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Transportation Research Procedia 62 (2022) 99–106

Transportation Research Procedia

www.elsevier.com/locate/procedia

24th EURO Working Group on Transportation Meeting, EWGT 2021, 8-10 September 2021, Aveiro, Portugal

Impacts of the COVID-19 pandemic in the demand for urban transportation in Budapest

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Abstract

Social distancing guidelines established amid the COVID-19 pandemic have decreased the number of trips in urban transportation networks; furthermore, travelers have shifted away from high occupancy modes due to the fear of contagion. This scenario has led to reduced public transportation ridership and increased shares of private cars, cycling and walking in urban areas. In the international literature, predictive models for this scenario of changed travel behavior and imminent needs for operations and planning adjustments, however, are still scarce or limited in scope.

Holt-Winter's multiplicative method was used to extrapolate pre-pandemic datasets as a means to evaluate the impacts of the pandemic in transportation activities in Budapest. Data from March 2020 indicate that stay-at-home orders have resulted in intra-city and commuter traffic reductions of about 35%, while public transportation ticket sales decreased by 90%. Bicycle traffic, on the other hand, increased by about 13% in the same period. These observations suggest that the COVID-19 pandemic has driven significant changes in trip generation and mode choice in Budapest.

This study proposes the adjustment of a pre-existing four-step transportation model of Budapest based on the introduction of contextual explanatory variables and on the recalibration of model parameters in order to reflect pandemic-related trends in trip generation and trip distribution. The recalibration and validation of the model were based on data from the first wave of the pandemic in Hungary. Validation results, although limited, suggest that the traditional four-step models are able to capture the impacts on transportation of the atypical scenario of a pandemic with relatively simple adjustments and few data requirements.

Keywords: COVID-19; macroscopic model; lockdown; mobility demand; Budapest

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10.1016/j.trpro.2022.02.013

1. Introduction

The high infectivity of the coronavirus SarS-COV-2, the pathogenic agent of the COVID-19 disease, has made it quickly disseminate around the world and led to a worldwide pandemic in a matter of weeks (World Health Organization, 2020). As of the end of the first semester of 2021, the total number of COVID-19 cases had surpassed 182 million on a worldwide level, and the death toll was of nearly 4 million people; in Hungary, these numbers were of 800 000 and 30 000, respectively (Ritchie et al., 2020). Most countries have dealt with this pandemic by adopting public health strategies that aimed to slow down the spread of the virus and prevent rapid growths in the number of infected citizens (Hale et al., 2021). The establishment of lockdowns or curfews have been proposed, at different levels, by a large number of countries – with Hungary included – and social distancing has been widely encouraged.

These containment measures and guidelines resulted in profound impacts on lifestyle. People became more inclined to perform activities at home, such as socializing on a virtual setting and purchasing goods through online shopping. Teleworking, or working from home, became more popular (Beck et al., 2020; Shamshiripour et al., 2020) especially for management, scientific and technical jobs (Dingel and Neiman, 2020). Eurofound (2020) estimates that about 28% of Hungarian professionals worked from home during the first wave of the COVID-19 pandemic. Online education has been adopted as an alternative to in-person education in countries where universities or schools were closed, including Hungary.

A survey conducted in Japan identified that, at the beginning of the pandemic, trip frequencies, for most trip purposes, decreased as the number of COVID-19 cases increased in the country (Parady et al., 2020). In general, traffic volumes decreased in most urban areas, leading to decreased average travel times and increased average vehicle speeds that sometimes reached free-flow conditions (Wang et al., 2020; Zuo et al., 2020).

