Investigating the potential of aggregated mobility indices for inferring public transport ridership changes

Maximiliano Lizana[1,2], Charisma Choudhury[1]*, David Watling[1]

[1]Institute for Transport Studies, University of Leeds, Leeds, United Kingdom

[2]Department of Civil Engineering, Universidad de La Frontera, Temuco, Chile

SHORT SUMMARY

ICT mobility indices derived from information and communications technologies have recently emerged as a new data source for transport planners. Despite the popularity of these indices, it remains largely untested whether they can provide a reasonable characterisation of actual PT ridership changes. This study aims to address this research gap by investigating the reliability of using ICT mobility indices for inferring PT ridership changes by offering the first rigorous benchmarking between them and ridership data derived from smart card validations and tickets. For the comparison, we use monthly and daily ridership data from 12 cities worldwide and two ICT indices shared globally by Google and Apple during periods of major change in 2020-22. The comparative analysis revealed that the index based on human mobility (Google) exhibited a notable alignment with the trends reported by ridership data. Moreover, we demonstrated that ICT mobility indices can also complement data from smart card records when ticketing is missing or of doubtful quality.

Keywords: Aggregated mobility indices, mobile phone apps, mobility reports, ridership, public transport.

1. INTRODUCTION

Public transport demand data

The availability of proper data is critical to facing current and future challenges in urban mobility (UITP, 2018). In this context, a correct characterization of public transport (PT) ridership changes is essential for authorities and PT operators. Ridership data, defined as the aggregate PT demand for a certain area and temporal resolution (e.g. daily, monthly and annual), has been historically employed for planning and operation. In the last twenty years, the innovation in ridership data collection has focussed on adopting automated fare collection (AFC) systems in replacement of manually collected data. AFC systems have allowed passively gathered demand information from smart cards and digital transactions. Despite the widespread popularity of AFC systems, several limitations on ridership data collection are still present. For example, even though many medium and big cities already run AFC systems, more still need to make that transition. Further, most cities in the Global South still rely fully or partially on non-centralised cash-based PT systems, making it challenging for their PT authorities and operators to analyse PT demand and quantify the impacts of disruptions (Zannat et al. 2019). Additionally, even in the regions where AFC systems are implemented, ridership data may be available only at an aggregate temporal resolution and with limited transparency for the different stakeholders. All these limitations have fostered the innovation in new digital tools to provide proxies of PT demand based on Information and Communications Technologies (ICT).

ICT mobility indices

The increasing penetration of Information and Communication Technologies (ICT) in society has allowed several emerging datasets to be harnessed to face mobility challenges. ICT mobility indices were globally provided by tech companies during the COVID-19 pandemic to describe human mobility patterns in cities. ICT mobility indices were based on data collected from the regular use of mobile devices associated with GPS and apps, technologies that were already part of tech companies' products and services. The information was aggregated to describe human mobility behaviour, offering a near-complete coverage of the urban grid, covering a large proportion of the population and being easily accessible. This aggregate information helped to analyse mobility trends and scenarios, and assess the effectiveness of mobility restrictions on human mobility. ICT indices were also employed in studying COVID-19 transmission, pandemic indicators, air quality and economic recovery, among other topics. Big Tech companies such as Google and Apple shared reports on the aggregate mobility changes of the population at a city or regional scale between 2020 and 2022 (Apple, 2022; Google, 2023).

Among the ICT mobility indices proposed, Google COVID-19 Community Mobility Reports (GCMR) and Apple Mobility Trend Reports (AMTR) were the most popular. GCMR were based on the variation of human movements across different categories of locations (residential, workplace and public transport stations, among others). To estimate the mobility changes related to PT, GCMR considered the access frequencies and the time spent on PT hubs (bus stops, train stations, etc.). The relative change was estimated by comparing a mobility level with a pre-pandemic baseline value. Some uses of the GCMR's PT index were the characterization of the use of PT, the clustering of cities with similar PT demand change levels, and the assessment of the effectiveness of mobility restrictions. On the other hand, AMTR were estimated based on navigation data from the Apple Maps app service to characterise its users' mobility trends. AMTR showed daily relative changes for three transport modes (public transport, walking and driving) by estimating the quotient between the volume of direction requests for a specific day and pre-pandemic baseline.

