Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 9964912, 12 pages
https://doi.org/10.1155/2023/9964912

Research Article

The Influence of the COVID-19 Pandemic on Travel Behaviour in the Greater Copenhagen Area

Vincent Henrion,[1,2] Jesper Bláfoss Ingvardson,[1] and Otto Anker Nielsen[1]

[1]*Department of Technology, Management and Economics, Technical University of Denmark, Akademivej, Kongens Lyngby 2800, Denmark*
[2]*École Polytechnique de Bruxelles, Université Libre de Bruxelles, Avenue Franklin Roosevelt 50, Bruxelles 1050, Belgium*

Correspondence should be addressed to Jesper Bláfoss Ingvardson; jbin@dtu.dk

Received 11 July 2023; Revised 14 December 2023; Accepted 16 December 2023; Published 29 December 2023

Academic Editor: Tiziana Campisi

The COVID-19 pandemic drastically changed the way of living for billions of people and severe restrictions were implemented by governments around the world, affecting the travel patterns of all citizens. This article investigates how travel patterns changed in the Greater Copenhagen area of Denmark during the full two-year period covering 2020 and 2021, thus allowing for an analysis of both the short-term and medium-term impacts as society gradually reopened and restrictions were lifted. The analysis covers large-scale travel survey data as well as a segmentation clustering analysis of public transport smart card data. The results showed that impacts were strongly linked to changes in trip purpose and were thus not uniformly distributed throughout the public transport system. User segmentation analysis revealed that most users changed to less intense travel use of public transport. The results highlight important policy implications in terms of how to adapt service provision within a public transport network more efficiently.

1. Introduction

The worldwide spreading of the COVID-19 virus during the beginning of 2020 drastically changed the way of living for billions of people. All over the world, public authorities introduced restrictions to contain the spread of the virus. A large variety of measures were implemented, including the recommendation to wear a face mask, teleworking obligations, or the imposition of hard lockdowns. This affected the everyday lives of countless people and thus changed the travel patterns of many public transport (PT) users, as also seen in several studies from the early COVID-19 period. In Sweden, it led to a drop in PT ridership of 40–60% during spring 2020 as travellers switched from monthly passes to single-trip tickets [1], and in Fuenlabrada, Spain, the drop was even larger, at up to 95% [2]. In Taipei, Taiwan, the drop was less pronounced, but detailed results from automated fare collection (AFC) data showed large spatio-temporal differences in flows due to COVID-19 [3]. While multiple studies have looked into the short-term impacts, no studies have analysed the effects of the COVID-19 pandemic over a longer time period using a large-scale dataset.

Within this particular context, the contribution of the present study is twofold. First, we analyse the general consequences of the pandemic for travel behaviour and travel patterns, covering all modes of transport, but with a specific focus on PT usage. We consider the full two-year period of January 2020 to December 2021 in the Greater Copenhagen area, thus allowing for an analysis of both the short-term and medium-term impacts. Second, we analyse individual travel behaviour over time through the application of clustering analysis of automated fare collection (AFC) data. This allows for a user segmentation analysis, which can reveal travel differences across user types throughout the study period. The analysis is based on a combination of representative travel survey data covering all modes of transport and large-scale AFC data covering PT users.

The remainder of the paper is structured as follows. Section 2 reviews the literature on the impacts of the pandemic on PT usage. In Section 3, the proposed methodology is described. The case study is presented in Section 4. The results are presented and discussed in Section 5. Section 6 concludes the work.

2. International Experiences

The COVID-19 pandemic has had a large impact on travel behaviour. Many studies have therefore already analysed this from various angles, focusing on overall travel behaviour changes (e.g., Arellana et al. [4]; Labonté-LeMoyne et al. [5]; Eisenmann et al. [6]) or impacts on the usage of specific modes of transport such as PT (e.g., Vallejo-Borda et al. [7]; Marra et al. [8]; Nikolaidou et al. [9]) or active modes (e.g., Hunter et al. [10]; Buehler and Pucher [11]).

The consequences of PT have been analysed in numerous studies globally, finding large short-term impacts on ridership. In Sweden, PT ridership dropped by 40–60% during spring 2020 [1]; in Daejon, South Korea, the number of bus trips decreased by 40% [12]; in Santiago, Chile, the drop was estimated at around 72% [13]; and in Spain, the drop was even larger, at up to 95% in Madrid and Fuenlabrada [2, 14]. Generally, ridership reductions of 70–95% were observed across North American, South American, European, and Asian cities during the first COVID-19 wave in 2020 [7, 15].

The reasons for the large short-term reduction have been the focus of several studies across the world, most of which were based on survey data. Many studies found evidence of passengers' health concerns leading to lower satisfaction [16] and shifts to other modes of transport, especially cars [7, 17]. Aaditya and Rahul [18] found significant impacts of awareness of the disease and perception of the strictness of lockdown measures on the willingness to use PT. Similarly, Downey et al. [19] found that the perceived risk of infections negatively influenced the willingness to use PT post-pandemic. However, in Teheran, satisfaction with PT increased during the pandemic due to better comfort, less crowding, and better reliability; however, ridership and loyalty to PT were lower [20]. Hence, a general dispreference for PT was found in most studies [5, 21] due to, for example, concerns about crowding onboard the vehicles [17, 22] and transfers [6, 8, 9]. More specifically, the value of travel time in crowded PT was 3–5 higher during the pandemic in Santiago, Chile, than before the pandemic [23], and the value of transfers was much higher in 2020 compared to 2019 in Switzerland [8]. Hence, only captive users and those less concerned with COVID-19 continued using PT [17, 24, 25]. Some studies analysed in greater detail the characteristics of the users who abandoned PT. Basnak et al. [23] found that passengers belonging to younger age groups and from lower income areas were less sensitive to crowding and thus continued to use PT to a greater extent and that women were more sensitive to mask use. Similarly, Shelat et al. [22] found that older passengers and women were more likely to have higher sensitivity to crowding and infection rates. While young people continued using PT due to feeling less risk, low-income passengers likely continued using it due to their reliance on it [14].

Several studies analysed the spatio-temporal changes to trip patterns, but with different results. In Daejon, South Korea, bus usage dropped most during the daytime and weekends [12]; in Taipei, Taiwan, the largest reductions were observed during peak hours compared to off-peak [3]; and in Chicago, USA, the largest drops were observed among commuters rather than leisure travellers [26]. Similar findings were observed in Santiago, where the share of work trips increased and leisure trips decreased [27]. Considering the changes across geographical areas, Kim et al. [12] found reductions to be larger in crowded areas, such as commercial areas, and in high-income areas compared to lower-income areas. On the other hand, Mützel and Scheiner [3] found that reductions were consistently spread out over the city. Finally, Pozo et al. [14] found a high correlation between neighborhood income levels and the local decline in PT ridership, thus confirming that lower-income areas suffered a lower decrease in ridership due to greater reliance on PT. This is in line with findings from Lahore, Pakistan, where high-income passengers were less likely to use PT during the pandemic [28], and from Santiago, Chile, where work trips decreased more in high-income compared to low-income areas [27].

