moving trains or tunnels). This enrichment is based on historical information and logical navigation using all available raw trip data. The map matching process considers all infrastructures (e.g. roads, railroads, bicycle lanes, canals). The second component is mode detection of trip legs (i.e. parts of the complete trip made by the same modality). This means the algorithm used, combined with the multi-modal map matching process, is capable of detecting mode transitions as well. Modes are deduced from the enhanced trip data using probabilistic Bayesian mode deduction models, comparable to the Bayesian belief networks, extensively trained using over 40 features. After the mode detection, a quality and sanity check is used to classify the correctness and cancel out strange mode detection outcomes. The last component is updating and postprocessing. In this component, additional information is derived based on frequently made trips (routes and destinations) combined with spatial context data on activities and land use to deduce the most likely motives and improve the mode detection for different trip legs (e.g. transfers at bus stops and train stations).

Using a smartphone app has its challenges, as described in Section 2. The smartphone app has been improved in the past years based on the deployment in various studies and continuous calibration using feedback of a subset of users. Thomas et al. (2018) reported that the success rates in their deployment of this smartphone app ranged between 78% for distances less than 2 km to 95% for distances more than 20 km. However, it also showed that the application has a better quality in detecting trips (i.e. underreporting issues of traditional survey methods) with a relatively low respondent burden.

In combination with additional knowledge about the participants being part of the panel, the resulting trip data set per participant is used in this research to analyse the travel behaviour of the Dutch population during the COVID-19 developments. Table 1 shows the sociodemographic characteristics of the sample used in the analyses and the Dutch population[1]. Younger people and students are underrepresented in our sample, and employed people are overrepresented. Other sociodemographic characteristics are comparable with the total population, such as gender, the urban density of the residential location, education level and household composition. Overall, our sample fairly represents the composition of the Dutch population. Also, the composition of the sample is very stable over time.

Table 1. Sociodemographic characteristics of the sample

Variable	Categories	Sample March	Sample May	Sample August	Population
gender (%)	male	46.8	46.8	47.5	49.7
	female	53.2	53.2	52.8	50.6
age	16-24	2.0	1.8	2.1	13.5
	25-44	33.7	35.8	33.4	29.9
	45-64	44.0	42.3	44.6	34.3
	65+	20.3	20.0	19.9	22.3
urban density (inhabitants/km2, %)	low (<500)	9.2	9.1	8.9	7.8
	medium (500-1500)	38.2	38.2	37.8	37.2
	high (>1500)	52.6	52.7	53.3	55.0
education (%)	low	20.9	19.9	20.1	22.2
	medium	41.1	41.8	40.7	41.1
	high	38.0	38.3	39.2	36.7
main occupation (%)	unemployed	32.5	32.0	31.2	38.1
	employed	66.0	66.5	67.0	54.4
	student	1.5	1.5	1.8	7.5
household size (%)	1 person	19.8	19.2	19.0	21.1
	2 persons	41.7	41.7	42.8	35.7
	>2 persons	38.5	39.1	38.1	42.9
household composition (%)	single	19.8	19.2	19.0	21.1
	family with children <12 yr	21.7	22.7	21.5	20.2
	family with children >12 yr	7.8	8.1	8.2	10.0
	multiple adults	50.7	50.1	51.3	48.6

4. Method

The cleaned, map matched, and classified trips and the background information available of the participants (see Section 3) are used to analyse the travel behaviour over time. All calculations have been done by using a PostgreSQL relational database that contains all trips and statics. A trip is stored as a single record that describes the trajectory, mode of transport, start time, duration, destination, user id and many other characteristics. If someone uses multiple modes of transport to get from A to B, multiple trips will be stored in the database. For example, if somebody commutes to work by public transport but first cycles to the railway station, then takes the train, and finally walks to the office, this is considered as three separate trips with different transport modes. A static is a single record that captures the time and location between subsequent trips, for example, the time a participant spends at the office or home.

[1] Population statistics conform the 'Gouden Standaard' at 2019 (MOA, 2020)

The analysis focuses on the observed trends of the following aspects:

- the average number of trips, trip distance and travel time per modality
- the destination/motives of trips
- the demand profile per modality per day of the week
- the modal split depending on trip length.

4.1 Average number of trips, trip length and travel time per modality

The average number of trips, the average travel distance and the average travel time per participant is calculated to provide insight into the amount of mobility per day. Since the number of participants of the NVP is not necessarily constant over time (e.g. because participants drop out, are no longer willing to participate), the daily totals are divided by the number of participants on that specific day. The daily number of participants includes those who stayed at home all day. The normalisation makes it possible to compare average travel patterns over time. All calculations were done for each transport mode. Using the participants' background characteristics makes it possible to compare the travel patterns based on, for instance, income and different age groups.