Avoiding contact with other passengers can be hard in public transportation, especially during peak hours, when high levels of passenger occupancy are common. The existence of multiple surfaces that can carry pathogenic agents, such as ticket machine displays, vehicle seats and handholds, may also discourage users from opting for transit alternatives during a pandemic. In fact, public transportation ridership has reportedly decreased in various countries at the beginning of the pandemic, while private motoring shares increased. In Budapest, a 90% drop in passenger numbers in the public transportation was observed in the last week of March, 2020 while the mode share of passenger cars increased from 43% to 65% (Bucsky, 2020). In New York City, subway and car trips had reductions of 89% and 58%, respectively, in March, 2020 (Wang et al., 2020). In Chicago, from March 2020 to April 2020, an average ridership reduction of 72% was observed in transit stations (Hu and Chen, 2021). In Stockholm, the metro and the commuter trains had a ridership reduction of about 60% in mid-March, 2020 (Jenelius and Cebecauer, 2020).

Increased teleworking frequencies were found to play a key role in the reduction of commuter trips in the first wave of the pandemic in Australia; their relationship was modeled through ordered choice logit models in conjunction with Poisson regressions (Beck et al., 2020). A logistic model has been used to describe the probability that a user opted for rail transportation during the pandemic in China. The study identified that occupation, walking time to the nearest station, commuting tools before the pandemic and the perception of risk of infection had a major influence on a traveler's mode choice (Tan and Ma, 2020). A linear regression was used to model the shift of travelers from the subway to bike sharing alternatives in New York City; this shift became more prominent as the daily number of new cases in the city increased (Teixeira and Lopes, 2020). An agent-based simulation of New York City's transportation system was updated for pandemic conditions by introducing work from home statistics into its synthetic population layer and by adjusting the mode-specific constants in its underlying mode choice model. The study concluded that, due to behavioral inertia, public transportation would likely operate with decreased ridership in a post-COVID reopening, whereas car traffic could reach 142% of pre-COVID levels without transit capacity restrictions (Wang et al., 2020).

Although impacts of the pandemic in trip generation and mode choice have been widely reported, modelling frameworks that take into consideration traveler behavior changes within traditional four-step models are still scarce or limited in scope. On that point, the aim of this paper is to build on a pre-existing four-step model of Budapest in order to account for reported changes in trip generation and in mode choice that resulted from the restrictive measures adopted in Hungary during the first wave of the COVID-19 pandemic (March and April of 2020). By doing that, we intend to propose a framework for the adjustment of trip-based demand models, with relatively few data requirements, so that transport planners and policymakers are able to react to changed network conditions due to the pandemic.

2. Methodology

2.1. Data collection and cleaning

Data were gathered from a wide set of sources: bike sharing data from MOL-Bubi system; bicycle counts from 5 collection points; traffic counts from 6 bridges over the Danube river and from main routes in the suburbs of Budapest; public transportation ticket sales from the Centre for Budapest Transport (BKK) and ridership data from 4 public transportation lines. The spatial distribution of these collection points, as well as their time coverage and level of aggregation are in Souza (2020). For the datasets comprising at least 3 years of monthly observations prior to March 2020, Holt Winters' (Winters, 1960) triple exponential smoothing method, in its multiplicative form, was used to extrapolate a baseline time series from which the impacts of the pandemic were assessed. Alternatively, for the datasets in which that condition was not satisfied, a year-to-year comparison was performed between analog periods in 2019 and 2020. The daily distribution of trips was also compared between pre-pandemic and post-pandemic datasets. Minor data gaps, when present, were filled by using linear regressions with correlated datasets.

2.2. 4-step modelling

A four-step transportation model was developed with the purpose of depicting Budapest's transportation network conditions under the restrictive measures adopted during the COVID-19 pandemic. It builds on the transportation module of Juhász's LUTI model for Budapest (Juhász and Koren, 2017) by introducing or recalibrating parameters in order to capture changed traveler behaviors during that period.