Many studies have analysed the recovery of PT. Arellana et al. [4] found that ridership had only recovered to 20–40% of pre-COVID-19 levels by mid-2020 in Columbia, when the pandemic was still peaking. Wang et al. [29] found that ridership among commuters was almost back to pre-COVID-19 levels by September 2020 in Kunming, China, whereas ridership for leisure travellers was still around 60% below normal. In Madrid, ridership was back at around 50% in September 2020 [14]. In terms of the long-term evolution of PT ridership, Campisi et al. [30] found that travel behaviour changed notably during 2020 and 2021 among PT users in Sicily, Italy. While 52.9% of survey respondents were regular users before the pandemic, this dropped to 0% in the second half of 2020, while increasing slightly to 7.7% in 2021. Similarly, the percentage of rare users changed from 4.6% prepandemic to 81.5% in late 2020, and then to 37.2% in 2021. Similar results were found in Greece and Turkey. In Thessaloniki, among university travellers, the number of frequent users had dropped around 75% by mid-2021 [25], and in Istanbul, the demand for PT was still much lower in mid-2021 than before the pandemic among students [31]. In Santiago, Chile, Pezoa et al. [27] found that travel had dropped 95.6% by mid-2020, and by late 2021, it had only rebounded to 48.8% of prepandemic levels.

While the above-mentioned studies highlight the vast body of research that has been dedicated to the impacts of the pandemic on PT usage and its recovery over time, most is based on small surveys, often using nonrepresentative sampling or only focusing on short-term impacts, and mostly using data from 2020 and early 2021. Hence, few studies have a combined focus on long-term impacts using large-scale data sources while focusing on individual travel behaviour.

To the knowledge of the authors, very few studies have conducted specific passenger-type analyses using AFC data. Wang et al. [29] and Pozo et al. [14] focused solely on short-term impacts evaluated within the first year of the pandemic in fall 2020, whereas Pezoa et al. [27] analysed impacts in both July 2020 and October 2021, thus extending coverage beyond short-term impacts. Therefore, there remains a research gap in analysing the individual travel behaviour of PT users over time using large-scale revealed-preference data, especially considering that PT ridership can be expected to remain at much lower levels than pre-COVID-19 considering the large impacts on teleworking, hence affecting commuting patterns significantly [32].

3. Methodology

Our analysis of the impacts of COVID-19 on travel behaviour is performed in two steps. First, we focus on the overall impacts on mode shares and PT ridership. This includes analysing the aggregate impacts on ridership, as well as changes to trip purposes and spatio-temporal changes, with the aim of investigating the underlying reasons for the changes to travel behaviour. Second, we perform a PT passenger segmentation analysis using k-means clustering. This allows for analysing changes to individual travel behaviour across different groups of passengers during the COVID-19 pandemic. By means of these two steps, the analysis incorporates how travel patterns changed over time, both at the aggregate and individual levels.

It is important to recognise that individual travel behaviour is known to change over time, even without major changes to, for example, infrastructure or policies (e.g., due to seasonality or general trends). Hence, when analysing the effects over time during the study period, we also include a reference period outside the study period for the purpose of explicitly considering changes to general trends.

3.1. Overall Impacts. The analysis of the overall trends in travel behaviour was performed using various key performance indicators. This included focusing on not only overall ridership but also how this was related to changes in trip characteristics such as trip purpose, travel distances, and time of travel as well as changes across different geographical areas. This facilitated a more comprehensive analysis of the interrelationships, thus providing insights on the main causes for the changes in ridership on an aggregate level.

3.2. Segmentation Analysis. The analysis of how individual travel habits changed during the COVID-19 pandemic was conducted by grouping passengers according to their travel patterns using AFC smart card data. To ensure that all relevant cards were included, we only included those cards which were active before and after the analysis period (i.e., with active trips). This subset of cards was used for the segmentation analysis. This allowed us to identify specific passenger types and examined how their behaviour changed over time (e.g., one individual can move from one group in the preperiod to another group in the postperiod as a result of changed travel patterns). The variables used for clustering the AFC smart card data, shown in Table 1, were similar to those used by Eltved et al. [33].

The criteria included both travel frequency within weeks and across weeks, thus incorporating two important aspects related to consistent travel behaviour. In addition, the ratio between weekend and weekday travel was included explicitly, which is important for differentiating travel patterns related to different trip purposes. Furthermore, this method allowed for differentiation between, for example, daily commuters, sporadic commuters, leisure travellers, and weekend travellers.

For the analysis, we applied k-means clustering, as this has been extensively used in travel behaviour research using smart card data (e.g., Ma et al. [34]; Deschaintres et al. [35]; and Eltved et al. [33]). Other clustering algorithms were considered, but due to it being the state-of-practice in previous research as well as being simple to implement, we chose k-means clustering. The clustering analysis was performed using the entire dataset; each card was included with an observation for each analysis period (i.e., before and after the pandemic). For the analysis, we normalised all variables to have a mean of 0 and a standard deviation of 1 as the variables have different domains, thereby avoiding skewed clustering results.

3.3. Measuring COVID-19 Impacts. The effects of the COVID-19 pandemic on travel behaviour have varied notably over time due to the large changes in the restrictive measures adopted by governments. To analyse effects across a longer time period, it is therefore relevant to define a measure for the degree of restrictions imposed. For this study, we adopted the so-called Stringency Index, which is a measure of the severity of lockdown measures [36]. It is mainly based on indicators related to containment and closures (e.g., cancellation of public events, restrictions on gatherings and internal movement, closure of schools, universities, and workplaces, and stay-at-home requirements). The measure is an index between 0 and 100 with 0 corresponding to a fully open society and 100 a fully closed society. Using this measure allowed for the analysis and evaluation of travel behaviour changes and PT ridership during the study period in a consistent manner.

4. Case Study and Data

The study focuses on travel behaviour and PT usage in the Greater Copenhagen Area of Denmark, covering 2.1 million inhabitants during the two-year period between January 2020 and December 2021. During the analysis period, several lockdowns in Danish society were enforced, resulting in severe restrictions on mobility. Most importantly, people had to work from home (if possible), schools and educational institutions were closed, with teaching being carried out online, and many shops and restaurants had to close. The restrictions varied throughout the analysis period, with the most severe lockdowns in spring 2020 (March–May) and winter 2020–2021 (December–April). Specifically, for PT

Table 1: Clustering variables.

Variable	Domain	Description
ShareActiveWeeks	0-1	Proportion of weeks during the period with at least one trip
ActiveDaysPerActiveWeek	1–7	Number of days per active week with trips
ShareWeekend	0-1	Proportion of trips made during the weekend

further restrictions were enforced during the period, with a seat reservation policy being introduced on regional trains from March 2020. From May 2020 to May 2021, the maximum allowed occupancy of trains was set to 50–70% to avoid crowding, and from August 2020 to August 2021, there was an additional requirement of wearing face masks on all PT. A graphical overview of the degree of restrictions is presented in Figure 1 in Section 5.1, which shows the Stringency Index for Denmark during the entire study period [36].

The study is based on two sources of information: (i) the Danish National Travel Survey (TU survey) which contains detailed information on individuals' travel habits over the course of a full day, and (ii) AFC data provided by the smart card system used in the PT system in Denmark, called Rejsekort.

The TU survey is an interview-based survey documenting the travel patterns of the Danish population. Every year since 2006, approximately 10,000 respondents have been questioned about their travel patterns throughout a full day, thus including all modes of transport [37]. The survey runs continuously, with respondents being recruited and asked every day throughout the year. The data cover the full spectrum of users' travel patterns, including background information on trips (e.g., trip purpose), the respondents (e.g., gender, age, employment, and income), and their households (e.g., car ownership).