Ridership data versus ICT mobility indices

Despite the widespread use of the ICT mobility indices provided by tech companies during the COVID-19 pandemic, limited evidence of the reliability of these indices to represent actual PT demand shifts is available. As the importance of mobility data availability transcends the COVID-19 pandemic, a proper assessment of the potential of ICT indices in PT is desirable. So far, comparisons between ICT mobility indices for PT and ridership data have been provided tangentially by a few studies that analysed both data sources when characterising COVID-19's impact on PT demand (Padmakumar & Patil, 2022; Fernández Pozo et al, 2022; Jenelius & Cebecauer, 2020). Therefore, the benchmarking required for properly comparing the datasets is yet to be conducted. Finally, no previous attempts have been made to leverage ICT indices in terms of exploring its potential role to complement traditional ridership data (e.g. fill in spatial and temporal gaps in the data).

2. METHODOLOGY

This study investigates the reliability of using ICT mobility indices for inferring PT ridership changes. **Figure 1** shows the methodology followed in this study. First, we retrieved data on ICT mobility indices and ridership data between 2020 and 2022 for several cities. Then, a common baseline was defined and adopted, allowing the comparison between datasets. ICT mobility indices and ridership were then analysed, and practical applications were explored. A detailed definition of each step is presented next.

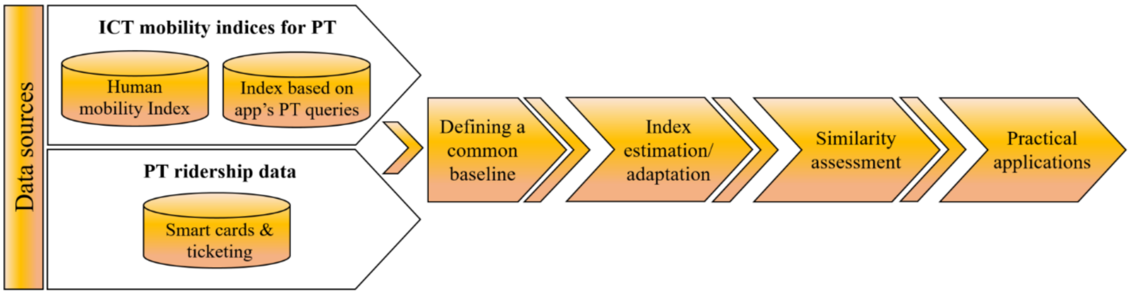


Figure 1. Methodological approach followed in this study.

Data

Two ICT mobility indices for PT were retrieved to be tested in their alignment with ridership changes. We selected Google COVID-19 Community Mobility Reports (GCMR) and Apple Mobility Trends (AMTR) as they offered global coverage and the most prolonged availability. Additionally, they present proxies for PT use based on a different ICT source: GCMR used GPS traces from smartphones, and AMTR employed PT app queries. In this work, we will call Google's human mobility index (HMI) the particular index in the GCMR that measured the changes in human mobility in PT hubs (train stations, bus stops, etc.). Analogously, we will use the term Apple's query index (QMI) to refer to the category of AMTR that compared the level of queries for PT directions in Apple Maps. Both indices were updated daily from 2020 to 2022. Specifically, HMI was provided from 15 February 2020 to 15 October 2022 and QMI from 13 January 2020 to 12 April 2022. On the other hand, ridership data came from validations made by smart cards and paper or digital tickets and were directly retrieved from the official portals of several PT operators.

Preparing the data and measuring the degree of similarity

We first generate comparable datasets for estimating mobility changes. This process considered the baseline definitions adopted for the case studies where daily ridership was available and the baseline of the ICT indices used. The degree of similarity between the values reported by ICT indices (HMI and QMI) and RRC was assessed by applying metrics under a time series approach. For the monthly analysis, we included the mean Euclidean distance (MED). The MED provides a straightforward interpretation of the differences observed. In fact, as the time series values are all relative changes (%), the distance between each pair of values for each month/day is just percentage points.