The proposed trip generation model introduced three multiplying factors to the original one. Productions and attractions in a zone i were calculated as follows (Juhász and Koren, 2017):

$$Prod_i = (\gamma a)R_i + (\alpha b)W_i + (\beta c)S_i + (7\gamma a + \alpha bd)WPS_i + (\alpha bd)WPP_i + (\beta ce)SP_i \quad (1)$$

$$Attr_i = (\gamma a)R_i + (\alpha bd)W_i + (\beta ce)S_i + (\alpha b + 7\gamma a)WPS_i + (\alpha b)WPP_i + (\beta c)SP_i \quad (2)$$

where R_i, W_i, S_i, SP_i, WPS_i and WPP_i are the number of residentes, the number of workers, the number of students, the number of school places, the number of service workplaces and the number of production workplaces in zone i; the α, β and γ parameters were introduced to the original model in order to account for teleworking, reduced in-person education and other social distancing trends, respectively; b, c, d and e are coefficients that need to be calibrated and whose values were extracted from the original model; a is a coefficient that can be calculated as (Juhász and Koren, 2017):

$$a = \frac{TTB^t\, R^t - T_{WR}^{t-1} ATT_{WR}^{t-1}}{ATT_{NWR}^{t-1}(R^t + 7WPS^t)} \quad (3)$$

where TTB is the travel time budget for an average resident (in minutes); T_{WR} is the total of work-related trips; ATT_{WR} is the average travel time of work-related trips; and ATT_{NWR} is the average travel time of non-work-related trips. The superscripts t and t-1 denote the time period, in the original LUTI model, from which each parameter must be taken.

Trip generation (Beck et al., 2020; Borkowski et al., 2021; Morita et al., 2020; Parady et al., 2020; Pawar et al., 2021; Wang et al., 2020) and mode choice (Luan et al., 2021; Tan and Ma, 2020; Teixeira and Lopes, 2020; Wang et al., 2020; Zhang and Fricker, 2021) were remarkably affected by the pandemic circumstances. Trip distribution may have been somewhat affected, especially for trips with relatively flexible destinations, such as trips with leisure or shopping purposes; route choice, on the other hand, may have been affected by diminished traffic loads. The impacts of the pandemic over these demand modelling steps, however, have not been stressed. Juhász and Koren's original double constrained gravitational model for trip distribution was assumed to remain valid in this study (Juhász and Koren, 2017).

Mode choice was modeled as a two-level nested logit model and comprised private cars, public transportation and bicycle as mode alternatives for travelers. Car availability, which comprises car ownership and occupancy, was taken into consideration at the first decision level of the model. The numbers of interzonal trips performed by car, public transportation and bicycle were respectively calculated as (Juhász and Koren, 2017):

$$T_{c,ij,pc} = \sum_c T_{c,ij} CA_i \frac{Imp_{c,ij,pc}}{Imp_{c,ij,pc}+Imp_{c,ij,pt}+Imp_{c,ij,bi}} \tag{4}$$

$$T_{c,ij,pt} = \sum_c T_{c,ij} \frac{Imp_{c,ij,pt}}{Imp_{c,ij,pt}+Imp_{c,ij,bi}} \tag{5}$$

$$T_{c,ij,bi} = \sum_c T_{c,ij} \frac{Imp_{c,ij,bi}}{Imp_{c,ij,pt}+Imp_{c,ij,bi}} \tag{6}$$

$$CA_i = \begin{cases} COw_i COcc, if\ COw_i\ COcc < 1 \\ 1\ otherwise \end{cases} \tag{7}$$

$$Imp_{c,ij,pc} = exp\ (a_{pc,c} + b_{pc,c}tt_{ij,pc} + c_{pc,c}pt_{ij} + d_{pc,c}\frac{rc_{ij}}{VOT_c} + e_{pc,c}\frac{VOC_{ij}}{VOT_c}) \tag{8}$$

$$Imp_{c,ij,pt} = exp\ (a_{pt,c} + b_{pt,c}ivt_{ij} + c_{pt,c}cht_{ij} + d_{pt,c}wt_{ij} + e_{pt,c}\frac{PTF_{ij}}{VOT_c}) \tag{9}$$