The Rejsekort data contain information on tap-ins and tap-outs within the PT system for each smart card, hence containing information on the entire route travelled by the users, including transfer locations and modes of transport used. The sample used in this study includes more than 300,000 daily trips in the Greater Copenhagen area, representing approximately 40% of all PT trips in the area. The remaining trips not included in the data were paid for mainly by monthly cards and student cards.

5. Results

The results are divided into two sections. The first describes the changes to overall travel patterns focusing on the reasons for the changes to PT ridership by analysing the spatio-temporal evolution of the trips and trip purposes. In the second section, the results for the individual travel patterns are analysed through a clustering analysis. The travel survey data are used for the first part as they contain information on all modes of transport as well as trip information (e.g., trip purposes), whereas the smart card data is mainly used for the second part.

5.1. Overall Trends. The overall changes to PT usage are shown in Figure 1, which shows the evolution of PT ridership, according to the AFC data, together with the evolution of the Stringency Index for Denmark during the period 2020–2021. The ridership in February 2020, before the lockdown, is taken as the reference point. The hypothesis that ridership decreases when lockdown measures are imposed and vice versa is confirmed through the correlation of −0.78 between the two time series. More specifically, the ridership dropped approximately 85% when the first lockdown measures were imposed in March 2020 and again in December 2020 after the second hard lockdown was announced. Conversely, a slow recovery period happened in spring 2020 and spring 2021 while restrictions were gradually lifted after the two lockdowns. In fall 2021, ridership almost reached pre-COVID-19 levels as most restrictions were lifted. However, the onset of the Omicron variant in December 2021 resulted in further restrictions and a resulting large drop in ridership.

Digging further into the reasons for the large reduction in PT ridership reveals behavioural changes related to trip purpose. The distribution of trip purposes taken from the Danish National Travel Survey (TU) is shown in Figure 2. This shows that commuting trips to workplaces and education dropped notably during the two lockdown periods (highlighted in red in Figure 2) due to work-from-home and online teaching restrictions. Simultaneously, leisure trips increased as people spent more time walking and bicycling for recreational purposes. This is in line with previous research from Abdullah et al. [38], which also found a large drop in commuting trips and a large increase in shopping trips, which corresponds to errands in this analysis. However, Pezoa et al. [27] found a large decrease in errands and leisure trips, with most trips conducted still being commuting trips, potentially due to specific restrictions and curfews limiting non-necessary travel. Figure 3 shows the modal shares across walking, bicycling, PT, and car. Before the pandemic, modal shares were stable, whereas the pandemic caused a large increase in the walking mode shares and a decrease in all other modes, but especially PT. This trend is also seen in Figure 4, which shows that the average trip distance decreased from 13 km in the last part of 2019 to 9 km in spring 2021. Hence, the generally longer commuting trips undertaken by PT or car were fewer, whereas shorter local recreational trips on foot increased.

Another look at the changes to commuting patterns is shown in Figure 5, which presents the ridership on weekdays over five weeks throughout the analysis period, using week 9 in February 2020 as a reference. It is noticeable that the largest drops occur during morning (7–9) and afternoon (15–18) peak hours. Conversely, the drop in the early morning hours (5–6) is less pronounced. This is probably due to commuters with fixed working hours still needing to

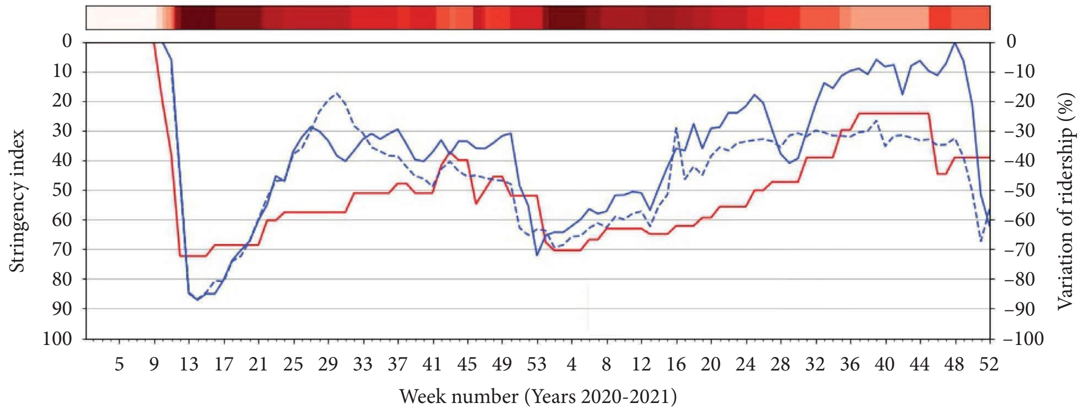

FIGURE 1: Evolution of public transport ridership for the Greater Copenhagen area and the Stringency Index for Denmark during 2020-2021.

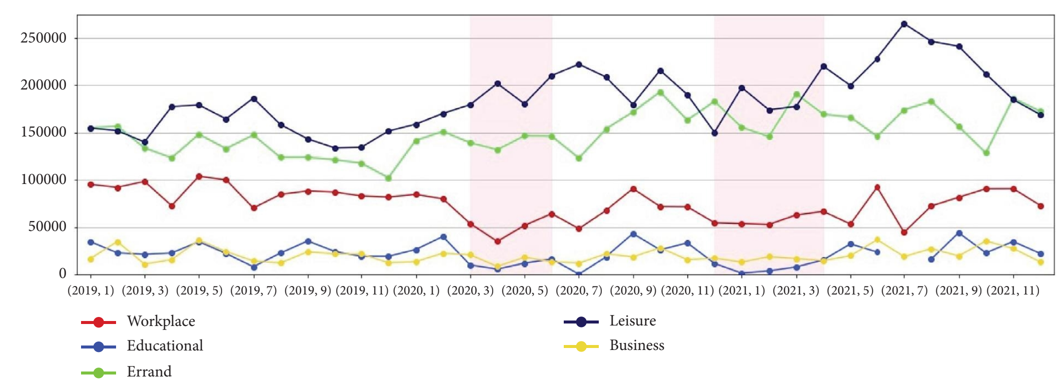

FIGURE 2: Ridership across trip purposes using all types of transport. The principal lockdown periods are highlighted in pink. (Source: Danish National Travel Survey).

commute to work (e.g., health care workers), whereas other industries (e.g., office workers, service sectors, and teachers) could work from home.

5.1.1. Spatial Analysis. The changes to spatial travel patterns were analysed across seven selected areas of the Greater Copenhagen area, as shown in Figure 6. The highlighted areas contain different land use functions (universities, airport, shopping centers, industrial zones, etc.) and are thus hypothesised to be affected differently. This is evidenced in Figure 7, which shows the evolution of PT ridership throughout the analysis period across the selected areas, normalised to week 9 in February 2020. Indeed, in April 2020, the closure of the international borders and universities resulted in a massive ridership drop (more than −90%) for travellers to Kastrup Airport and the campus of the Technical University of Denmark in Lyngby (DTU Lyngby). On the other hand, the drops in zones related to recreational areas were less pronounced (i.e., around −70% for Ballerup and Høje Taastrup). The industrial areas were also less affected, as exemplified by the Avedøre Holme area, which also experienced a drop of around −70%. This is probably explained by the lower proportion of employees who were able to work from home.