4.2 Destination/motives of trips

Each trip is enriched with a destination type and trip motive. This classification is done in the second stage of the automatic trip detection (see section 3). It makes it possible to calculate the percentage of participants that visited a specific destination, or cluster of destinations, on a particular day. The following destinations were taken into account: offices, education, healthcare, sports, supermarkets, and shopping. The number of unique users that visited a specific destination type was calculated for each day. The number of unique users was divided by all participants on that day to calculate the percentage of users who visited that specific destination type. All values were normalised using a reference day or week to make the visits to different destinations more comparable. Indexing makes it easier to analyse trends over time.

4.3 Demand profile per modality per day of the week

Many traffic-related problems and bottlenecks occur at specific periods of the day. Traditionally, the morning and evening peak hours are the periods of the day when the traffic volumes max out. Spreading travellers over the day is an important goal during the COVID crisis. To monitor this, insights into the number of people that travel at specific periods of the day are required. For this purpose, the percentage of people travelling at each minute of the day was calculated per mode. Time steps of 1 minute per day were intersected with the trip records. This results in the number of participants travelling per minute and per transport mode. These numbers per minute were compared by the total number of panel members on that specific day, resulting in the percentage of people that travelled during that specific minute per mode. By computing, this percentage for all minutes of that day provides a demand profile per mode.

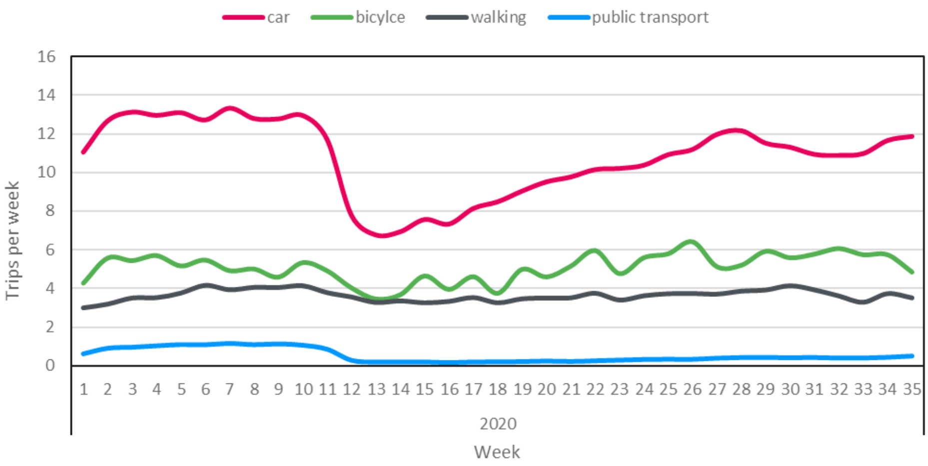
4.4 Modal split depending on trip length

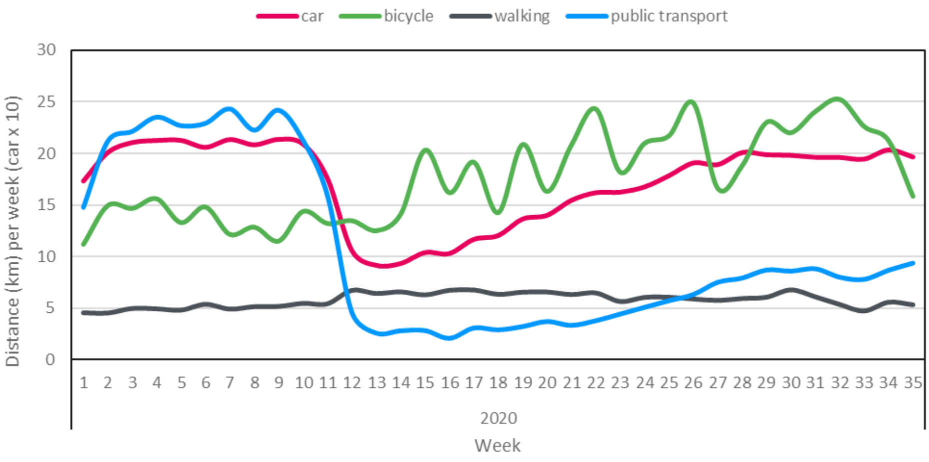
Insights in the modal split per trip length is another important indicator for policymakers. It makes it, for example, possible to study the share of public transport for trips longer than 10 km. Or the share of the active modes for trips shorter than 2,5 km. Modal split percentages were calculated by dividing all trips of a specific mode of transport per day by the total number of trips on that same day. The calculations were done for different trip lengths: <1 km, 1–2,5 km, 2,5– 10 km, 10–25 km, 25–50 km, and ≥50 km. Finally, daily numbers were aggregated to weekly averages on workdays, excluding national holidays and weekends.

