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The impact of COVID-19 pandemic on public transport usage and route choice: Evidences from a long-term tracking study in urban area

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ARTICLE INFO

Keywords:
COVID-19
Public transport
Tracking
Route choice
User behaviour

ABSTRACT

The COVID-19 pandemic strongly affected mobility around the world. Public transport was particularly hindered, since people may perceive it as unsafe and decide to avoid it. Moreover, in Switzerland, several restrictions were applied at the beginning of the first pandemic wave (16/03/2020), to reduce the contagion. This study observes how the pandemic affected travel behaviour of public transport users, focusing on route choice and recurrent trips. We conducted a travel survey based on GPS tracking during the first pandemic wave, following 48 users for more than 4 months. The very same users were also tracked in spring 2019, allowing a precise comparison of travel behaviour before and during the pandemic. We analyse how the pandemic affected users, in terms of travel distance, mode share and location during the day. We specifically focus on recurrent trips, commuting and non-commuting, observing how mode and route changed between the two different periods. Finally, we estimate a route choice model for public transport (Mixed Path Size Logit), based on trips during the two different years, to identify how the route choice criteria changed during the pandemic. The main differences identified in travel behaviour during the pandemic are a different perception of costs of transfers and of travel time in train, and that users no longer have a clear preferred route for a recurrent trip, but often choose different routes.

1. Introduction

The outbreak of the COVID-19 pandemic dramatically affected the world’s population in early 2020. Mobility was particularly affected, since several governments imposed restrictions, as lockdowns, remote working and closure of shops. Moreover, people tried to reduce their movements and social contacts, to reduce the risk of a contagion. Public transport suffered particularly from the pandemic, since passengers may perceive the system as unsafe and a possible source of infection (Aloi et al., 2020).

This work aims to understand how the COVID-19 pandemic affected travel behaviour of public transport passengers in Zürich, Switzerland. We focus on the effects of the pandemic in general, observing travellers in that period. Therefore, we do not isolate the effects of specific aspects, such as imposed restrictions, the progress of the infection, or passengers’ perception of safety and risk. Previous works in this field focus mainly on analysing general mobility trends before and during the pandemic, such as mode share, travel distance or traffic reduction (Aloi et al., 2020; Molloy et al., 2021). They are also mostly based on online surveys (Bhaduri et al., 2020; Abdullah et al., 2020) or third-party data (Jenelius and Cebeauer, 2020; Aloi et al., 2020). In this study, we exploit two long-term travel surveys based on GPS tracking, one collected in spring 2019 and the other during the first pandemic wave in 2020 (from 14 February to 13 July), including data of the very same 48 users. The surveys contain a travel diary for each user, including information on activities, trips, mode choices and route choices. The long duration of the surveys, the high level of detail of the collected information, and the possibility to track the same users during both an entire pandemic wave and the same period of the previous year make this dataset a unique opportunity to observe the effects of a pandemic on travel behaviour. We analyse several aspects of travel behaviour during the COVID-19 pandemic, which result in the following contributions:

- Two long-term travel surveys based on GPS tracking are conducted in 2019 and 2020 in Zürich, on the same users. The users were continuously tracked during the first wave of COVID-19 pandemic to observe changes in travel behaviour, compared to the previous year.
General changes in travel distance, mode share and visited locations during the day are shown.

1. From the travel surveys, we identify recurrent trips, and differentiate them in commuting and non-commuting, based on imputation of home and work locations. Variations in mode and route chosen are analysed for those trips.

2. We estimate two route choice models for public transport, one on trips before the pandemic (2019) and the other during the pandemic (2020). This allows to identify the main criteria for route choice during the pandemic and compare them with the ones in 2019. The differences identified pertain to preferences towards transfers and trains.

To the best of our knowledge, this is the first work in literature analysing route choice in public transport during the COVID-19 pandemic, and how mode and route changed for recurrent trips.

The paper is organized as follows: Section 2 describes the evolution of the pandemic in Switzerland; Section 3 presents the state of the art on travel behaviour during a pandemic and on route choice; Section 4 describes the datasets; Section 5 presents the methodology; Section 6 presents the results; Section 7 discusses the results; Section 8 discusses the limitations; Section 9 shows the conclusions.

2. The first wave of the COVID-19 pandemic in Switzerland

This Section summarizes the evolution of the pandemic in Switzerland during the study period, with a focus on mobility.

On February 25, 2020 the first case of COVID-19 was confirmed in Switzerland. Following, the number of reported infections increased quickly, and on March 16, more than 1000 daily cases were reported. The first pandemic wave continued until May, with a peak of 1464 reported cases on March 23. Afterwards, in May and June, the number of cases daily reported remained below 100 on most days. In July the cases started to increase towards the second wave in fall 2020, which is out of the analyses in this paper.

To mitigate the contagion, several restrictions were applied by the Swiss government. Starting from March 16, schools and most of the businesses were closed, with only essential stores and institutions remaining open. Working from home was implemented whenever possible.

Restrictions were applied also regarding movements. Traffic with neighbouring countries was strongly limited. People were not forced to stay at home (like in Italy, France and Austria) but a limit of 5 people for gatherings in public places was imposed. The Federal Office of Public Health recommended to avoid public transport at peak times, especially for risk categories. Nevertheless, public transport services were maintained (sometimes with reduced service frequency, depending on cantons and the evolution of the pandemic).

The restricting measures were kept until April 26, and released in three successive steps, driven by the decrease of infections in the country. From April 27 only certain businesses were allowed to re-open. From May 11 mandatory schools and most of the businesses, as shops and restaurants, were allowed to re-open. On June 8 universities and entertainment businesses re-opened to public. The limit of people for gatherings increased from 5 to 30. The general obligation to wear masks in public transport became mandatory only from July 6.