RRC forecasting using time series modelling

The ICT index that performed better in replicating ridership changes was calibrated to explore its capabilities to predict RRC using time series modelling in different contexts. We focussed this analysis on a context where ridership data did not capture the actual PT demand. Particularly, on the free bus travel period in London during the pandemic outbreak. From 20 April to 30 May 2020, Transport for London introduced middle/rear-door-only boarding in bus services. ICT indices were used here to reveal an approximation of the actual PT demand in this period where ridership was under-reported.

Autoregressive Integrated Moving Average (ARIMA) models were employed to calibrate the relationship between the recorded RRC and the ICT index that performed better. ARIMA models are particularly efficient and appropriate when successive observations show serial dependence (e.g. in this case, daily observations). At the same time, this modelling approach allows testing whether the ICT index contribution to explain RRC is statistically significant. To consider daily and weekly correlations we use seasonal ARIMA model. If s is the seasonal period of the time series (considering weekly seasonality s=7), then the seasonal ARIMAX $(p, d, q) \times (P, D, Q)[s]$ can be written as follow:

$$\Phi_P^*(L^s)\Phi_p(L)(1 - L^s)^D(1 - L)^d y_t = \mu + \Theta_Q^*(L^s)\Theta_q(L)\varepsilon_t + \omega ICT_t \tag{1}$$

where y_t is the value of the time series for the time t (the recorded RRC_t in our case). $\Phi_p(L)$ is the polynomial of order p that describe the AR component and $\Theta_q(L)$ the polynomial of order q of the MA. d differences can be applied on the dependent variable to obtain a stationary time series. $\Phi_P^*(L^s)$ is the operator of the seasonal auto-regressive component with order P, D is the seasonal differences number and $\Theta_Q^*(L^s)$ is the operator for the seasonal moving average component with order Q. The backshift or Lag operator L is defined as $Ly_t = y_{t-1}$ and ε_t is the white noise process (i.e. random error, i.i.d. Gaussian (0, σ_ε^2)). Note that we have added in the last term of Equation (1) the ICT index, which is an exogenous variable in the modelling with coefficient ω.

3. RESULTS AND DISCUSSION

Similarity analysis – monthly data

A monthly analysis of 12 cities from eight countries showed that HMI and QMI were capable of replicating the RRC with different degrees of accuracy. **Figure 2** presents the monthly variability of each index for the entire study period per case study. Overall, ICT indices correctly mimicked the main direction of changes depicted by RRC. In all the cases considered ICT indices properly replicated the drop in PT demand during the pandemic outbreak. However, in most cases, ICT indices reported higher PT demand recoveries than the RRC. The average MED for the HMI and QMI were 14.4 and 26.6 percentage points, respectively. Cities like London and Sidney exhibited the greatest match between HMI and RRC, with small MED obtained (5.1 and 4.0, respectively). However, common MED were between 10 and 20 percentage points for most studied cases. Regarding the QMI, this index exhibited a similar adjustment to HMI until April 2021. After this date, QMI showed a general increase until August 2021, when the index stabilised around 60 percentage points above RRC values.