5. Results

5.1 Average statistics

Figure 2 provides the trend in the weekly average number of trips, trip distances, and travel times per modality. The statistics show that mobility reduced substantially after communicating the restrictions in week 12 (start of the first lockdown). Still, it took one more week to reach the highest reduction in terms of the number of trips and trip length. The combination of closure of schools one week later, the communication, and possibly the time needed to adjust probably explains this latency. Public transport usage reduced by 90% and car usage by almost 50%. Cycling remained relatively constant in terms of distance. However, the number of trips decreased by nearly 50%. Walking also remained stable, although a slight decrease is visible in the number of trips at the end of March. Travel times also substantially reduced for car and public transport, however, remained constant or even increased for cycling and walking. However, the data also show that mobility gradually increased directly after this substantial reduction, partly associated with the relaxation of measures taken. Public transport remained low, although they normally operated from June 2020 and people were allowed to use it. Furthermore, in this period, there is an increase in cycling visible. However, the latter can also be due to seasonal impacts (weather). At the end of June, the beginning of July 2020, travel distances made by car are almost similar to before the first lockdown, as is the case for travel times. The number of car trips is slightly lower, which might be influenced by increased bicycle usage.





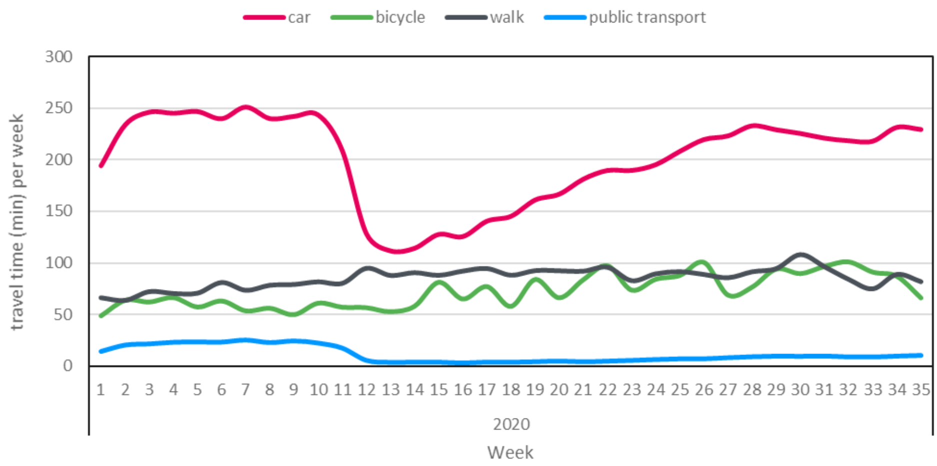


Figure 2. Average number of trips, distance travelled and travel time per week (Source: NVP)

If we further zoom in (see Figure 3), we see that the average travel time for cycling in the pre-covid period was higher in the highly urbanised areas than non-urbanised. However, the average travel times became more similar after the lockdown independent of the urbanisation level. The decrease in cycling in urbanised areas is mainly because using the bicycle as a first or last-mile solution for public transport reduced substantially, and students did not attend the university. The figure also shows an increase in travel times on aggregated level during the first lockdown, which indicates the higher use of bicycles as a transport mode.

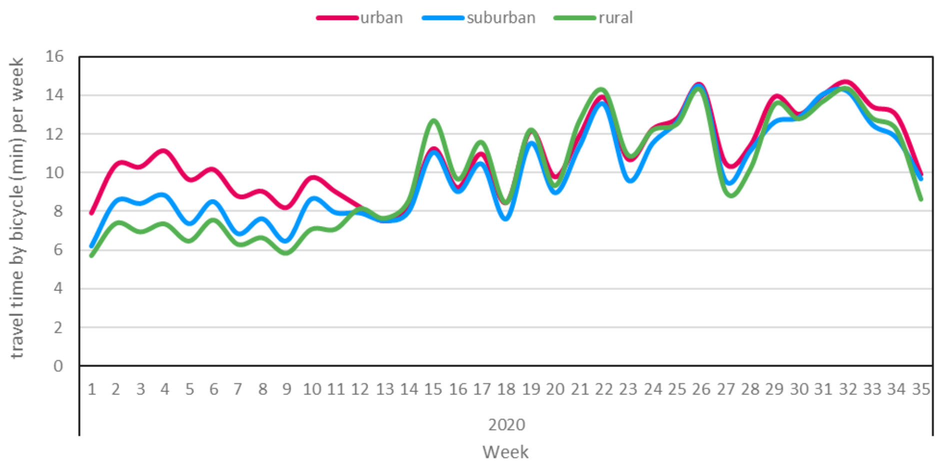


Figure 3. Average travel time per week by bicycle per urbanisation grade (Source: NVP)