Summarizing, the study period of this work can be divided into three phases: pre-lockdown (from 14 February to 15 March); lockdown (from 16 March to 27 April); post-lockdown (from 27 April to 13 July).

3. State of the art

3.1. Transport studies during the COVID-19 pandemic

During a pandemic, characteristics of a transport system and the passenger volume may affect the spread of the infection (Carteni et al., 2021; Lau et al., 2020). On the other end, the pandemic itself affects the transport system and the passengers, which may drastically change their behaviour. This paper focuses on this second aspect. In this regard, restricting measures decided by authorities may forbid or discourage movements or specific transport modes. Moreover, public transport systems, especially if crowded, might be perceived as unsafe (Aloi et al., 2020), encouraging a shift to private modes. In fact, Badr et al. (2020) identified in the USA that behavioural changes were observable days to weeks before the restrictions, implying that individuals anticipated public health directives. This is also confirmed by this study and Molloy et al. (2021). Other individuals, in contrast, may be captive to public transport and need to use it in any case (Awad-Núnez et al., 2021).

Table 1 reports the main studies on travel behaviour in public transport during the COVID-19 pandemic (other studies are also available, which do not make significantly different analyses). Different studies analysed the effects of the pandemic in different countries. They are mostly based on online surveys (Bhaduri et al., 2020; Abdullah et al., 2020) or third-party data, such as ticketing data (Jenelius and Cebecauer, 2020; Aloi et al., 2020), reports from google (Tirachini and Cats, 2020) or data from Baidu maps (Huang et al., 2020).

Most of the work focuses on general mobility trends, such as mode share, public transport usage or travel distance. For instance, Aloi et al. (2020) identified a drop of 93% of public transport users in Santander (Spain) due to the imposed quarantine. Abdullah et al. (2020) identified during the pandemic in various countries a significant variation of trip purpose, mode choice, distance travelled, and frequency of trips for the primary travel. In particular, they observed a shift from public transport to private modes. Similarly, Bhaduri et al. (2020) identified in India a propensity to shift to private modes from shared ones, but also a significant inertia to continue using pre-COVID modes. They reported heterogeneity based on age, income and working status.

Despite in this work we consider the effects of the pandemic in general, some works analysed specific factors influencing changes in travel behaviour. Abdullah et al. (2021) identified the relationships between the intention to use public transport and underlying factors,

Table 1

| Study                        | Data                                                | Country                | Focus                                |
|------------------------------|-----------------------------------------------------|------------------------|--------------------------------------|
| Aloi et al. (2020)           | Traffic counters, ticketing data                    | Spain                  | p.t. usage, mode share, travel distance |
| Abdullah et al. (2020)       | Online survey                                       | World                  | Mode choice, trip purpose, travel distance |
| Abdullah et al. (2021)       | Questionnaire survey                                 | Pakistan               | Intention to use p.t.                |
| Awad-Núnez et al. (2021)     | Online survey                                       | Spain                  | Intention to use p.t.                |
| Bhaduri et al. (2020)        | Online survey                                       | India                  | Mode choice                          |
| Dai et al. (2021)            | Subway passenger flow data                          | China                  | Role of fare-free p.t. policy         |
| Huang et al. (2020)          | OD with mode from Baidu Maps                        | China                  | Mode choice, visited venues, travel distance, OD patterns |
| Intervista AG (2021)         | Long-term tracking data                             | Switzerland            | Mode share, travel distance, trip purpose, p.t. usage |
| Jenelius and Cebecauer (2020)| Smart-card data                                     | Sweden                 | p.t. usage                           |
| Molloy et al. (2021)         | Long-term tracking data                             | Switzerland            | Mode share, travel distance, p.t. usage and substitution distance, route choice, recurrent trips |
| Schaefer et al. (2021)       | Online survey                                       | Germany                | p.t. usage                           |
| This Paper                   | Long-term tracking data in 2019 and 2020            | Switzerland (Zürich)   | Mode share, travel distance, route choice, recurrent trips |
such as a positive relationship with the awareness about the disease. Dai et al. (2021) analysed the effects of fare-free policies to increase subway ridership during the pandemic. Unfortunately, these works focus only on public transport usage and they are limited to the factors and locations considered.

From online surveys general changes in mobility and overall trends can be observed. In contrast, to observe long-term variations for specific users, longitudinal data are needed. In this regard, Jenelius and Cebecauer (2020) analysed mobility in Sweden from smart-card data, focusing on public transport ridership and reduction of the number of trips due to the pandemic. Molloy et al. (2021), instead, collected a GPS tracking panel of 1439 Swiss residents. They focused on behavioural shifts in terms of mode share, travel distance, travel speed, and socio-demographic variations.

Google (2021) and Apple (2021) provide reports regarding mobility in several countries of the world, including Switzerland. Apple (2021) report the number of search requests by transport mode, while Google (2021) focus on the usage of different categories of places such as retail, supermarkets and public transport. Intervista AG (2021) carried out a mobility tracking study in Switzerland, observing the daily distances covered and the trip purpose. In this regard, mobility tracking, besides providing highly detailed information, avoids some of the modelling problems of traditional surveys, such as the difficulty for respondents to describe their routes (Zhu et al., 2010).

To the best of our knowledge, only two works analysed longitudinal data of several individuals (Molloy et al., 2021; Jenelius and Cebecauer, 2020), but they presented mainly aggregated results and general trends. Therefore, additional specific insights are extremely relevant, to answer open questions on users’ behaviour and extend the little literature available on this topic. This paper contributes to the scientific literature analysing longitudinal data in urban environment collected with GPS tracking. A major characteristic of the current study is the availability of tracking data collected both during spring 2019 and the entire first pandemic wave in spring 2020. Given that the pandemic was an unforeseen event, and there was no time to prepare a tracking study, which includes data of the previous year and just before the pandemic outbreak, our dataset represents a unique resource, which cannot be collected again. Moreover, this paper analyses aspects of travel behaviour during the pandemic, which have not been analysed yet from previous works. In fact, we focus on route choice in public transport and how recurrent trips changed during the pandemic.