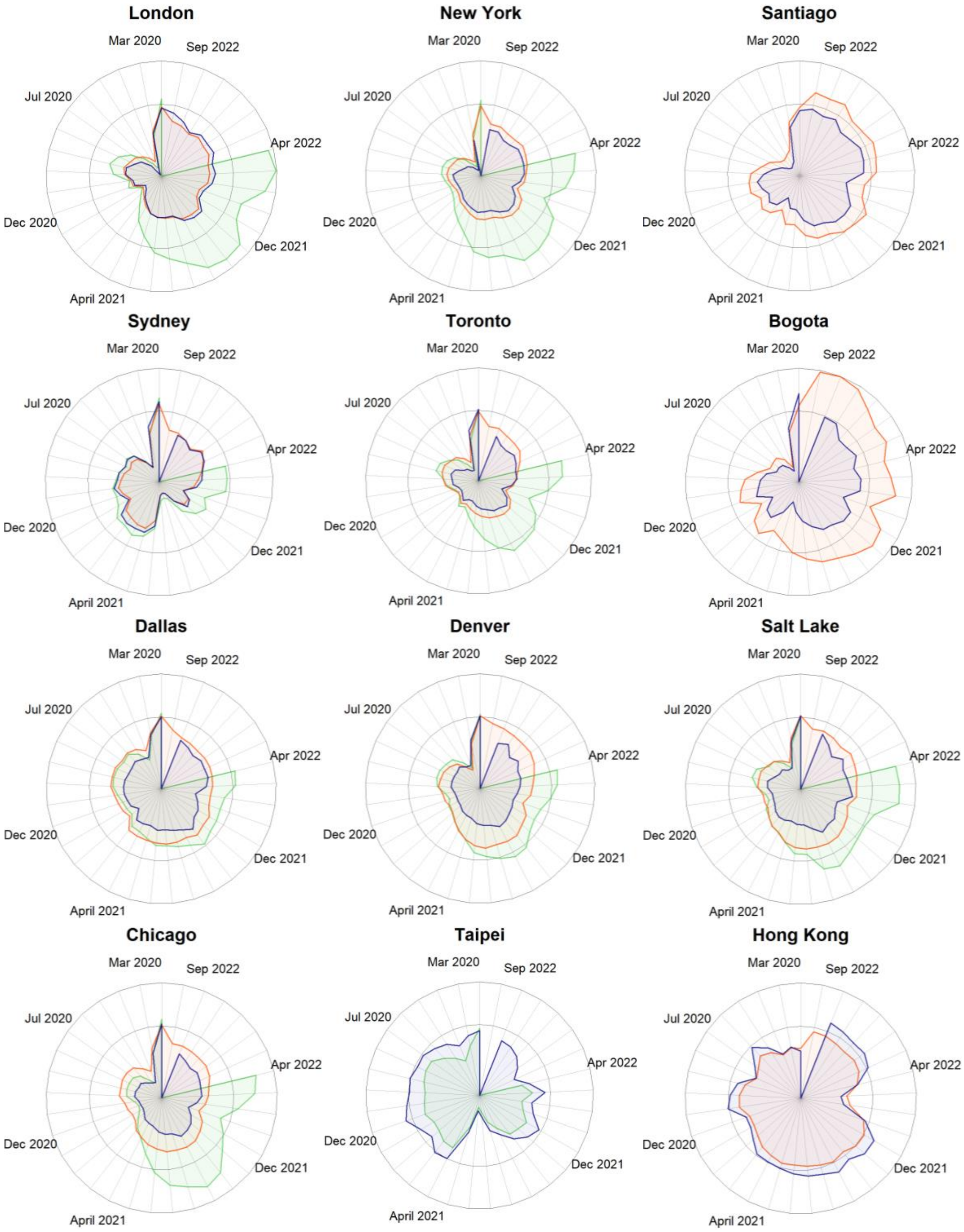
Similarity analysis – Daily analysis

The daily analysis compared HMI and QMI with RRC for the cities of London, New York and Santiago. **Figure 3** provides a graphical illustration of the time series of the three indices. The HMI was found to match surprisingly well with RRC time series. At the same time, the QMI displayed a reasonable fit in terms of the magnitude of the PT demand recovery until the first half of 2021. The main trends of peaks and troughs of the RRC time series were also depicted appropriately by HMI and QMI, including short sharp reductions during holidays. A particular concurrence of the values of all indices was observed during the periods where the stricter mobility restrictions were in place.