Figure 4 shows the average car travel time per week depending on income class. The figure shows that people with high incomes spent the most time in the car in the pre-covid period and showed the largest decline during the first lockdown. As a result, the average travel times became more similar for all income classes, which indicates that higher income classes have more opportunities to reduce travel (e.g. better options to work from home). Also, the reason to travel by car during the first lockdown period could be more similar, for example, related to necessary trips like getting groceries or recreational trips like visiting nature, less dependent on income (also see paragraph 5.2).

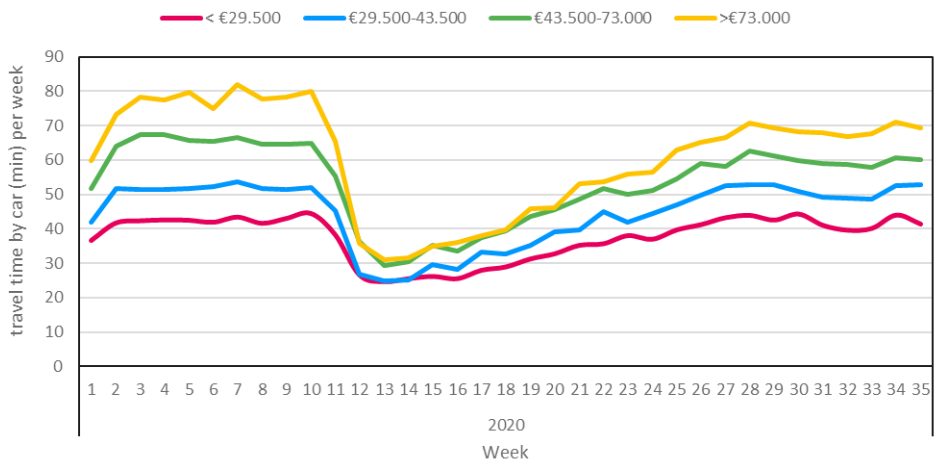


Figure 4. Average travel time per week by car per income class (Source: NVP)

Figure 5 shows the average travel time for all modes depending on age. The results show that the travel times of age groups 18–34 years and 35–64 years declined more substantially compared to the age group 65 years and older. This is directly related to employed people working from home and the closure of universities, as shown in the next paragraph in which the changes in destination and motives are presented. The fact that the average travel time for the age group 65 and older shows less or almost no decline indicates that the reasons for this age group to travel are in general closely related to necessary travel or activities which were still possible during the first lockdown. The 'Breverwet', also known as Marchetti's constant, states that the travel time budget people use to travel on average is relatively constant between 60 and 90 minutes per day. Although there is a discussion about whether the travel time budget is stable and the interpretation of this constant travel time budget (e.g. Van Wee et al. 2006), this does certainly not hold when there are severe restrictions on activities.

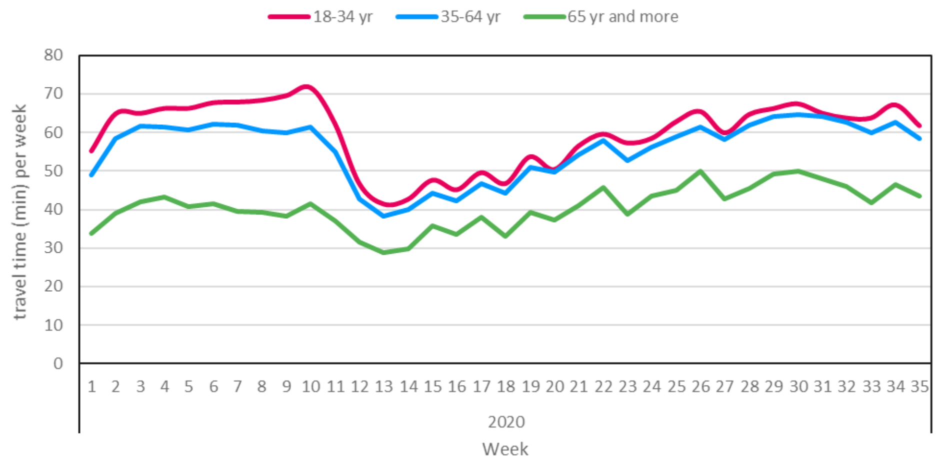


Figure 5. Average travel time per week by per age group (Source: NVP)