$$Imp_{c,ij,bi} = exp\ (a_{bi,c} + b_{bi,c}tt_{ij,bi})geo_{ij} \tag{10}$$

where c indexes the purpose of the trip (work-related on non-work-related); COw_i is the car ownership of zone i (the number of cars per 1000 residents); COcc is the average car occupancy in the city; $tt_{ij,pc}$ is the travel time, by car, between zones i and j (in minutes); pt_{ij} is the parking time between zones i and j (in minutes); rc_{ij} is the road charge (with parking fees included) between zones i and j (in Euros); VOT_c is the value of time for a traveler (in Euros per minute); VOC_{ij} is the vehicle operating cost between zones i and j (in Euros); ivt_{ij} is the in-vehicle time between zones i and j (in minutes); cht_{ij} is the transfer time between zones i and j (in minutes); wt_{ij} is the origin waiting time between zones i and j (in minutes); PTF_{ij} is the public transportation fare between zones i and j (in Euros); $tt_{ij,bi}$ is the travel time, by bicycle, between zones i and j (in minutes); and geo_{ij} is a geographical factor between zones i and j. The other terms in the equations are mode-specific coefficients that need to be calibrated.

For the assignment of trips to the network model, the PTV VISUM 2020 software with a standard equilibrium assignment method was used for private modes and a headway-based assignment was used for public transportation. The zoning system comprised 192 zones in total - 162 subdistricts of Budapest and 30 suburban agglomeration areas. (Juhász and Koren, 2017).

3. Discussion

3.1. Observed trends in Budapest

Public transportation ticket sales saw an abrupt decrease during the pandemic. Daily-use ticket sales decreased by 67% in March 2020 and by 97% in April 2020, while single-use ticket sales (either bought as single ticket or a bundle of 10) decreased by 52% in March 2020 and by 90% in April 2020. These observations suggest a large reduction in the number of tourists in Budapest as a result of the closure of Hungarian borders. Fig. 1 displays actual sales and forecasted sales for these ticket types between 2017 and 2020.

Bucsky (2020) suggests that, overall, the public transportation system in Budapest may have experienced a ridership reduction of up to 90% in March. This number is quite similar to those reported to the subway network in New York City (Wang et al., 2020) and to the public transportation network in Italy (Moovit, 2020). In November 2020, public transportation lines 25 and 196A had ridership reductions of 49% and 30% in comparison to the same periods in 2019.