Modelling results – The London case study

Based on the results of the similarity analysis, the HMI was selected as the best candidate for exploring the capability of ICT indices to complement information from traditional ridership data. Seasonal ARIMAX models were used to calibrate the relationship between HMI and RRC and then to forecast RRC for two particular cases (which have already been described in detail in section 3.4): a free bus travel period in London, and the day with the highest recorded RRC in Santiago during late 2022. A seasonal component of seven days was considered as the correlograms of the time series identified weekly periodicity. The periods used to fitting and validate the models were selected considering the nearest interval to the research periods with homogeneous differences between the HMI and RRC. Two models were fitted for London, one with data located before the research period and a second with data after it. For fitting and validation purposes, the selected data were split into two segments considering a proportion 5:1.

The fitted and forecasted RRC for the London case study are shown in **Figure 4.** Modelling results suggest a substantial under-reporting in ridership due to the free-bus policy enacted from 20 April to 24 May 2022 (see **Figure 4B**). The predicted RRC (using forward and backward forecasting) coincided with the under-reporting magnitude, showing the forward forecasting a slightly more conservative prediction of the RRC. The difference between recorded and predicted RRC was at least 20 percentage points when the free-bus trip policy started on 20 April 2020. The results also revealed that even when the free-bus policy finished on 24 May, the under-reporting in ridership continued for several months, gradually decreasing. In fact, according to **Figure 4B**, it took at least two months after the end of the free bus policy to observe the unification between the recorded and predicted RRC. This finding revealed a gradual adaptation process of PT users to return to normal payment behaviour after experiencing a free bus ride policy.



HMI (orange), QMI (green), RRC (blue)

Centre of the graphic: -100% change, first grid circumference: 0% change,
External grid circumference: +60% change. All compared with baseline values.

Figure 2. Average monthly changes in HMI, QMI, and RRC from February 2020 to October 2022 (for some case studies, available ridership data end in July 2022).