5.2 Destination of trips

Figure 6 shows the trend in destinations of trips made for non-recreational and recreational trips. The results show that almost all destinations reduced at the beginning of the first lockdown (i.e. more people stayed at home). Especially offices, schools and medical care were less visited. Sport practically completely vanished because it was almost impossible to practice sports because of all the closures. Furthermore, a substantial increase is found in people making a short trip around the block, as well as a reduction in shopping. The trend in the following weeks shows a slight increase in people travelling to their work again. However, this remained substantially low while visiting nature and shopping turned out to be higher than before the lockdown. After the reopening of several sports facilities, visiting these locations increased again. However, it remained below the level before the lockdown, which is also related to the fact that not all sports facilities were reopened. The short trips around the block slightly decreased again over time.

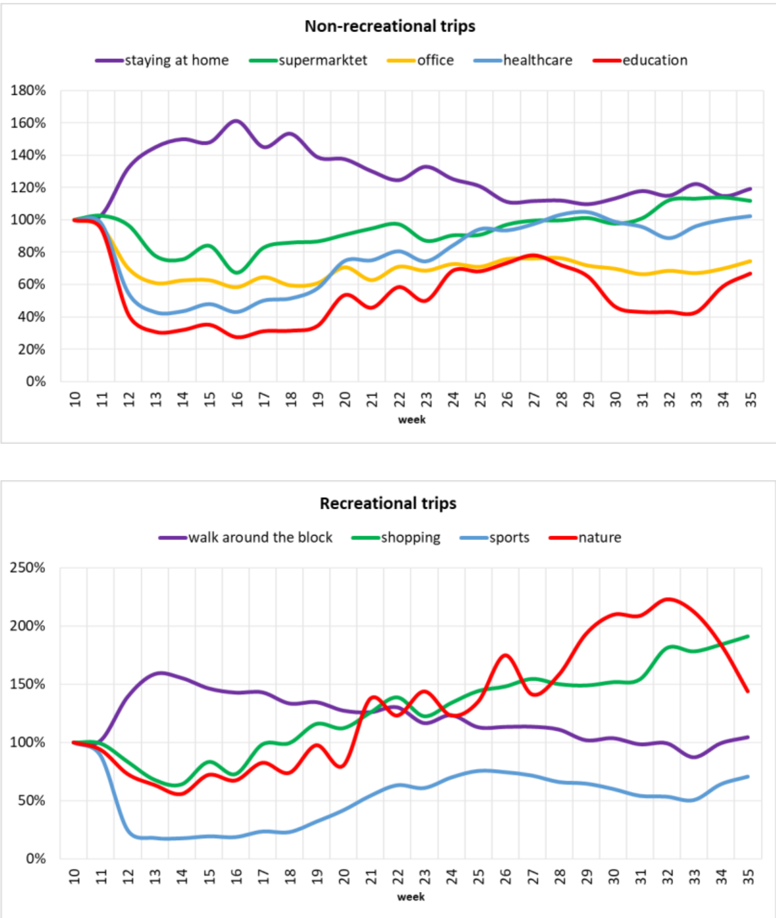


Figure 6. Destination of trips per week, index week 10/11=100 (Source= NVP)

5.3 Demand profile per modality

Figure 7 shows the car and public transport demand profiles at the beginning of the first lockdown on Tuesday 7 April (red) and on Tuesday 23 June (blue). The figures also show a reference demand profile derived from data of the week of 1 March before the first lockdown. The demand profiles show that public transport is still hardly used. Concerning the car, the demand profile flattened for the weekdays, with less peak demand during the rush hours. Although the absolute demand levels increased during the weeks after the beginning of April, resulting in almost similar levels as before the first lockdown, the profile itself remained relatively flat. This means that the typical rush-hour demand (especially the morning rush hour) was less visible. Although mobility statistics show similar averages, the purpose of travel is different than before the first lockdown, which is also shown in the analysis of destinations (decrease of home-work trips). The demand profiles of the active modes (not shown) are similar or higher, especially regarding cycling, than the reference demand profiles (week of 1 March before the lockdown), confirming the increase of use of active modes, while the demand profiles in weekends show similar patterns compared to the reference.