3.2. Route choice in public transport

Route choice models in public transport are used to analyse or predict the chosen routes in a public transport network. Most of the work divide the modelling into two steps (Bovy, 2009; Anderson et al., 2017; Marra and Corman, 2020): a choice set generation algorithm, enumerating the available alternatives; and a route choice model, estimating the passengers’ behaviour. The choice set generation is a complex task, often solved using heuristics, since enumerating all possible alternatives is typically not feasible. In this work, we apply the choice set generation algorithm described in Marra and Corman (2020), based on constrained enumeration, a family of algorithms widely used in literature (Bovy, 2009; Prato, 2009; Cats, 2011). Further details in that paper and in Section 5.1.

Regarding the route choice, different models are used in literature (Prato, 2009). The most used one is the Path Size Logit, which is a variation of the standard Multinomial Logit, including a penalizing parameter for overlapping alternatives. Anderson et al. (2017) estimated a Mixed Path Size correction Logit in the public transport network of the greater Copenhagen area, from a revealed preference survey. Similarly, Montini et al. (2017) estimated the Path Size Logit from public transport trips in Zürich, collected from GPS data. Yap and Cats (2021) estimated a Path Size Logit to evaluate denied boarding in crowded public transport systems.

In this work, we estimate two Mixed Path Size Logit models: one with data of 2019 and the other with data during the pandemic in 2020. The Path Size Logit has been already estimated with success on the dataset of 2019 in Marra and Corman (2020). We refer to that work for further details on the model and the literature on both choice set generation and route choice models. We also believe that a comparison with alternative models (Nested Logit, see Nassir et al. (2015), or Recursive Logit, see Zimmermann and Freijinger (2020)) is out of the scope of this paper.

A main contribution of this study is the estimation of a route choice model during the COVID-19 pandemic, and its comparison with a model estimated before the pandemic. In literature, route choice has not yet been analysed during a pandemic. Moreover, Weis et al. (2021) highlights that there are only few repeated studies in the field of transport planning. Repeating a study allows observing changes in respondents’ preferences, if the survey methodology and the sample characteristics stay consistent over time.

In the current paper, the tracking of the very same respondents before and during the pandemic, and the use of the same methodology, guarantee a fair comparison between the two different periods.

4. Datasets and study period

The travel diaries used in this study are collected during two different periods from the same group of users, which are all residents of Zürich. In spring 2019, 172 participants installed a smartphone app, the ETH-IVT Travel Diary (Marra et al., 2019), which continuously collect GPS data without affecting the battery consumption. On average each participant was tracked for 22 days. In February 2020 (few weeks before the outbreak of the pandemic in Switzerland), the same participants were contacted again, and 48 of them decided to participate again to the study. This time the participants were tracked until early July 2020, with an average of 112 days per user. Only data and trips collected inside the city of Zürich are considered in this analysis.

To derive travel diaries from the GPS data, we applied a mode detection algorithm, described in Marra et al. (2019). The algorithm automatically identifies activities, trips, stages and transport modes used. Each public transport stage is described with information on the line, the vehicle of that line, the departure stop and time, and the arrival stop and time. The mode detection algorithm has an average accuracy of 86.14% and has been already validated in previous studies. In particular, Marra and Corman (2020) used the same dataset of this study (the one of 2019), showing a realistic mode share and realistic estimations of route choice models.

Table 2 shows information on the users in our surveys and their representativeness. We remark that the survey in 2020 contains only 48 of the 172 users of the survey in 2019, used in Marra and Corman (2020). Therefore, in this paper, we will consider only these users, for both years. Regarding the representativeness, our survey contains in general younger and highly educated participants. A possible explanation is the nature of the survey, requiring installing a smartphone application, which might not be attractive for older people. Gender, household size and income follow quite regularly the actual distribution, despite there are fewer participants in the lowest income range, and slightly more men than women.

Table 3 compares the travel diaries collected in 2019 and 2020. The duration of the data collection is much longer in 2020 (almost 5 months) compared to 2019 (2 months), and on average each person was tracked 4 times longer in 2020. This led to a larger number of trips and activities in 2020. Despite this, due to the effects of the pandemic, the number of trips in 2020 is just 2.6 times that of 2019 (1.7 times for public transport).

In this work, we discard trips outside Zürich or with an absence of signal longer than 7 min (as in Marra et al., 2019). In total, we analyse 2266 trips in 2019 and 6316 trips in 2020. The mode share in 2019 (see Table 3) is close to the official one in 2015 (Zürich, 2021, 41% public transport, 26% walk, 25% motorized private mode, 8% bike), especially...
for public transport (42% instead of 41%), which is the focus of this paper. We remark that mixed trips (public and private transport) are not reported in the official statistics, but only in our survey. In contrast, the mode share in 2020 is remarkably different: the public transport share is strongly reduced (26%, more details in Section 6).

Trips without transfers increased in 2020 from 58% to 68%, suggesting passengers prefer to reduce the transfers. This might come from a perception of each vehicle as additional source of contagion; we analyse this aspect in details in Section 6.3. A further difference concerns the length of the trips, which decreases from 2.99 km to 2.35 km.

Finally, there is no particular difference in the mode share among public transport modes (tram, bus and train).

Further details on the limitations of this dataset are in Section 8.

5. Methodology

5.1. Route choice model formulation

In this Section, we present the route choice model estimated for public transport trips. We estimate the same model both on data of 2019 and of 2020, to observe the differences between before and during the pandemic. To understand route choices of public transport passengers, a route choice model requires two types of information: a set of observed choices, describing alternative choices discarded by the passenger (taking the same line at a near stop is considered the same alternative). No information on network conditions and delays is assumed for the choice set generation, i.e. the alternatives are generated from the timetable.