While ridership increased across all areas during the reopening of the society during the springs of 2020 and 2021, the effects on ridership to and from the airport and areas with universities were less pronounced. Only in the summer of 2021, when air travel slowly recovered in Europe, did ridership to and from the airport increase again. Similarly, ridership to and from areas with large universities recovered in fall 2021 when universities returned to physical classes. However, these were notably still below pre-COVID-19 ridership levels, whereas ridership in areas that were mostly residential-, shopping-, and industrial workplace-related had almost fully recovered. Thus, the recovery did not happen uniformly across areas, but rather at a pace related to the types of restrictions still in effect and the land use types.

5.2. User Segmentation. In order to identify and analyse the evolution of individual travel patterns, a clustering analysis was carried out. Two study periods were selected to analyse the cluster movements due to the pandemic (see Figure 8). Both cover a full 12-week period from September to

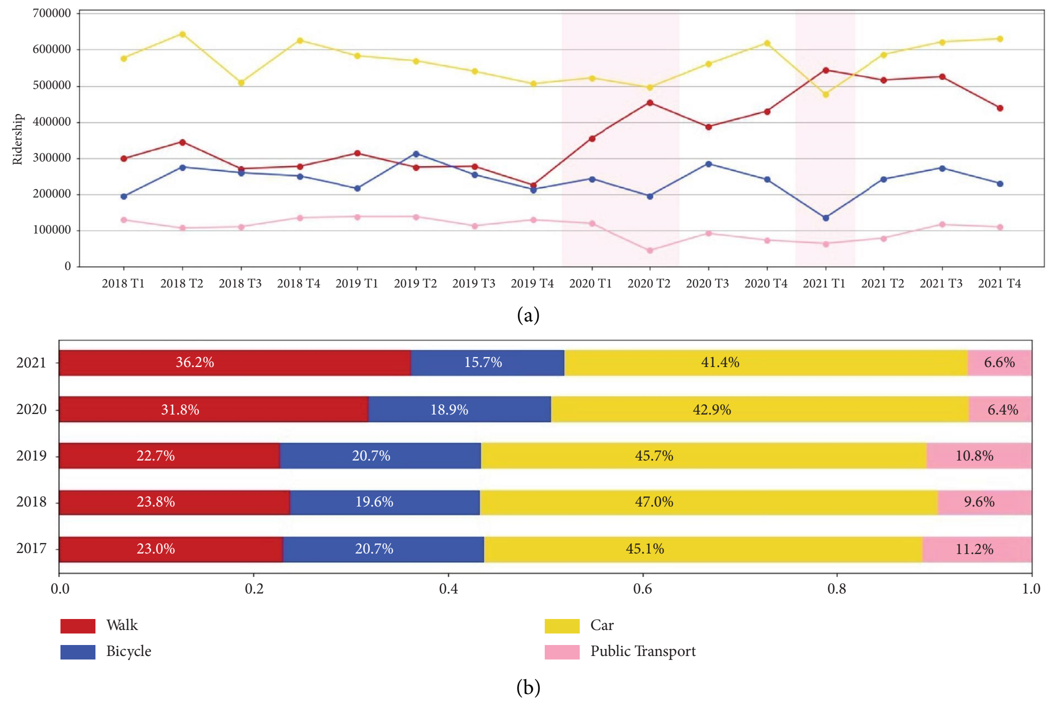

Figure 3: Ridership across modes (a) and mode share per year (b). (Source: Danish National Travel Survey Data).

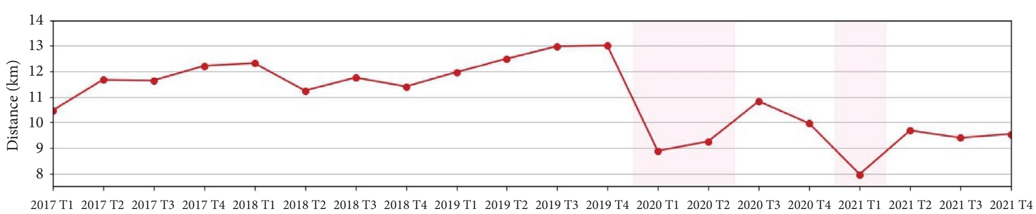

Figure 4: Average distance travelled for all trips. (Source: the Danish National Travel Survey).

November in 2019 (pre-COVID-19) and 2021 (post-COVID-19), respectively. The periods were chosen carefully to ensure limited impacts of seasonal effects. Hence, week 42 was excluded as this week is autumn vacation for many people in Denmark. Moreover, to explicitly consider general changes to travel patterns over time, we include a second analysis of changes between 2017 and 2019, again using the months of September to November. Those relative long periods (12 weeks) ensure capturing passengers' consistency in using PT as measured by the `ShareActiveWeeks` variable. Furthermore, the month of December was avoided as travel patterns might be out of the ordinary due to Christmas. Only smart cards with active trips across each of the two analysis periods were kept for analysis (i.e., around 40% of the cards) in order to remove lost or expired cards. Consequently, the clustering analysis was performed on a total of 541,344 cards for the 2017–2019 analysis and 548,383 for the 2019–2021 analysis.

5.2.1. Travel Behaviour Clusters. The number of clusters k was chosen based on an overall evaluation of the total within-cluster sum of squared distances for each k and a manual evaluation of the interpretability of each cluster. We increased k incrementally until the within-cluster sum of squares did not decrease notably while simultaneously evaluating the cluster characteristics as measured through the three cluster variables. While the evaluation of the within-cluster sum of squares suggested a 5–7 cluster solution, we decided on an 8-cluster solution due to manual considerations regarding the interpretability of the clusters. In Figure 9, a boxplot representing the characteristics of each cluster and its denomination is shown. Clusters are ordered by the average number of active days per week over the entire analysis period, which is obtained by multiplying the `ShareActiveWeeks` by the number of `ActiveDaysperActiveWeek`.

Cluster 1 (*Rare Weekend*) and cluster 2 (*Rare Weekday*) refer to users travelling rarely and not more than once per week (either only on the weekend or on weekdays). Clusters 3–5 represent occasional travellers. Cluster 3 (*Occasional Leisure*) characterises users travelling occasionally, often during the weekend. Cluster 4 (*Fortnightly*) represents users travelling on average once every two weeks, mostly on a weekday. Cluster 5 (*Irregular Worker*) describes the behaviour of an occasional user who travels a few days a week,