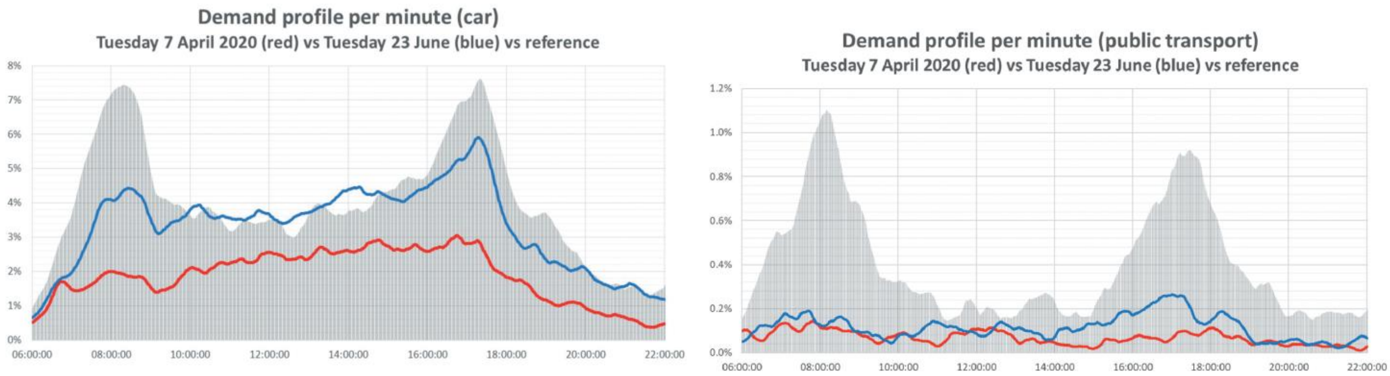


Figure 7. Demand profiles for the car and public transport (Source= NVP)

5.4 Modal split

Figure 8 shows the modal split depending on trip length at the beginning of the first lockdown (week 14, 30 March–5 April) compared with the reference week (determined based on data of the week of 1 March before the first lockdown). In general, the figure shows that the trip length distribution slightly changed at the beginning of the first lockdown (more shorter trips). During the period after the presented week 14, the trip length distribution gradually changed in the direction of the reference week. However, in terms of the modal split, the considerable reduction in public transport usage remained and the increase of active modes for longer distances. This indicates that cycling was an alternative for public transport for medium distances (10–25 km) and coincides with the substantial reported increase in sold e-bikes. However, part of these longer cycling trips is related to recreational purposes, and part of the decrease in public transport usage is related to not travelling at all.

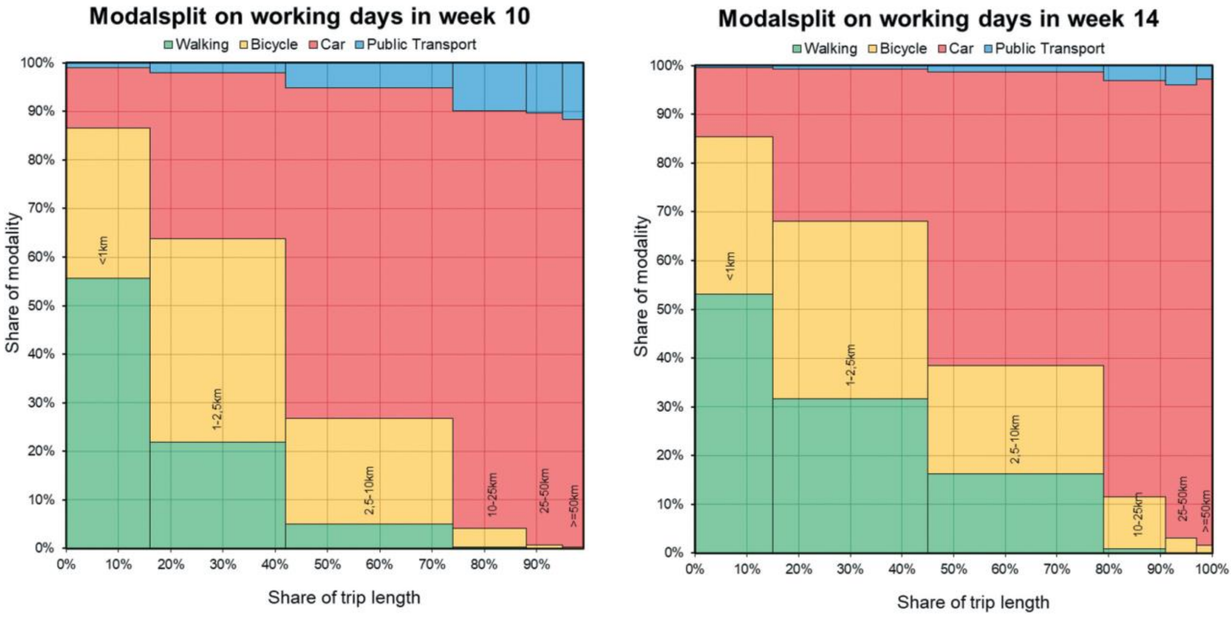


Figure 8. Modal split trip length distribution (Source= NVP)