We estimate a Mixed Path Size Logit model, which is an extension of the Path Size Logit, allowing for random taste variations across users. The Path Size Logit is a variant of the standard Logit, including a penalty for overlapping alternatives in the utility function. For each route, we consider the utility function in Equation (1), including travel time (in public transport vehicles alternated by walks. We consider an alternative matching the passenger’s choice, when it has the same lines used by the passenger (taking the same line at a near stop is considered the same alternative). No information on network conditions and delays is assumed for the choice set generation, i.e. the alternatives are generated from the timetable.

We estimate a Mixed Path Size Logit model, which is an extension of the Path Size Logit, allowing for random taste variations across users. The Path Size Logit is a variant of the standard Logit, including a penalty for overlapping alternatives in the utility function. For each route, we consider the utility function in Equation (1), including travel time (in bus, tram and train), walking time, transfer time and the number of transfers. The walking time refers to the time between the start of the trip (at the origin) and the departure of the first vehicle (at the first stop), plus the time between the arrival of the last vehicle (at the last stop) and the arrival at the destination. The transfer time is the entire time during a transfer. Therefore, the waiting time is included both in the walking time and the transfer time, since the quality of the GPS data did not allow a precise discrimination between walking and waiting. Monetary costs were not considered, since in Zürich there is a fixed price for public transport, which does not depend on the route.

\[
U_j = -C_j = \beta_{\text{trip} \rightarrow \text{route}} \times \text{trip} + \beta_{\text{bus} \rightarrow \text{bus}} \times \text{bus time} + \beta_{\text{walk} \rightarrow \text{walk}} \times \text{walk time} + \beta_{\text{transfer} \rightarrow \text{transfer}} \times \text{#transfers} + \beta_{\text{PathSize}} \times \text{PathSize}_j
\]

(1)

\[
\text{PathSize}_j = - \sum_{s \in \text{choiceset}} \frac{\text{duration}(s)}{\text{duration}(\text{trip})} \ln(\text{times } s \in \text{choiceset})
\]

(2)

\[
P(\text{trip|choiceset}; \bar{\beta}) = \frac{e^{\bar{\beta}U_j}}{\sum_{j \in \text{choiceset}} e^{\bar{\beta}U_j}}
\]

(3)

The PathSize is a penalty attribute, based on the formulation in Bovy et al. (2008), which penalizes alternatives using the same stage (public transport line). The penalty increases with the duration of an overlapping stage in the trip and the number of times the stage appears in the choice set. After estimating the model, the probability to choose an alternative is the one in Equation (3).

To observe possible panel effects and heterogeneity among users in the perception of costs, we estimated a Mixed Path Size Logit model.

### Table 2
Comparison of socio-demographic characteristics between the survey and the official statistics in Zürich in 2016 (Zürich Statistic Office, 2021). The income information in Zürich Statistic Office (2021) is based on a survey in 2015 and the ranges are slightly different from the ones of our survey.

|        | Survey 2020 (%) | Zürich, 2016 (%) |
|--------|----------------|------------------|
| Gender |                |                  |
| Male   | 54             | 50               |
| Female | 46             | 50               |
| Age    |                |                  |
| <18    | 0              | 15               |
| 18-24  | 23             | 8                |
| 24-34  | 37             | 22               |
| 34-44  | 21             | 18               |
| 44-54  | 19             | 14               |
| >54    | 0              | 24               |
| Education |        |                  |
| Mandatory | 6         | 18               |
| Secondary | 29        | 34               |
| Higher  | 65             | 48               |
| Household size |      |                  |
| 1      | 29             | 22               |
| 2      | 33             | 30               |
| 3      | 9              | 18               |
| 4      | 21             | 19               |
| 5+     | 8              | 12               |
| Income |                |                  |
| <$4000 | 9              | 24 (<$5000)      |
| 4000-8000 | 29      | 24 (5000-7500)  |
| 8000-12000 | 31     | 31 (7500-12 5000)|
| 12000-16000 | 13   | 11 (12 500-16 666) |
| >16000 | 8              | 9 (>16 666)     |
| No answer | 10        |                  |

### Table 3
Comparison of travel diaries in 2019 and 2020. Mode share in Zürich in parentheses.

|          | 2019          | 2020          |
|----------|---------------|---------------|
| Period   | 03.04.2019-02.06.2019 | 14.02.2020-13.07.2020 |
| Users    | 48            | 48            |
| Avg. days per user | 25  | 112          |
| Activities | 4617        | 12 234        |
| Trips    | 4597          | 12 157        |
| Trips inside Zürich | 2266 | 6316        |
| Car trips in Zürich | 382 (17%)  | 1371 (22%)  |
| Bike trips in Zürich | 279 (12%)  | 1089 (17%)  |
| Walk trips in Zürich | 396 (18%)  | 1520 (24%)  |
| Zürich Mixed trips in Zürich | 244 (11%) | 687 (11%) |
| Public transport trips in Zürich | 963 (42%) | 1649 (26%) |
| # transfers per p.t. trip (%) | (0: 58%, 1: 31%, 2: 8%, 3+: 0%) | (0: 68%, 1: 25%, 2-6%, 3+: 1%) |
| p.t. modes used | (Tram: 52%, Bus: 41%, Train: 7%) | (Train: 8%) |
| Avg. duration per p.t. trip | 22 min | 20 min |
| Avg. air distance per p.t. trip | 2.99 km | 2.35 km |
In this model, the coefficients (\( \hat{\beta} \)) are assumed random parameters following a probability density function \( f(\hat{\beta}|\theta) \). In literature, the normal and log-normal distributions are used for the parameters. Despite the log-normal distribution allows to restrict the values to only one sign, it may result in a wide distribution, given its long tail. Therefore, we assume normally distributed parameters, described by a mean and a standard deviation. A high standard deviation for a parameter indicates high heterogeneity in the perception of its cost among the users. The probability of choosing an alternative is the following:

\[
P(\text{trip}|\text{choiceset}) = \int \left( \sum_{j \in \text{choiceset}} e^{U_j(\hat{\beta})} \right) \theta(\hat{\beta}|\theta) d\hat{\beta}
\] (4)

The model was estimated with the software mixl (Molloy et al., 2019), using 500 draws to simulate the probabilities.