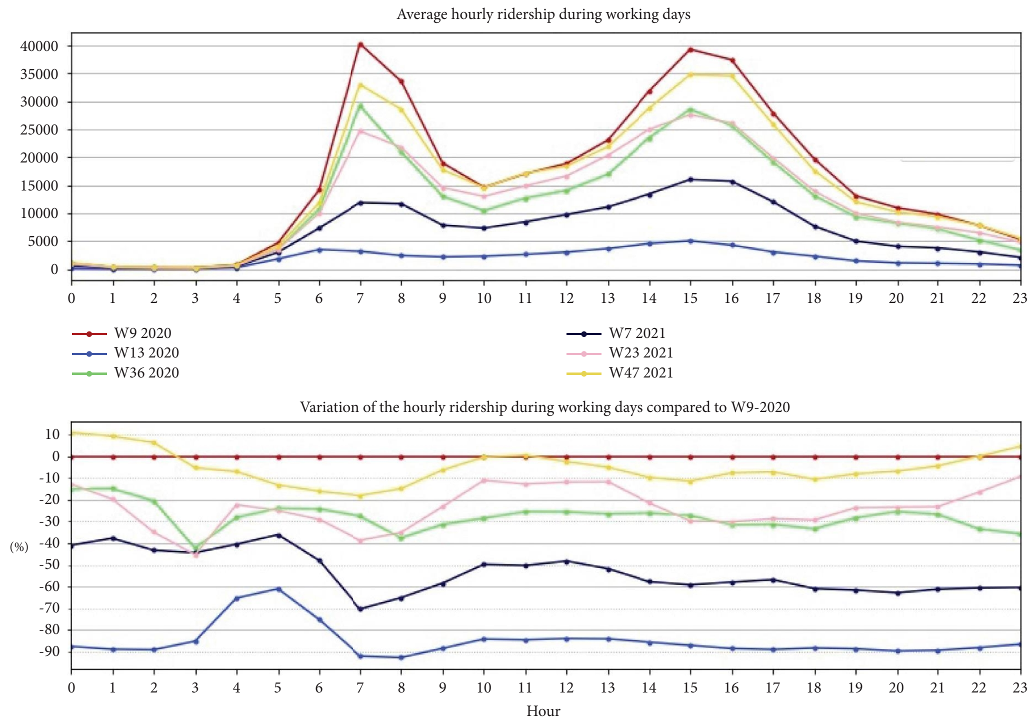

Figure 5: Public transport ridership on weekdays in six specific weeks throughout the analysis period; index compared to pre-COVID-19 level (week 9 in February 2020).

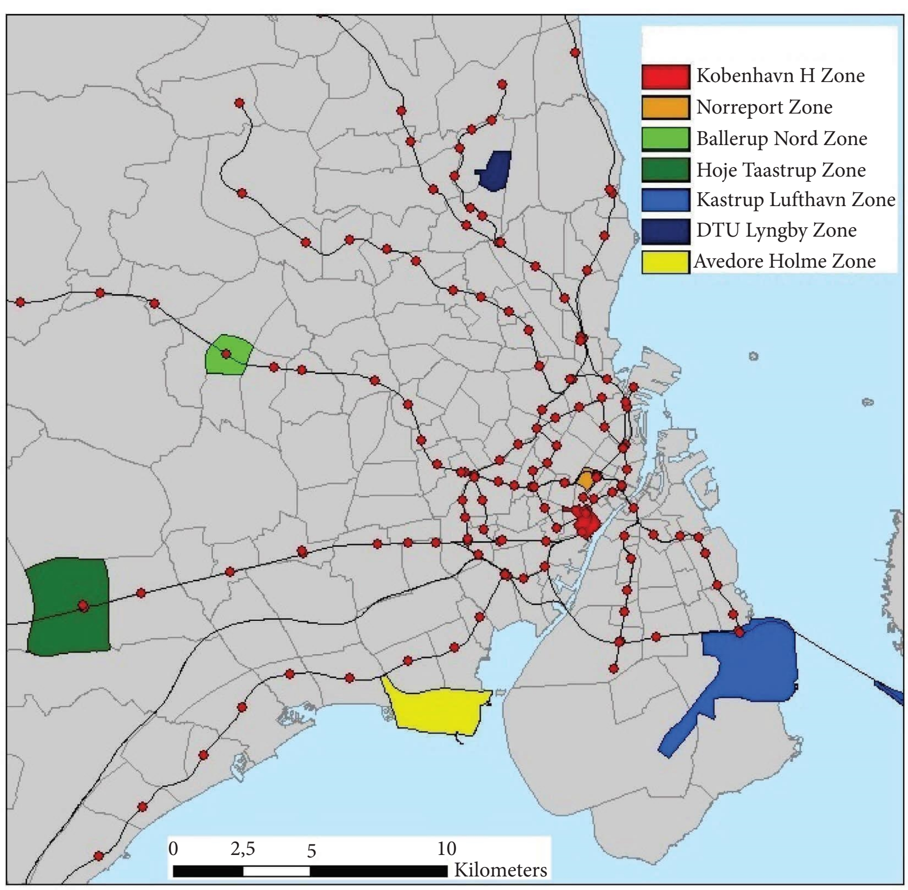

Figure 6: Zones of various land use types in the Greater Copenhagen area.

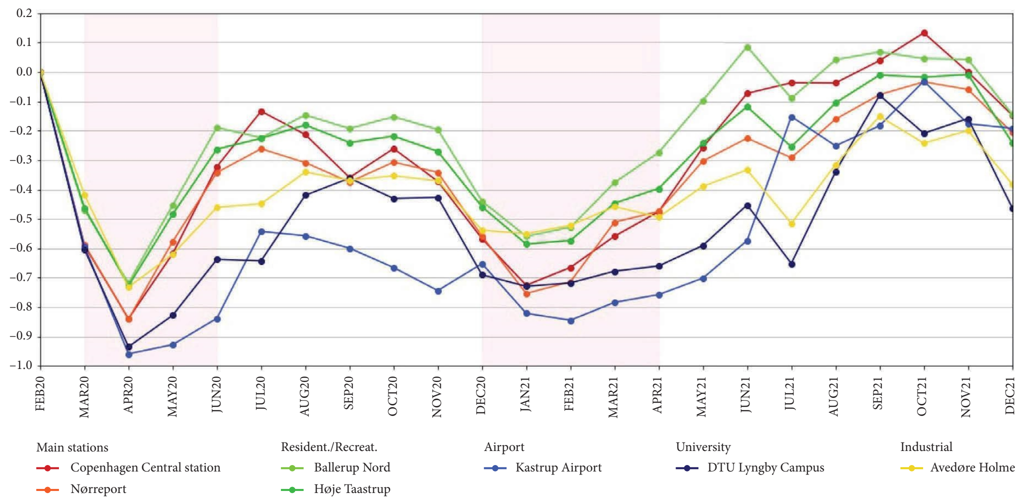

Figure 7: Total Rejsekort ridership travelling to various geographical areas, compared to February 2020 levels.

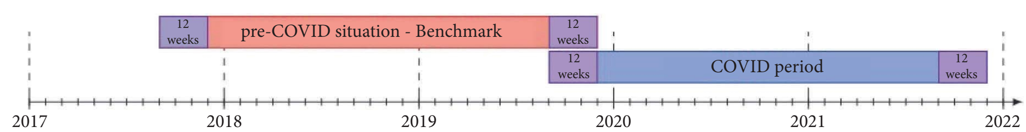

Figure 8: Study periods chosen for the segmentation analysis due to the pandemic (2019–2021) and the reference analysis (2017–2019).