5.6 Synthesis

Combining the statistics shows that at the beginning of the first lockdown in March, it took one additional week before the most significant impact on mobility was found. Car usage decreased on average by almost 50%, and public transport was avoided and practically not used. Active modes did show some differences, but average levels remained similar or were even higher. Making a short walk around the block increased substantially in the first weeks of the lockdown. The travel behaviour analysis depending on urbanisation level, income, and age shows that during the lockdown, the travel patterns became more similar (i.e. independent of age or income) than pre-COVID-19. This indicates that travel became more similar (related to necessary trips like visiting the supermarket or recreational activities that were allowed like visiting nature). People began to travel more again from mid-April, especially for leisure and shopping. From June, car travel increased again, showing almost similar car usage as before the first lockdown, especially during the traditional off-peak periods and weekends. With the increase of trips related to visiting nature and shopping, the short walks around the block decreased again. The increase in trips can partly be related to the measures taken, especially the reopening of schools which also impacts the possibility for parents to travel again. Commuter travel increased, but less than other motives, resulting in lower rush hour peak demands. Public transport usage remained low, although busses and trains operated following the regular timetables again from the first of June and also the 1.5 m obligation was relaxed for this modality. Cycling increased substantially as an alternative mode, not only in terms of the number of trips but also the distance travelled. The peak demand for cycling showed similar or higher usage of bicycles and substantially higher usage during off-peak periods compared with the period before the first lockdown. However, this can also be partly explained due to seasonal effects.

6. Conclusions

There are a lot of uncertainties about the travel information collected through smartphones. Mainly, the unavailability of demographic characteristics of smartphone users makes it difficult to analyse the data from a behavioural perspective. The NVP is designed to include such information along with a continuous recording of spatial mobility information. The COVID-19 crisis had an enormous impact on society, with regrettably many casualties around the world and severe economic consequences. Also, the COVID-19 outbreak and associated restrictions had a disruptive impact on mobility, but not necessarily a negative impact (e.g. less travel, less congestion and less emissions). Because the NVP already existed before the COVID-19 outbreak, it contains valuable information to analyse and compare the travel behaviour before, during and in the future after the COVID-19 outbreak.

Using the NVP, the changes in travel behaviour were analysed weekly, including a comparison of behaviour dependent on the characteristics of participants. Based on this analysis, it becomes clear that not everyone needs to travel during peak hours. Commuter travel is also not the main reason for the increase of car usage towards similar levels as before the first lockdown during the phase in which measures were taken lifted again. During the first lockdown, travel behaviour also became more similar independent of age and income. Furthermore, cycling has shown to be an alternative option for travellers. Although public transport is hardly used, this mode is next to active modes, an essential part of the mobility transition needed. It will be a challenge to increase its use after COVID-19 because we do not yet know to what extent users will return to public transport again. If it is possible to sustain the lower level of car usage and integrate public transport as an important alternative for travel again, the COVID-19 impact on mobility could have a substantial remaining positive impact.

The findings found are in coherence with other recently reported research; however, the added value of this data is continuous measurements. The Ministry of Infrastructure and Water Management received the most recent data from the NVP weekly. The Ministry used this data to monitor the travel behaviour of different groups and with varying modes of transport every week during COVID-19 and to provide insight into changes in travel behaviour. From the beginning of the first lockdown, the central message of the government was to work at home, avoid busy places and areas, and travel outside peak hours as much as possible. The actual data from the NVP enabled the Ministry to monitor to what extent people followed these rules. Traditional travel surveys are not able to provide this up-to-date data. In addition, these data are used to evaluate the impact of different policy measures taken and the possible consequences of up-or-downscaling these measures. For example, after reopening the primary schools in the Netherlands, there were some concerns that too many parents would take their children to school by car and that this would create bottlenecks by dropping off and picking up the children. However, the data showed an apparent increase in walking and cycling trips to and from primary schools after reopening. Also, the week-to-week indicators of travel behaviour showed some exciting trends for policymakers. Although people are already used to cycle a lot in the Netherlands, during COVID-19 both the number of cycling trips and the distance travelled by bicycle increased. Partly because of changing weather conditions, but also because people switched from public transport or car to the bicycle. Especially for home-based commuting trips, the share of cycling increased. This is in line with the ambition of the Ministry to stimulate cycling for commuting. Because the NVP provides insight into sociodemographic characteristics of people who change behaviour and who do not change, this information helps develop policy measures for different groups. It also means that the data about changes in travel behaviour can also be used for implementing future policy after COVID-19.