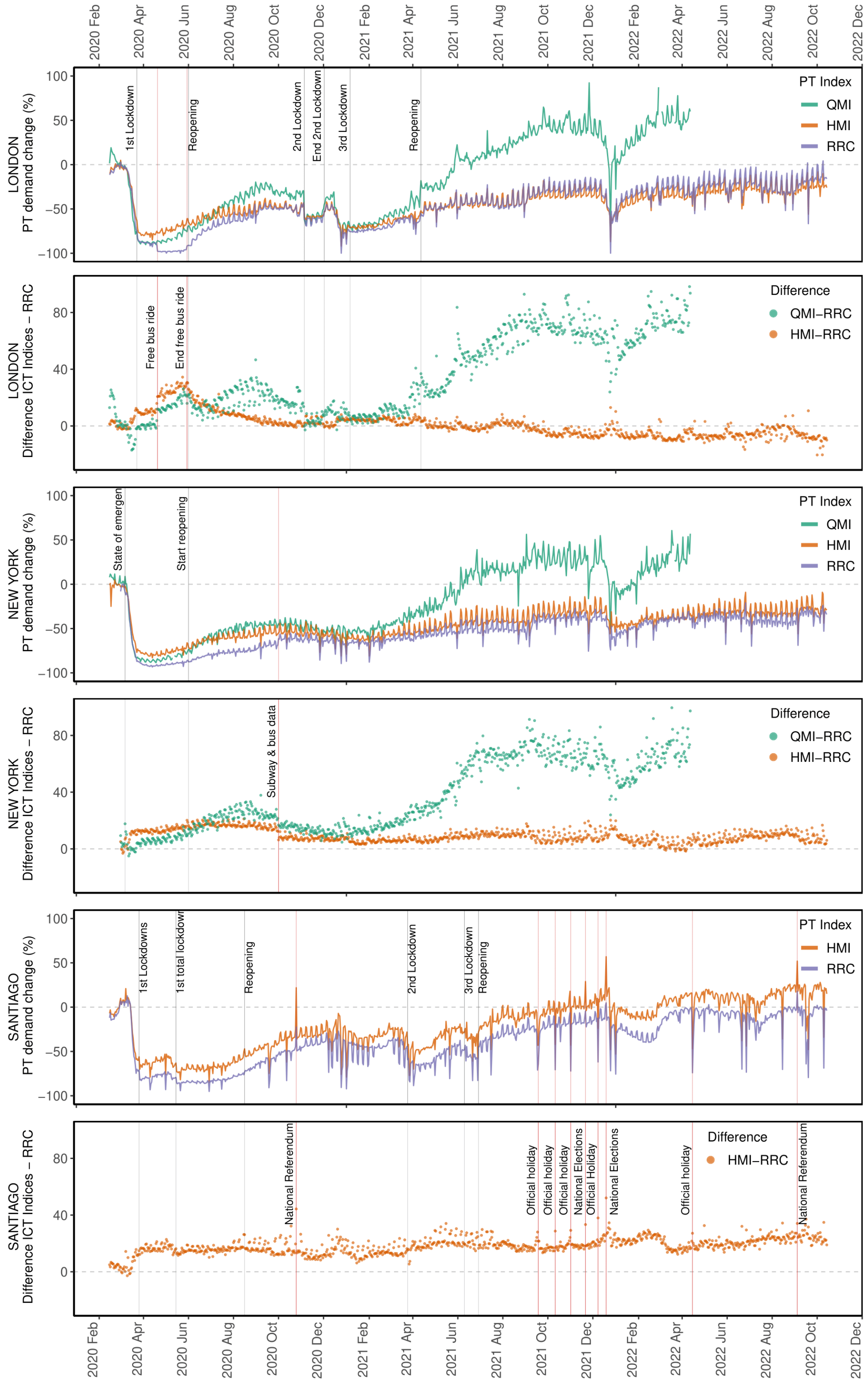


Figure 3. Daily variation of PT mobility indices (HMI, QMI and RRC) for the case studies of London, New York and Santiago.