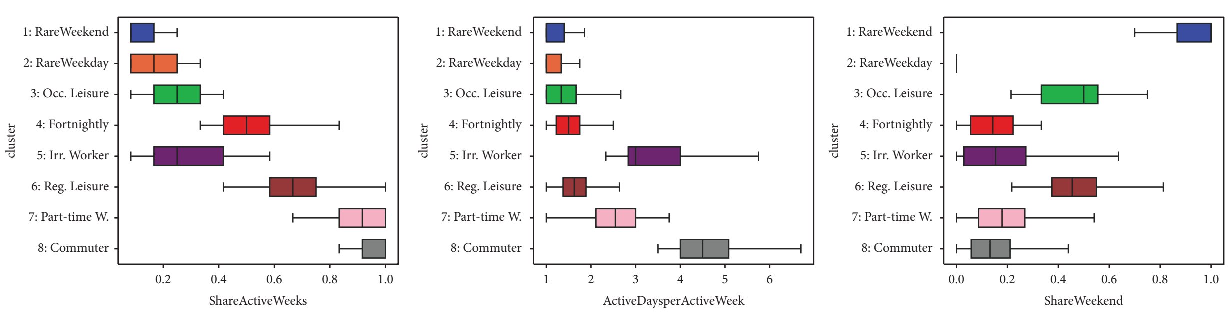

Figure 9: Travel behaviour characteristics for passenger clusters (algo: Kmeans).

mostly on weekdays, but only during some weeks. The three last clusters represent the most regular users. Cluster 6 (*Regular Leisure*) denotes those travelling consistently across both weekdays and weekends, but with very few trips per week, whereas Clusters 7 and 8 denote two types of public transport commuters, namely those travelling 2–3 times per week on weekdays (*Part-time Worker*) and those travelling more consistently 4–5 times per week (*Commuter*). While those using monthly commuter tickets are not included in the Rejsekort data, the results do include a group of users with commuting patterns. As seen in Table 2, this cluster represents 6.8% to 8.7% of cards, but around one-third of all trips. Conversely, cluster 2 (*Rare Weekday*) is the largest cluster, representing around 20% of all cards, but only 3–4% of all trips.

5.2.2. Impacts of COVID-19. The impacts on individual travel behaviour are visualised in the Sankey diagram in Figure 10, which shows the distribution of users across clusters, with pre-COVID-19 on the left-hand side and post-COVID-19 on the right-hand side. The actual percentage changes can be seen in Table 3, revealing several interesting insights on the changes between the pre- and post-COVID-19 periods.

First, most users move across clusters between the two analysis periods, thus suggesting large changes in individual travel behaviour between the periods. For example, only 34.3% are commuters in both periods, whereas 65.7% of pre-COVID-19 commuters change to using PT less frequently in the after period. This change in behaviour tested to be statistically significant at the 99% confidence level by applying a chi-square test hypothesising that the cluster distribution pre-COVID-19 is similar to that during COVID. Hence, most users change their behaviour rather than keeping the same consistent behaviour.

Second, the results suggest a tendency whereby users belonging to less-frequent travel patterns stay within the same clusters, whereas those belonging to more frequent travel patterns in the preperiod change to a less frequent

Table 2: Card and trip shares among the clusters.

	Pre-COVID-19		Post-COVID-19	
	Card share (%)	Trip share (%)	Card share (%)	Trip share (%)
1: rare weekend	8.1	1.5	9.5	1.8
2: rare weekday	19.1	3.3	21.9	4.1
3: occasional leisure	16.2	5.0	17.3	5.9
4: fortnightly	16.6	10.7	16.0	11.7
5: irregular worker	5.2	4.7	4.5	4.4
6: regular leisure	11.1	10.5	10.3	10.9
7: part-time worker	15.0	28.0	13.7	29.4
8: commuter	8.7	36.4	6.8	31.7

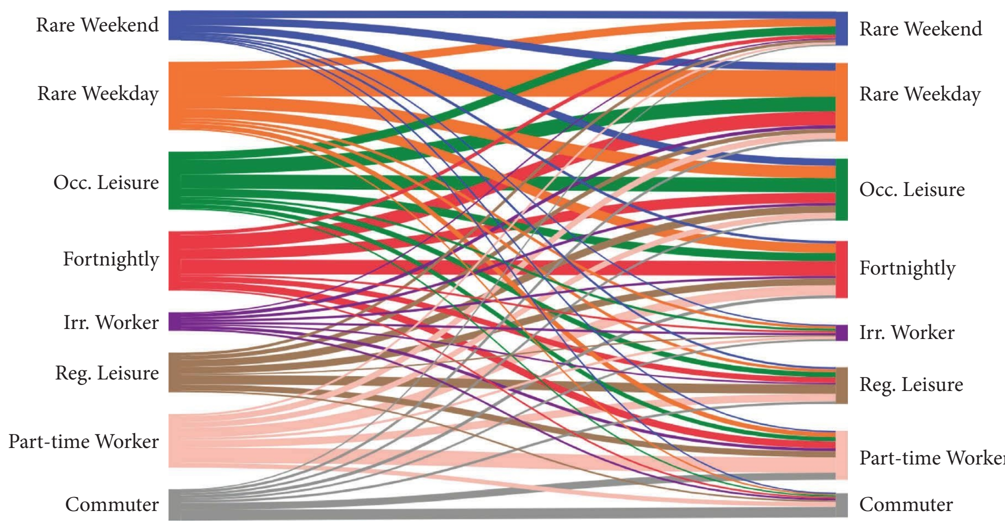

Figure 10: Sankey diagram—cluster movement between the initial period in Sep–Nov 2019 (on the left) and the final period in Sep–Nov 2021 (on the right).

Table 3: Proportion of cards from the initial clusters (row) moving to each final cluster (column) for the pre-COVID-19 (2019) and post-COVID-19 (2021) periods.

	1: rare weekend (%)	2: rare weekday (%)	3: occ. leisure (%)	4: fortnightly (%)	5: irr. worker (%)	6: reg. leisure (%)	7: part-timeW (%)	8: commuter (%)
1: rare weekend	23.0	25.9	24.4	8.8	3.8	7.0	5.2	2.1
2: rare weekday	11.6	38.6	18.4	14.0	3.9	4.2	7.0	2.2
3: occasional leisure	14.0	24.9	24.6	14.0	3.9	9.0	7.2	2.4
4: fortnightly	6.3	23.6	17.4	25.0	3.4	9.3	12.0	2.9
5: irr. worker	7.5	18.2	14.5	12.6	11.8	8.7	16.2	10.6
6: reg. leisure	7.2	10.7	18.2	17.4	3.2	23.8	15.2	4.2
7: part-timeW	4.0	11.1	10.4	18.6	4.6	14.1	28.6	8.7
8: commuter	3.2	8.1	7.1	9.9	6.6	7.9	22.9	34.3

travel pattern in the postperiod. This is clearly visible when analysing the summarised proportions of users travelling less and more frequently between periods, as shown in Table 4(a). In this table, for instance, 38.9% of the users belonging to cluster 3 (*Occasional Leisure*) travel less frequently in the postperiod. More generally, we observe that for each of the six clusters representing more frequent travellers (clusters 3–8), the proportion of the users travelling less often is higher than those travelling more often. Hence, a large share of the frequent travellers reduced their travel frequency after the pandemic. This is in line with the observed drop in ridership, but also reveals that the change to using PT less is observed across all user types rather than limited to specific user groups. Similar findings were observed in Sweden, where commuters switched from 30-day period tickets to single tickets [1].

While these results are likely to be attributed to the pandemic, it is important to consider that this evolution might also be due to exogenous factors unrelated to the pandemic (e.g., changes in residence, workplace location, or other individual reasons). Hence, to validate the results, Table 4(b) shows cluster movements for the reference period (i.e., between 2017 and 2019), and Table 4(c) shows the difference between the pre- and post-COVID-19 periods

Table 4: Proportion of cards from the initial clusters (column) which have shifted to a less-frequent use cluster or more-frequent use cluster.