This study shows the added value of actual and continuous GPS tracking data to examine changes in travel and activity patterns, which is not possible with traditional cross-sectional surveys and 1- of 3-day travel diaries. he NVP continues, and the data collected will also be used to analyse future behaviour 'after' the COVID-19 crisis, which was still ongoing when submitting this article. The NVP measures revealed preferences and already provided valuable insights as reported, but can be further exploited to understand better the behavioural changes related to the available background information of participants. Furthermore, an additional survey can be done among the participants to collect additional information on preferences and intentions. Future work focuses on gaining this more in-depth knowledge, estimating behavioural models based on this data to explain the behaviour. This knowledge can be used as an input for policy to sustain the positive behavioural impacts found. Furthermore, the NVP also provides several opportunities to investigate, such as the differences in choices people make after COVID-19 (i.e. what is the impact on travel behaviour in the long run) as well as the difference between the actual access and choices people make for activities related to the 15-min neighbourhood which has been introduced as part of the solution for the mobility transition.

References

Allström, A., Kristoffersson I., Susilo, Y. (2017). Smartphone Based Travel Diary Collection: Experiences from a Field Trial in Stockholm. In Transportation Research Procedia, 32–38.

Bricka, S., Bhat, C. R. (2006). Comparative analysis of Global Positioning System–based and travel survey–based data. Transportation Research Record, 1972(1), 9-20.

Ettema, D., Timmermans, H., van Veghel, L. (1996). Effects of data collection methods in travel and activity research.

Wolf, J. L. (2000). Using GPS data loggers to replace travel diaries in the collection of travel data (Doctoral dissertation, School of Civil and Environmental Engineering, Georgia Institute of Technology).

Geurs, K.T., Thomas, T., Bijlsma, M., Douhou, S. (2015). Automatic Trip and Mode Detection with Move Smarter: First Results from the Dutch Mobile Mobility Panel. Transportation Research Procedia 11: 247–262.

Harding, C., Faghih Imani A., Srikukenthiran, S., Miller, E., Nurul Habib, K. (2020). Are We There Yet? Assessing Smartphone Apps as Full-fledged Tools for Activity-travel Surveys. Transportation 201: 4.

Olde Kalter, M.J.T., Geurs, K.T., Wismans, L.W.J. (2021). Post COVID-19 teleworking and car use intentions. Evidence from large scale GPS-tracking and survey data in the Netherlands. Transportation Interdisciplinay Perspectives, 100498.

Patterson, Z., Fitzsimmons, K. (2016). DataMobile: Smartphone Travel Survey Experiment. Transportation Research Record: Journal of the Transportation Research Board 2594 (1): 35–43.

Prelipcean, A. C., Yamamoto, T. (2018). Workshop Synthesis: New Developments in Travel Diary Collection Systems Based on Smartphones and GPS Receivers. In: Transportation Research Procedia, 119–125.Rodrigue, J. P. 2020. The Geography of Transport Systems, 456. 5th ed. New York: Routledge.

Schönfelder, S., Axhausen, K., Antille, N., Bierlaire, M. (2002). Exploring the Potentials of Automatically Collected GPS Data for Travel Behaviour Analysis a Swedish Data Source. Arbeitsberichte Verkehrs- und Raumplanung, 124, working paper.

Thomas, T., Geurs, K.T., Koolwaaij, J., Bijlsma, M.E. (2018). Automatic Trip Detection with the Dutch Mobile Mobility Panel: Towards Reliable Multiple-Week Trip Registration for Large Samples. Journal of Urban Technology 25 (2): 143–161.

Wee, B., Rietveld, P., Meurs, H. (2006). Is Average Daily Travel Time Expenditure Constant? In Search of Explanations for an Increase in Average Travel Time. Journal of Transport Geography 14 (2): 109–122.

Wolf, J., Bricka, S., Ashby, T., Gorugantua, C. (2004). Advances in the Application of GPS to Household Travel Surveys. In: National Household Travel Survey Conference, Washington DC.