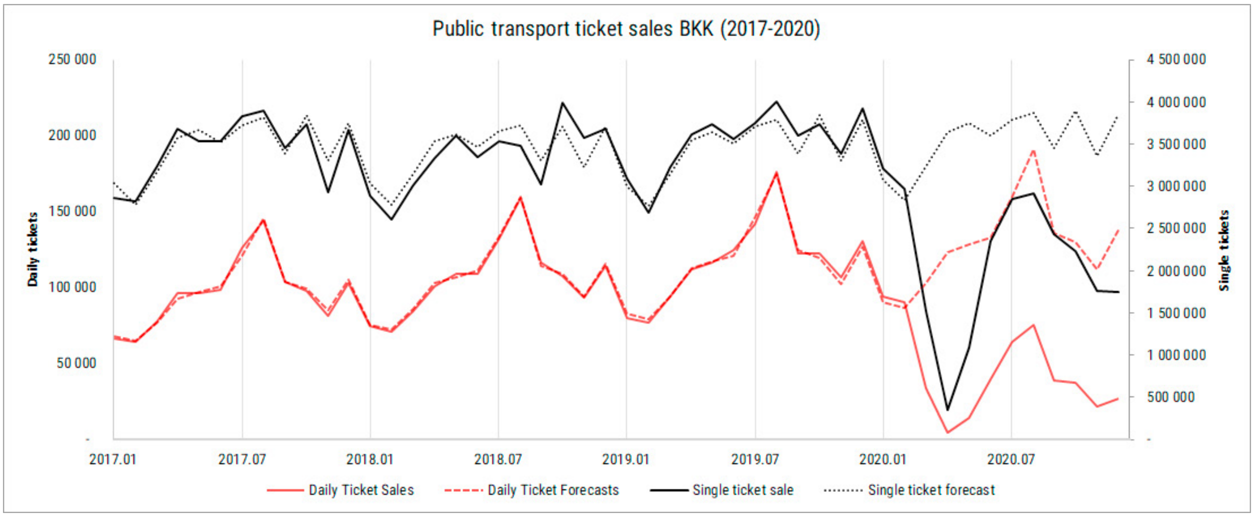


Fig. 1. Actual and forecasted single-use ticket and daily ticket sales by the BKK Centre for Budapest Transport (2017-2020).

In relation to forecasts, in March 2020, a growth of 56% in bicycle rentals was observed in the MOL-Bubi system, followed by a bigger growth of 101% in April. The aggregated data from the available Eco Counter datasets revealed bicycle traffics growths of 13% and 4% in March and April 2020, respectively. The monthly bicycle counts from the available datasets in 5 different locations are shown in Fig. 2 for 2019 and 2020.

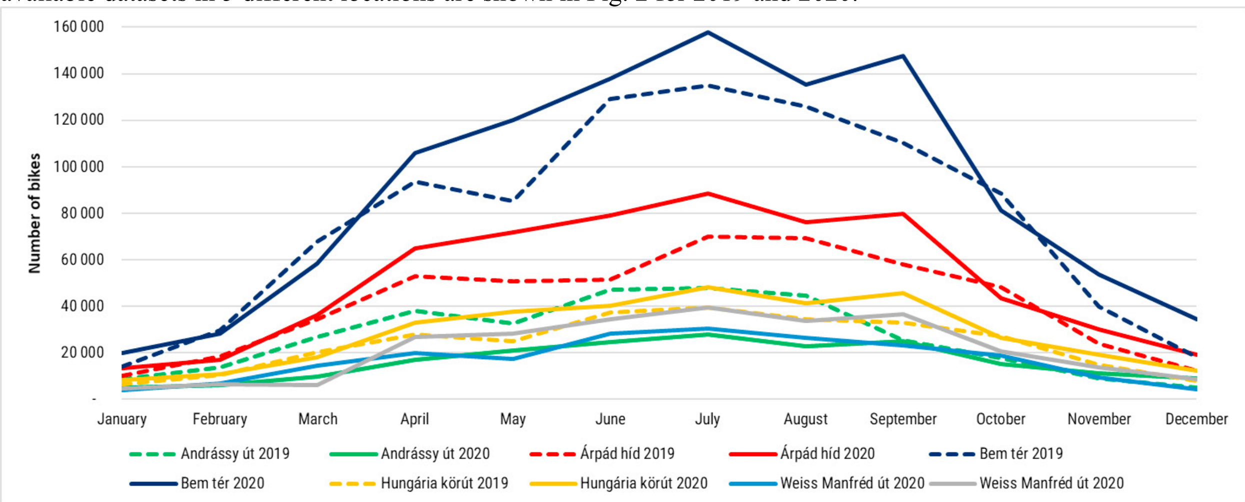
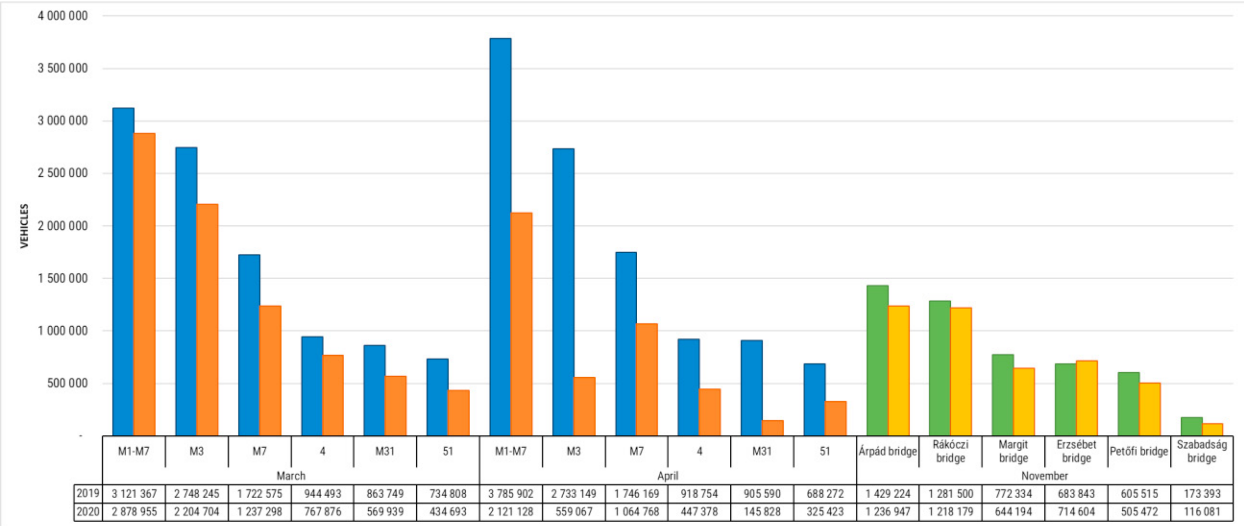