		1: rare weekend (%)	2: rare weekday (%)	3: occ. leisure (%)	4: fortnightly (%)	5: irr. worker (%)	6: reg. leisure (%)	7: part-timeW (%)	8: commuter (%)
Less frequent	(−)		11.6	38.9	47.4	52.8	56.8	62.8	65.7
Equal	(=)	23.0	38.6	24.6	25.0	11.8	23.8	28.6	34.3
More frequent	(+)	77.0	49.8	36.5	27.6	35.4	19.5	8.7	

(a) Between the pre-COVID (2019) and post-COVID (2021) periods

		1: rare weekend (%)	2: rare weekday (%)	3: occ. leisure (%)	4: fortnightly (%)	5: irr. worker (%)	6: reg. leisure (%)	7: part-timeW (%)	8: commuter (%)
Less frequent	(−)		9.9	35.0	40.9	52.6	48.4	55.5	63.5
Equal	(=)	21.2	40.4	23.1	26.3	13.0	25.6	31.4	36.5
More frequent	(+)	78.8	49.7	41.9	32.7	34.4	25.9	13.1	

(b) Between the two pre-COVID periods (2017 and 2019)

		1: rare weekend (%)	2: rare weekday (%)	3: occ. leisure (%)	4: fortnightly (%)	5: irr. worker (%)	6: reg. leisure (%)	7: part-timeW (%)	8: commuter (%)
Less frequent	(−)	0.0	1.7	3.8	6.5	0.2	8.3	7.2	2.2
Equal	(=)	1.8	−1.7	1.6	−1.4	−1.2	−1.9	−2.8	−2.2
More frequent	(+)	−1.8	0.0	−5.4	−5.1	1.0	−6.5	−4.4	0.0

(c) Difference between the two before-after analyses

(2019 to 2021) and the two pre-COVID-19 reference periods (2017–2019). The comparison of results reveals that the pattern of passengers moving to clusters representing less-frequent travel behaviour is more pronounced between 2019 and 2021 than between 2017 and 2019. More specifically, the percentage of users moving to less frequent travel behaviour in Table 4(a) is higher than in Table 4(b) for all clusters (i.e. positive difference in Table 4(c)). Similarly, the percentage of users adopting, more frequent travel behaviour is higher in Table 4(b) than in Table 4(a) for all clusters, except Clusters 2 and 5, which are mostly similar (i.e., negative difference in Table 4(c)).

5.3. Study Limitations. While the results yielded important insights on passengers' behavioural changes resulting from the COVID-19 pandemic over the course of a two-year period, a few limitations are worth mentioning.

First, the analysis of individual travel behaviour is based on the AFC data from the Greater Copenhagen area. While it contains detailed information on origins, destinations, and transfer locations, it only includes a subset of approximately 40% of all travellers. It does not include those travelling using monthly commuter passes, student passes, and passes for the elderly. Hence, these are not included in the analysis, which might have led to biased results. However, it should be stressed that commuter passes are only economically attractive for those commuting to work more than four times per week. Therefore, those commuting up to four times per week using PT are likely to use the AFC smart card and are thus included in the analysis. This can also be observed in the segmentation analysis in which the group travelling the most travels 4–5 times per week. Considering that the goal of the segmentation analysis was to provide insights into how travel patterns changed across user types and, in particular, not to focus on absolute ridership changes, this is believed to not have affected those results notably.

Second, it can be argued that changes in travel behaviour over time are influenced by many factors. Hence, the changes observed might be due to aspects not included in the analysis. However, this has been considered explicitly by including a reference period, during which no (or very limited) major changes occurred regarding infrastructure, policies, etc. The results from this analysis were robust, with clear and consistent differences between the two analyses.

6. Conclusions and Policy Implications

This study analysed the changes to PT ridership during the full two-year 2020–2021 analysis period in the Greater Copenhagen area of Denmark. The decrease in ridership was substantial throughout the period and was found to be highly correlated with the amount and severity of lockdown restrictions.

In the short term, PT ridership decreased by up to 85% at the beginning of the pandemic in March 2020. However, this large decrease was not distributed uniformly across the network in terms of time and space. Rather, it was found to be related to changes in trip purpose and the character of the lockdowns. The results showed that the early peak hours had a relatively lower ridership reduction, probably due to travellers on fixed working hours, whereas the late peak hours were influenced relatively more, probably due to a higher degree of work flexibility. These findings were also observed when analysing the changes to trip purpose, where commuting trips were mostly affected and leisure trips less so. Similarly, the ridership reductions were most pronounced in areas with a high density of workplaces and educational facilities, where people shifted to working and studying from home. Conversely, for areas with a high density of industry workplaces and recreational facilities, the reduction was less pronounced.

In the medium term, as measured in this study by the end of 2021, PT ridership had recovered notably, although not fully to prepandemic levels. The partial recovery happened as travellers reverted to using PT for commuting, including students after schools and universities reopened fully in fall 2021. At the same time, leisure travel decreased to prepandemic levels. However, ridership recovered most outside peak hours, whereas peak hour ridership was more affected, probably due to people still having the option to partly work from home. This was supported by the segmentation analysis, which showed that PT usage dropped across all user types rather than mainly being related to specific user groups. More specifically, more users changed their travel behaviour to a segment with markedly less frequent PT usage (e.g., prepandemic commuters changed to commuting only some days of the week).

The results bear important policy implications, despite the study limitations highlighted in Section 5.3. Most importantly, the influence of governmental policies, such as restrictions imposed during the pandemic, on travel behaviour and PT usage, vary notably. It is important to consider how such restrictions will affect various functions in the society to allow for more efficient adjustments to the PT network. This should include considerations of the service provision in specific geographical areas, as these are affected differently depending on for instance land use compositions. Similarly, service provision over the course of the day should be considered carefully, as the commute of essential workers is less affected than that of office workers, who have different and more flexible working hours, including the flexibility to work from home.

Data Availability

The data used in this study contain detailed trip data for a large number of users; hence, it is not possible to make it publicly available due to GDPR.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This research was supported and financed by the Independent Research Fund Denmark, grant no. 0130-00012B.

References

[1] E. Jenelius and M. Cebecauer, "Impacts of covid-19 on public transport ridership in Sweden: analysis of ticket validations, sales and passenger counts," *Transportation Research Interdisciplinary Perspectives*, vol. 8, Article ID 100242, 2020.

[2] A. B. Rodríguez González, M. R. Wilby, J. J. Vinagre Díaz, and R. Fernández Pozo, "Characterization of covid-19's impact on mobility and short-term prediction of public transport demand in a mid-size city in Spain," *Sensors*, vol. 21, no. 19, p. 6574, 2021.

[3] C. M. Mützel and J. Scheiner, "Investigating spatio-temporal mobility patterns and changes in metro usage under the impact of covid-19 using taipei metro smart card data," *Public Transport*, vol. 14, 2021.

[4] J. Arellana, L. Márquez, and V. Cantillo, "Covid-19 outbreak in Colombia: an analysis of its impacts on transport systems," *Journal of Advanced Transportation*, vol. 2020, p. 16, 2020.

[5] É. Labonté-LeMoyne, S. L. Chen, C. K. Coursaris, S. Sénécal, and P. M. Léger, "The unintended consequences of covid-19 mitigation measures on mass transit and car use," *Sustainability*, vol. 12, no. 23, p. 9892, 2020.

[6] C. Eisenmann, C. Nobis, V. Kolarova, B. Lenz, and C. Winkler, "Transport mode use during the covid-19 lockdown period in Germany: the car became more important, public transport lost ground," *Transport Policy*, vol. 103, pp. 60–67, 2021.

[7] J. A. Vallejo-Borda, R. Giesen, P. Basnak et al., "Characterising public transport shifting to active and private modes in south american capitals during the covid-19 pandemic," *Transportation Research Part A: Policy and Practice*, vol. 164, pp. 186–205, 2022.