The Path Size Logit model (and the Mixed Path Size Logit) has already been successfully estimated on the dataset of 2019 in Marra and Corman (2020), which also discuss details on the performance and validity. In this work, instead, we estimate the same model on data collected during the pandemic, from the same users, and we compare the two models and the estimated coefficients. While no remarkable heterogeneity estimating the Mixed model was identified in the dataset of 2019 in Marra and Corman (2020), we here analyse the heterogeneity in cost perception during the pandemic. The pandemic is an exceptional condition, and the passengers might consider also the risk of contagion during their choices, which may influence the perception of the travel cost components in different ways. We remark we estimate a single model, and not a model for each phase of the pandemic, since it would result in fewer observations per model and less reliable results.

5.2. Identification of visited locations and recurrent trips

To analyse how the pandemic affected recurrent trips, we need to understand from which location a trip is performed and to which destination. In the collected travel diaries, each activity of a user corresponds to a set of GPS points near to each other for a long time. Each activity is the end location of a previous trip and the start location of an upcoming trip. No semantic meaning is associated to the identified activities.

Therefore, in this work we apply an intuitive and effective method, to classify the activities in home, work (or secondary location) or other location. First, to identify activities representing the same location, we applied a clustering algorithm, the DBSCAN (Ester et al., 1996), which assigns a cluster to each activity. A simple rule-based approach can then classify the clusters (and the activities) in home, work and other.

The DBSCAN algorithm takes as input the GPS coordinates of all the activities of a user (mean point of each activity), and a maximum distance as parameter (100 m). No minimum number of activities for a cluster is specified. The advantage of this algorithm is that it does not require to specify the number of clusters, since the algorithm just groups together activities near to each other. Each isolated activity will form a cluster of its own. As result of the clustering, the activities in the same cluster represent the same location (e.g. the home).

After identifying the clusters, we apply two simple rules to identify home and work locations. We name home location the one corresponding to the cluster with highest number of activities (weighted by their duration) during weekdays, between 23:00 and 06:00. We name work location the one corresponding to the cluster with highest number of activities (weighted by their duration) during weekdays between 09:00–12:00 and 13:00–17:00 (excluding the home cluster). The activities belonging to other clusters are marked as other locations.

The proposed method finds several correspondences in the literature. Bhadane and Shah (2020) compare different clustering algorithms to identify Region of Interest (e.g. home, work, post office), concluding DBSCAN suits well for spatial data clustering. Liu et al. (2019) identify individual activity clusters from geo-tagged tweets, applying an adapted version of DBSCAN. Xiong et al. (2020) clusters points of interest in regions using DBSCAN. Moreover, existing research identifies home and work locations as the most frequently visited stop during nighttime and daytime hours, respectively (Chen et al., 2014; Kung et al., 2014; Calabrese et al., 2013; Phithakkitnukoon et al., 2012).

In our test case, the average distance between two activities in the same cluster is 27 m, which confirms they represent the same physical location. This method does not aim to be the state of the art in activity classification, but it is sufficient to show the general changes in users' location due to the pandemic. We remark that there are exceptions in users’ behaviour which are not considered in this method, as night workers or people with multiple work locations.

After assigning a location (i.e. a cluster) to each activity of a user, it is possible to assign each trip to an origin-destination couple (OD). In other words, two trips starting and ending in the same locations can be assigned to the same OD. We call those recurrent trips. We refer the recurrent trips between home and work (both directions), as commuting trips.

As a technical remark, we applied the clustering algorithm considering both the activities in 2019 and 2020, to have the same physical location (e.g. a supermarket) labelled as the same location/cluster in both years. In contrast, we identify the home and work location independently in 2019 and 2020, to identify people who potentially have changed home or workplace. Considering the two years independently or together for the clustering and/or the labelling does not change significantly the results. Therefore, a change of home or workplace does not affect our methodology and results. However, changing home may affect the travel behaviour of a user, as much as any other life change occurred between two periods. This is a limitation of every repeated study, since it is impossible to have identical conditions.

6. Results

6.1. Mobility trends during pandemic

In this Section, we show how the mobility changed during the different phases of the pandemic, studying mode share, travel distance and location during the day of the tracked users.

Fig. 1 shows the travel distance increase during 2020, compared to 2019. During the last weeks of February, at the begin of the outbreak, the travel distance for every mode is around 50% less than 2019. This can be explained both by a higher baseline (which is based on spring 2019, including Easter and other holidays), and by the first effects of the pandemic. In fact, Badr et al. (2020) show evidence of behavioural changes in US before the restrictions, indicating an anticipation of public health directives from the individuals. With the first restrictions implemented on 16 March, the travel distance drops significantly (more than 90% for public transport). With the first easing of the restrictions, it increases again. In June, with most of the restrictions removed, the travel distance of private modes reaches the values of 2019. In contrast, for public transport a decrease of around 40% remained (despite an increase for trains in the last days), probably due to ongoing policies, as the possibility to work from home, and a remaining perception of public transport as unsafe. We highlight that the same trend of travel distance was observed in two different surveys in Switzerland (Molloy et al., 2021; Intervista AG, 2021), based on larger samples. This shows the validity and representativeness of our approach. An exception is the distance by bike, which was found increasing significantly during the pandemic by Molloy et al. (2021), while not by this work and Intervista AG (2021). A possible explanation is given by the different baseline, based on fall 2019 in Molloy et al. (2021), while on spring 2019 in this work. In any case, this paper does not focus on bike trips.