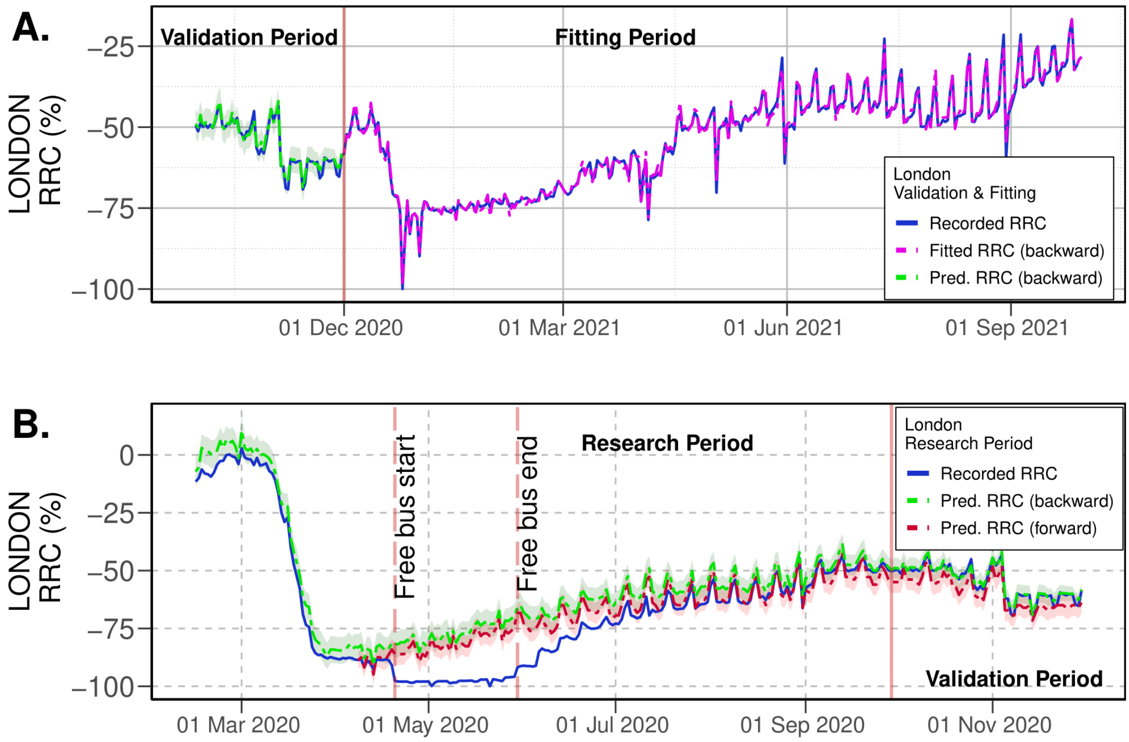


Figure 4. London's modelling results (95% confidence intervals). A) Fitting and validation results, B) RRC predicted on the research period.

4. CONCLUSIONS

Despite the extended use of these ICT mobility indices to describe PT demand changes during the COVID-19 pandemic, existing research is inconclusive as to what extent they could replicate the changes observed by actual ridership data. Considering that motivation, this study analysed the reliability of ICT mobility indices for inferring ridership data changes. The results reported here contribute to the existing literature of emerging data source for PT by providing the first rigorous assessment of the capabilities of ICT mobility indices to replicate the relative changes in aggregate PT demand reported by ridership data. The key findings of the research are as follows:

- Both Google' human mobility index (HMI) and the modified Apple query index (QMI) were able to capture the main changes in ridership trends. However, there was strong evidence that HMI performed better than the QMI. The results of this paper differ from previous findings conducted during the first half of 2020, which found substantial differences between ICT mobility indices and ridership data. However, in the same line of existing findings, we found proof that ICT mobility indices generally overestimated the recovery of PT demand reported by ridership during the study period.

- Observed limitations of ICT mobility indices as a proxy of aggregate PT demand shifts were related to the nature of the data sets used for their estimation. Indices based on PT queries would be more susceptible to experiencing higher variation than GPS-based indices and eventually could be less reliable.

Based on our results, ICT mobility indices based on data collected by smartphone apps have the potential to provide a reasonable proxy of the aggregate level shift in public transport (PT). This proxy can be obtained using phone's GPS traces to quantify human mobility in PT hubs or the number of queries in PT travel planner apps to collect users' information demand. ICT mobility indices can be employed to strongly support authorities in dealing with atypical events such as natural disasters, social unrest, and PT supply disruptions. The availability and employment of these data sets would be of particular practical importance for urban contexts where AFC systems are unavailable, as is the case for most cities in developing countries. ICT mobility indices could also play a complementary role in systems that already use smart cards. For instance, they can be employed to predict actual PT demand when information collected for that source halts or is partial.

ACKNOWLEDGEMENTS

The funding for this research has been provided by the Chilean Agency of Research and Development (ANID) through the Becas Chile scholarship (URL: https://www.anid.cl). Professor Charisma Choudhury's time was supported by the UKRI Future Leader Fellowship [MR/T020423/1] (URL: https://www.ukri.org/).

REFERENCES

Apple. Apple Mobility Trends Reports [Internet]. 2022 [cited 2023 Apr 14]. Available from: https://covid19.apple.com/mobility

Fernández Pozo, R., Wilby, MR., Vinagre, J.J., Rodríguez A.B. (2022) Data-driven analysis of the impact of COVID-19 on Madrid's public transport during each phase of the pandemic. Cities, 127.

Google. COVID-19 Community Mobility Reports [Internet]. 2023 [cited 2023 Jan 1]. Available from: https://www.google.com/covid19/mobility/

Jenelius, E., Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. Transp Res Interdiscip Perspect, 8.

Padmakumar, A., Patil, GR. (2022) COVID-19 effects on urban driving, walking, and transit usage trends: Evidence from Indian metropolitan cities. Cities,126.

UITP. The Value of Data for the Public Transport Sector [Internet]. 2018. Available from: https://www.uitp.org/publications/the-value-for-data-in-the-public-transport-sector/

Zannat, K., Choudhury, C. (2019) Emerging Big Data Sources for Public Transport Planning: A Systematic Review on Current State of Art and Future Research Directions. J Indian Inst Sci., 99(4).