[8] A. D. Marra, L. Sun, and F. Corman, "The impact of covid-19 pandemic on public transport usage and route choice: evidences from a long-term tracking study in urban area," *Transport Policy*, vol. 116, pp. 258–268, 2022.

[9] A. Nikolaidou, A. Kopsacheilis, G. Georgiadis, T. Noutsias, I. Politis, and I. Fyrogenis, "Factors affecting public transport performance due to the covid-19 outbreak: a worldwide analysis," *Cities*, vol. 134, Article ID 104206, 2023.

[10] R. F. Hunter, L. Garcia, T. H. de Sa et al., "Effect of covid-19 response policies on walking behavior in us cities," *Nature Communications*, vol. 12, no. 1, p. 3652, 2021.

[11] R. Buehler and J. Pucher, "Covid-19 impacts on cycling, 2019–2020," *Transport Reviews*, vol. 41, no. 4, pp. 393–400, 2021.

[12] S. Kim, S. Lee, E. Ko, K. Jang, and J. Yeo, "Changes in car and bus usage amid the covid-19 pandemic: relationship with land use and land price," *Journal of Transport Geography*, vol. 96, Article ID 103168, 2021.

[13] B. Gramsch, C. A. Guevara, M. Munizaga, D. Schwartz, and A. Tirachini, "The effect of dynamic lockdowns on public transport demand in times of covid-19: evidence from smartcard data," *Transport Policy*, vol. 126, pp. 136–150, 2022.

[14] R. Fernández Pozo, M. R. Wilby, J. J. Vinagre Díaz, and A. B. Rodríguez González, "Data-driven analysis of the impact of covid-19 on madrid's public transport during each phase of the pandemic," *Cities*, vol. 127, Article ID 103723, 2022.

[15] K. Gkiotsalitis and O. Cats, "Public transport planning adaption under the covid-19 pandemic crisis: literature review of research needs and directions," *Transport Reviews*, vol. 41, no. 3, pp. 374–392, 2021.

[16] H. Dong, S. Ma, N. Jia, and J. Tian, "Understanding public transport satisfaction in post covid-19 pandemic," *Transport Policy*, vol. 101, pp. 81–88, 2021.

[17] S. Das, A. Boruah, A. Banerjee, R. Raoniar, S. Nama, and A. K. Maurya, "Impact of covid-19: a radical modal shift from public to private transport mode," *Transport Policy*, vol. 109, pp. 1–11, 2021.

[18] B. Aaditya and T. Rahul, "Psychological impacts of covid-19 pandemic on the mode choice behaviour: a hybrid choice modelling approach," *Transport Policy*, vol. 108, pp. 47–58, 2021.

[19] L. Downey, A. Fonzone, G. Fountas, and T. Semple, "The impact of covid-19 on future public transport use in scotland," *Transportation Research Part A: Policy and Practice*, vol. 163, pp. 338–352, 2022.

[20] J. Esmailpour, K. Aghabayk, M. Aghajanzadeh, and C. De Gruyter, "Has covid-19 changed our loyalty towards

public transport? understanding the moderating role of the pandemic in the relationship between service quality, customer satisfaction and loyalty," *Transportation Research Part A: Policy and Practice*, vol. 162, pp. 80–103, 2022.

[21] N. Aydin, A. O. Kuşakcı, and M. Deveci, "The impacts of covid-19 on travel behavior and initial perception of public transport measures in istanbul," *Decision Analytics Journal*, vol. 2, Article ID 100029, 2022.

[22] S. Shelat, O. Cats, and S. van Cranenburgh, "Traveller behaviour in public transport in the early stages of the covid-19 pandemic in The Netherlands," *Transportation Research Part A: Policy and Practice*, vol. 159, pp. 357–371, 2022.

[23] P. Basnak, R. Giesen, and J. C. Muñoz, "Estimation of crowding factors for public transport during the covid-19 pandemic in santiago, Chile," *Transportation Research Part A: Policy and Practice*, vol. 159, pp. 140–156, 2022.

[24] C. Chen, T. Feng, X. Gu, and B. Yao, "Investigating the effectiveness of covid-19 pandemic countermeasures on the use of public transport: a case study of The Netherlands," *Transport Policy*, vol. 117, pp. 98–107, 2022.

[25] D. Tsavdari, V. Klimi, G. Georgiadis, G. Fountas, and S. Basbas, "The anticipated use of public transport in the post-pandemic era: insights from an academic community in thessaloniki, Greece," *Social Sciences*, vol. 11, no. 9, p. 400, 2022.

[26] M. R. Fissinger, *Behavioral Dynamics of Public Transit Ridership in chicago and Impacts of Covid-19*, Massachusetts Institute of Technology, Cambridge, MA, USA, 2020.

[27] R. Pezoa, F. Basso, P. Quilodrán, and M. Varas, "Estimation of trip purposes in public transport during the covid-19 pandemic: the case of santiago, Chile," *Journal of Transport Geography*, vol. 109, Article ID 103594, 2023.

[28] M. Abdullah, N. Ali, M. A. Javid, C. Dias, and T. Campisi, "Public transport versus solo travel mode choices during the covid-19 pandemic: self-reported evidence from a developing country," *Transport Engineer*, vol. 5, Article ID 100078, 2021.

[29] J. Wang, J. Huang, H. Yang, and D. Levinson, "Resilience and recovery of public transport use during covid-19," *Nature Portfolio journal Urban Sustainability*, vol. 2, no. 1, p. 18, 2022.

[30] T. Campisi, G. Georgiadis, S. Basbas, and M. A. A. Rashid, "The post-pandemic public transport crisis: a statistical analysis of travel habits in sicily, Italy," *Transportation Research Procedia*, vol. 69, pp. 576–583, 2023.

[31] M. E. C. Bagdatli and F. Ipek, "Transport mode preferences of university students in post-covid-19 pandemic," *Transport Policy*, vol. 118, pp. 20–32, 2022.

[32] R. Vickerman, "Will covid-19 put the public back in public transport? a UK perspective," *Transport Policy*, vol. 103, pp. 95–102, 2021.

[33] M. Eltved, N. Breyer, J. B. Ingvardson, and O. A. Nielsen, "Impacts of long-term service disruptions on passenger travel behaviour: a smart card analysis from the greater copenhagen area," *Transportation Research Part C: Emerging Technologies*, vol. 131, Article ID 103198, 2021.

[34] X. Ma, Y. J. Wu, Y. Wang, F. Chen, and J. Liu, "Mining smart card data for transit riders' travel patterns," *Transportation Research Part C: Emerging Technologies*, vol. 36, pp. 1–12, 2013.

[35] E. Deschaintres, C. Morency, and M. Trépanier, "Analyzing transit user behavior with 51 Weeks of smart card data," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2673, no. 6, pp. 33–45, 2019.

[36] T. Hale, N. Angrist, R. Goldszmidt et al., "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)," *Nature Human Behaviour*, vol. 5, no. 4, pp. 529–538, 2021.

[37] H. Christiansen and O. Baescu, *Transportvaneundersøgelsen-variabelkatalog*, 2020.

[38] M. Abdullah, C. Dias, D. Muley, and M. Shahin, "Exploring the impacts of covid-19 on travel behavior and mode preferences," *Transportation Research Interdisciplinary Perspectives*, vol. 8, Article ID 100255, 2020.