Fig. 2. Monthly bicycle counts from the available datasets in 5 different locations (2019-2020).

In March 2020, an average traffic reduction of 20% has been observed at the suburban motorways and major roads for which data were available, followed by an average reduction of 57% in April. Significant traffic reductions have also been observed in the second wave of the pandemic. In November 2020, the Danube river bridges had an average decrease of 10% in traffic, in comparison to November 2019. Fig. 3 shows data from different traffic counts. These are not full cross section numbers in all cases, but sometimes only one-way volumes. The relative decrease of the traffic counts between the two years is, therefore, the important information to be extracted from the graph. There is an anomaly at Erzsébet bridge, where the total number of cars in November is higher in 2020 than in 2019, which will be further analyzed later.



	March						April						November					
	M1-M7	M3	M7	4	M31	51	M1-M7	M3	M7	4	M31	51	Árpád bridge	Rákóczi bridge	Margit bridge	Erzsébet bridge	Petőfi bridge	Szabadság bridge
2019	3 121 367	2 748 245	1 722 575	944 493	863 749	734 808	3 785 902	2 733 149	1 746 169	918 754	905 590	688 272	1 429 224	1 281 500	772 334	683 843	605 515	173 393
2020	2 878 955	2 204 704	1 237 298	767 876	569 939	434 693	2 121 128	559 067	1 064 768	447 378	145 828	325 423	1 236 947	1 218 179	644 194	714 604	505 472	116 081

Fig. 3. Traffic counts in some incoming roads and bridges in Budapest (2019 – 2020).

3.2. Model considerations

During the modelling exercise, we tried to model the first wave of the COVID-19 in Budapest. The trip generation model was calibrated based on the observed traffic reduction in the second half of March 2020, assumed to be equal to that reported by Bucsky (2020) for the Danube river bridges. The α coefficient was determined based on Eurofound's estimation of a 28% rate of home office jobs during the first wave of the pandemic in Hungary (Eurofound, 2020). Trips performed by students to and from education centers were assumed to not happen. The β coefficient was therefore zeroed in an attempt to model that scenario. Once α and β were determined, the calculation of γ was made on Solver and yielded a value of 0,67 for the estimated reduction of 35% in the overall number of trips.