Fig. 2 shows the mode share in 2019 and 2020. In February 2020, the mode share in 2019 and 2020, to have the same physical location (e.g. a supermarket) labelled as the same location/cluster in both years. In contrast, we identify the home and work location independently in 2019 and 2020, to identify people who potentially have changed home or workplace. Considering the two years independently or together for the clustering and/or the labelling does not change significantly the results. Therefore, a change of home or workplace does not affect our methodology and results. However, changing home may affect the travel behaviour of a user, as much as any other life change occurred between two periods. This is a limitation of every repeated study, since it is impossible to have identical conditions.
in March, the share of public transport reduces in favour of walk and private modes. The share of public transport follows a similar pattern as for the travel distance, reaching a plateau (below 40%) at the second half of May, lower than the 2019 baseline (around 48%). Again, this can be explained by ongoing policies, as possibility to work from home, and by a perception of public transport as unsafe.

Fig. 3 shows the location of the users in 2019 and 2020 during the day. In 2019, during weekdays, most of the users stayed at home in the early morning and during the night, as expected. Around 8 and 18, there are the two travelling peaks, in conjunction with an increase and a decrease of people at work. In 2020, instead, the percentage of people staying at work decreases, from a peak of 50% to 14%. The trips also decreases, especially the ones in the morning. In contrast, the activities marked as other, i.e. everything else besides home and work, did not decrease substantially. In general, the location pattern during weekdays in 2020 is similar to the one in 2019 during weekend, with most of the trips occurring in the afternoon. Comparing the weekend in 2019 and 2020, the location of the users during the day is similar, with the difference of a higher percentage of people at home in 2020, unsurprisingly.

6.2. Analysis of recurrent trips: commuting and non-commuting

In this section, we analyse if in 2020 people choose a mode or route different from that of 2019 for recurrent trips. We selected for each user all ODs occurred at least 4 times in 2019, identifying 125 ODs. 51% of them occurred at least 4 times also in 2020, for a total of 64 ODs analysed.

Fig. 4 shows the public transport share for each OD in the two years. For example, a 80% in the x-axis means the user chose 80% of times public transport for that OD in 2019 (the remaining 20% includes walk, bike and car). We can divide the ODs in three groups: ODs with an increase in public transport share in 2020 by at least 10% (labelled I); ODs with a similar share between the two years (labelled II); ODs with a decrease in public transport share in 2020 by at least 10% (labelled III). The most of non-commuting ODs are in the second group (43%), compared to the third (36%) and the first (21%). Thus, for those trips the share of public transport decreased during the pandemic, but not...
significantly. In contrast, for commuting, the majority of users switched clearly from public transport to private modes (14% first group, 33% second group, 53% third group). This change can also be seen from the different distributions for commuting trips (in blue) in the two years.

In general, no ODs are located in the top-left corner of the figure, representing a switch from private to public transport. The few ODs in the bottom-left corner, with a higher public transport share in 2020, can be imputed to the shorter study period in 2019. In fact, an OD that is rarely travelled by public transport may result in a 0% of public transport usage in 2019 and a small percentage (5–20%) in 2020.

Fig. 5 shows how the frequency of the most chosen routes in 2019 changed in 2020. For example, the first 2 bars show that on average the most frequent route in commuting ODs is chosen 39% of times in 2019, while the same route is chosen 21% of times in 2020. On average, the chosen routes for the same OD in the two years are different. For commuting ODs, the preferred public transport route is chosen less, since passengers try different routes and partially switched to private modes. The usage of bike greatly increased, matching the observed reduced public transport share. Also for non-commuting trips the preferred public transport route is less chosen (from 25% in 2019 to 13% in 2020), and walking trips significantly increased.

### 6.3. Route choice

Table 4 shows the estimation of the Mixed Logit in 2019 and 2020. The observations include all identified public transport trips, covered by the choice set generation algorithm. Very short trips, where using public transport is unrealistic (i.e. walking takes less than half the time of any public transport trip), are discarded. The estimated model in 2019 is the same as in Marra and Corman (2020) (see Table 7 in that paper), except that the number of observations is lower, since in this work we consider only the users, which are also tracked in 2020. Nevertheless, the estimated coefficients and standard deviations are very close to the ones estimated in Marra and Corman (2020), showing a model robust to a reduction of users (48 instead of 152). The only difference is in the PathSize factor, which was not found significant in this work. The PathSize was not found significant also in one of the experiments in Marra and Corman (2020) and in Nielsen et al. (2021). Doubts on the validity of the PathSize were also raised in Duncan et al. (2020), which demonstrate issues with this model. Therefore, we also estimated the model without this parameter, as a Mixed Logit (testing different correction parameters is out of the scope of this work).

Here, we briefly discuss the model in 2019. We report the coefficients
scaled by the travel time in tram, to better discuss the rates of substitution among them. All mean values are statistically significant, and their sign and values are realistic and in line with the literature. The preferred mode is the tram, followed by the bus and the train, in accordance with previous works in Zürich (Meyer de Freitas et al., 2019; Montini et al., 2017). The walking time has a higher cost than the in-vehicle travel time, as expected (Meyer de Freitas et al., 2019). The transfer penalty is around 15 min of travel time in tram, which falls near the range identified by Garcia-Martinez et al. (2018), between 15.2 and 17.7 min of in-vehicle travel time, in the multi-modal urban network in Madrid. Looking at the standard deviations, the ones of travel time in bus, tram and walking are significant but low (between 18% and 23.4% of the respective mean value), showing low heterogeneity among the users. The standard deviations of the transfer penalty and the transfer time are not significant, showing that there is no heterogeneity in the perception of transfers among the users. The only parameter with a large standard deviation is the travel time in train (44.9%).

The model of 2020 has comparable coefficients of tram, bus and walk, as well as low standard deviations, which is non-significant for the bus. Remarkable differences are in the other coefficients. The in-train travel time is perceived with a lower cost and is comparable with the in-tram travel time. No heterogeneity was found related to this parameter. Looking at the transfer-related coefficients, compared to the 2019, the transfer penalty is much higher and the coefficient of the transfer time is lower. In addition, in 2020, there is heterogeneity in the perception of the transfer penalty.

7. Discussion

The availability of a long-term travel survey in 2019 and 2020, on the same users, allowed observing changes in travel behaviour during the COVID-19 pandemic. In particular, we analysed general mobility trends, but also aspects not analysed in previous works, such as recurrent trips and route choices.

Mobility has been strongly affected by the COVID-19 pandemic, even before any restriction, observing a strong decrease and a slow recovery. The situation in June 2020 did not return to the values of 2019, probably due to increased working from home, and perception of unsafe public transport. The observed shift to private modes can have negative consequences if it remains after the pandemic, such as increased traffic congestion and pollution. Therefore, keeping an attractive public transport system, especially with policy measures to improve its safety,
Table 4
Mixed Logit estimated in 2019 and 2020. Parameters distributed according to a normal distribution. * indicates a non-significant parameter (|t| < 1.96). The parameters are scaled (multiplied by the scaling factor) to have the in-tram travel time coefficient equal to -1.

| Parameter | 2019 | t-test | 2020 | t-test |
|-----------|------|--------|------|--------|
| In vehicle travel time (s) | | | | |
| $\mu$ Train | -1 | -8.34 | -1 | -9.17 |
| $\mu$ Bus | -1.17 | -8.57 | -1.16 | -10.09 |
| $\sigma$ Train | -1.85 | -4.97 | -1.00 | -4.54 |
| $\sigma$ Walking time | -2.39 | -14.10 | -2.44 | -20.22 |
| $\mu$ Transfer time | -1.06 | -13.70 | -0.91 | -10.49 |
| $\nu$ Number of transfers | -792 | -13.04 | -1008 | -12.44 |
| $\sigma$ Train | 0.18 | 1.96 | 0.17 | 4.74 |
| $\sigma$ Bus | 0.22 | 3.39 | 0.15* | 0.51 |
| $\sigma$ Train | 0.83 | 3.61 | 0.28* | 1.09 |
| $\sigma$ Walking time | 0.56 | 4.09 | 0.25 | 2.78 |
| $\sigma$ Transfer time | 0.01* | 0.12 | 0.01* | 0.03 |
| $\sigma$ Number of transfers | 88* | 0.74 | 200 | 3.31 |
| Observations | 977 | 1427 | | |
| Null log-likelihood | -2352 | | -3544 | |
| Final log-likelihood | -726 | | -1054 | |
| Adjusted $R^2$ | 0.69 | | 0.70 | |
| Scaling factor | 0.0040 | | 0.0041 | |

or its perception, would be crucial. The obligation for wearing masks (as of 06 July 2020) is indeed moving in this direction.

Looking at the locations visited during the pandemic, people spent much more time at home compared to the previous year, especially during weekdays. The workplace, instead, is visited roughly 3.5 times less. These changes show the impact of working-from-home, and temporary closures of most of working activities. Accordingly, the time spent travelling also decreased, and the daily routine during weekdays switched from a morning and an afternoon peak, to a single peak in the afternoon. If the working-from-home share is higher in the future, the demand will decrease, and especially the demand peaks, with a potential impact towards supply and infrastructure needs.

Focusing on recurrent trips, we identified that the chosen modes and routes strongly changed due to the pandemic. Public transport usage generally decreased in favour of private modes. For commuting trips, the increase was greater for bike; while, for non-commuting trips, the share of walk increased. This shows there is a large percentage of people willing to switch to private modes to avoid public transport. In this regard, the increase in bike usage is a positive trend, which can be maintained after the pandemic, given sufficient investments in bike infrastructure and bike sharing systems.

Regarding the public transport route choice, in 2020 the preferred route is chosen less, in proportion to other routes or private modes. In other terms, the routes are chosen more equally and there is a smaller gap between the most chosen route and the second most chosen. This may suggest the users reconsidered the main route to reach the destination, in favour of less common routes. The specific reasons for this change are not easy to identify and can be various, such as a different daily routine, different choice criteria, safety perception or a general reconsideration of the routes to take during the pandemic. Among the possible factors, we tested the walk, but without identifying a clear relationship between the chosen route and the expected crowding (average occupancy rate in 2019). Further investigation on crowding and safety perception are left for future works.

The estimation of a route choice model in 2019 and 2020 showed the route choice in public transport was affected by the pandemic. In fact, we identified important differences and similarities between the two periods (see Table 4). While the cost perception of tram, bus and walking is similar, the one for train and transfers is different. We hypothesize for the lower cost perception of the travel time in train that trains, being large vehicles, guarantee (or are perceived to guarantee) more easily an adequate social distance. Moreover, trains are used for short urban trips (rarely more than three stops). Passengers would therefore be for a very short period with other people, which could be potentially perceived as a threat.

The transfer penalty in 2020 is much higher than in 2019 (by 27%). We link this again to perceived contagion risks, as an additional transfer means more and different people encountered during the trip. In contrast, the perception of transfer time is lower in 2020 and it is lower than the travel time in any vehicle. As most of the transfers in Zürich takes place outdoors, the waiting time at a transfer stop could be perceived safer than being in a vehicle. No heterogeneity among users was found in 2020 related to trains, showing a general lower cost perceived by all the users. Instead, the transfer penalty is perceived differently among the users in 2020, while not in 2019.