The recalibration of the mode choice model was based on a set of assumptions and aimed at achieving the observed mode shares reported by Bucsky (2020) for the first wave of the pandemic. Firstly, it was assumed that the increased share of private cars led to an increased average vehicle occupancy. In fact, based on Juhász's original model, this assumption was inevitable in achieving the targeted results. Secondly, as a consequence of the free parking policy adopted in Budapest, it was assumed that the scarcity of free parking places resulted in decreased tolerance over parking place finding times in the utility function of private cars. In third instance, it was assumed that the fear of contagion with the novel coronavirus resulted in an increased disutility of in-vehicle times spent at the public transportation. At last, the mode-specific constant of the utility function of bicycles was assumed to increase given their increased popularity, whereas that of public transportation was assumed to decrease. Constants and other coefficients were extracted from the original model (Juhász and Koren, 2017); assignment-related parameters were extracted from VISUM results.

Figure 4 displays the differences between the use of the main transport modes (private cars, bicycles and public transportation), in the network, before and during the COVID-19 pandemic. It shows that the car usage increased, while public transport usage decreased, along with bike usage. As we do not have comprehensive data collected in several cross-sections of the city, we used strategic inductive loop detector data. This data can show us the total change in volume, but it is inadequate for direct validation purposes. For this reason, we used modal share as the basis for validation together with observed changes in volume. Modal share baseline values (innermost circle) were extracted from Budapest's mobility plan (City of Budapest, 2019). The observed modal shares during the first wave of the pandemic were based on Bucsky's estimates and are shown in the middle circle (Bucsky, 2020). The outermost circle displays the modal shares obtained after recalibrating Juhász and Koren's original model (Juhász and Koren, 2017) and pivoting the synthetic matrices. Based on the validation results, some deviation exists, especially in the cycling layer, but the present model can be accepted as a basis for further research.

Figure 4. Pre-pandemic and first wave model results and modal shares in Budapest.

4. Conclusion

The restrictive measures and social distancing guidelines adopted during the pandemic in Hungary had a large impact on traveler behavior, especially in trip generation and mode choice. In April 2020, traffic volumes in the suburban motorways of Budapest decreased by an average of 57%; in November 2020, traffic volumes on the bridges over the Danube river decreased by an average of 10%. These observations can be explained by work from home rates of about 28% in Hungary, by the closure of universities, schools and kindergartens and by other pandemic trends, such as online shopping and at-home leisure and socialization, introduced into Juhász and Koren's original trip generation model through the use of the α, β and γ coefficients (Juhász and Koren, 2017).

Public transportation had an abrupt decrease in ridership; short-term ticket sales dropped by more than 90% in April 2020. The fear of contagion with the novel coronavirus may have increased travelers' perception of disutility over in-vehicle times in high occupancy modes. Private cars have thus gained popularity, and car sharing by people in the same household may have increased car availability. Crowded parking spaces, on the other hand, may have increased the disutility of parking times. Cycling gained popularity during the pandemic in Budapest. Bicycle traffic remained above forecasts in both March and April of 2020, while the number of rentals in the MOL-Bubi system more than doubled relative to forecasts.

One of the limitations of this study was to not incorporate walking as a mode of transport into the modelling; this decision was mostly driven by the unavailability of official city-wide datasets of pedestrian traffic in Budapest. Impacts of the pandemic over freight traffic were also disregarded; online shopping trends, however, may have increased the demand for shipping in some industries.

Validation results suggest that traditional four-step models are able to capture the impacts of the atypical scenario of a pandemic with relatively simple adjustments and few data requirements. This is particularly important in a context where data collection may be difficult and operative planning is necessary as a response to changed network conditions. Further investigation still needs to be carried out on the long-term effects of the pandemic over travel behavior, with a particular attention to the predictive capacity of pandemic-related variables, the effects of behavioral inertia and the dynamics of travelers' perception of risk.

Acknowledgements

The research was supported by the Hungarian Government and co-financed by the European Social Fund through the project "Talent management in autonomous vehicle control technologies" (*EFOP-3.6.3-VEKOP-16-2017-00001*). The research was supported by *OTKA - K20 - 134760* - Heterogeneity in user preferences and its impact on transport project appraisal led by Adam TOROK. The authors are thankful for the support related to data collection from the colleagues at BKK (Centre for Budapest Transport) and from the National Road Databank in Hungary.

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