Overall, the identified changes in route choice criteria help predicting the traffic flow and prepare a response for current or future waves or pandemics. The new estimated coefficients and the resulting utility function can be used for a more accurate traffic assignment model, which can predict the use of public transport services during a pandemic. Such a model helps public transport planning, for instance, identifying potentially crowded vehicles, which may expose people to a high risk of contagion. In this regard, the collected data hints towards redesigning the network to increase direct connections and reduce transfers, or increasing frequency and capacity of the lines for which crowding is expected.

The differences in mode share and travel distance can be explained both by personal factors (any change in perception, need or habit of the user, as safety perception, crowd avoidance or change of daily routine) and by external factors (as mandatory working from home or other restrictions). Regarding the route choice, no restrictions or other external factors affected its setting (public transport offer, available alternatives and travel times), which remained substantially the same as before the pandemic. The only differences in the public transport service are a general reduction of crowding and a more reliable service. A marginal change in the public transport offer occurred from March 30 to May 4, 2020, consisting in a reduction of the frequency of some tram and bus lines, from a run every 7.5 min to every 10 min. Anyhow, this period corresponds to the highest restrictions and therefore a small fraction of observations in our dataset. We thus believe personal factors are the main ones determining the observed changes in route choice. The identification of how specific factors affect travel behaviour is out of the scope of this paper.

8. Limitations of the study

The dataset of this study represents a unique data source, containing long-term travel diaries of several users before and during the pandemic. We believe the relatively small number of users (48) does not represent a significant limitation, for the following reasons: most of the socio-demographic characteristics reflects the official reports, with few exceptions; the number of trips observed is not small (6316 in Zürich); the mode share in 2019 is representative and does not differ significantly from the real one; general characteristics of mobility, as mode share and travel distance during pandemic are in line with other studies in Switzerland (see Section 6.1); the main differences in users’ location and recurrent trips are large and evident (e.g. decrease of work activities from 50% to 14%); Regarding the route choice, the dataset of 2019 was already tested successfully in a previous work (Marra and Corman, 2020). The model estimated in Table 4 is very close to the one estimated in Marra and Corman (2020), despite the reduction of users (48 instead of 152) and trips (877 instead of 2719). Further reducing the users by 33% (32 users) results in coefficients that do not differ by more than 7%, showing the model is robust to a reduction of users. Moreover, no heterogeneity among participants was found regarding public transport route choice, which is the focus of this paper. This suggests that the results are significant and representative, without the need of a larger dataset (which would be in any case impossible to collect). Finally, we believe the results in this work should be interpreted qualitatively.
focusing on the main differences, and not quantitatively, focusing on the exact values.

In the route choice analysis, we did not discriminate by trip purpose. Considering the trip purpose was not possible in 2020, because there were very few work trips, due to the pandemic. We are aware that trips with different purposes might result in different choice criteria, but we decided to estimate a single model for all trips. Dividing by trip purpose would result in fewer observations per model (especially for work trips) and less reliable results. Instead, a single model guarantees more reliable results, considering the same choice criteria for different trip purposes.

As a thought exercise, we could think of the trips in 2019 as predominantly work-oriented and the ones in 2020 as predominantly leisure-oriented. In such a case, we can look if the identified differences match the literature comparing working and leisure trips. If so, the differences can be imputed to the trip purpose and not to the pandemic. In Switzerland, Weis et al. (2021) identify for both the transfer penalty and the transfer time a higher cost (respect to the travel time) in non-working trips. Nielsen et al. (2021) identify in leisure trips a higher and the transfer time a higher cost (respect to the travel time) in in-train time, transfer penalty and transfer time. In our case, instead, we have identified a different situation, with higher transfer penalty (in 2020), but lower costs for transfer time and in-train time. Therefore, we link the identified differences between the two periods to the pandemic, and not to the different trip purposes.

9. Conclusions

In this work, we observed travel behaviour during the COVID-19 pandemic from GPS tracking. This technology proved to be an efficient method, to collect long-term travel diaries without a significant burden on the users. Moreover, the observation of the very same users in 2019 allows a precise comparison of travel behaviour before and during the pandemic. The resulting dataset used here is an unrepeatable opportunity to observe travel behaviour during a pandemic. In fact, this work is the first one in literature analysing route choice in public transport during the COVID-19 pandemic, and how mode and route changed in recurrent trips.

We observed how the mode share and the travel distance changed during the different phases of the pandemic. Public transport modes resulted as the most affected ones, with a reduced traffic persisting even after the first wave. We exploited the long-term nature of the dataset to observe how recurrent trips changed in 2020. The share of public transport decreased, in favour of private modes, with a significant increase of bike usage for commuting trips. Moreover, public transport users have not anymore a precise preferred route, and they often choose different routes for the same OD.

We estimated two route choice models, based on trips before and during the pandemic, identifying important differences in perception of travel time in train and transfers. Given an already exiguous literature on comparing route choices of the same population in different periods, our work represents an important contribution on understanding how travel behaviour evolves in time, especially during a pandemic.

Therefore, for future work, we encourage the repetition of long-term surveys in different years. An interesting possibility is comparing a pre-pandemic period with a post-pandemic one, when the emergency may be considered over. Finally, in this work we analysed the effects on travel behaviour of the pandemic in general, while further research is needed to observe the consequences of specific restrictions or how passengers’ perception of safety affect their behaviour.

Author statement

Alessio Daniele Marra: Conceptualization; Methodology; Data curation; Formal analysis; Visualization; Writing - original draft; Writing - review & editing. Linghang Sun: Methodology; Formal analysis; Visualization. Francesco Corman: Conceptualization; Writing - original draft; Writing - review & editing.

Writing - review & editing.

Declaration of competing interest

None.

Acknowledgements

The authors wish to thank all study participants. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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