The Effects of a Real-Time Public Transport Information App on Travel Behaviour, Traffic Levels and the Environment

Bastián Henríquez-Jara[1,2], Jacqueline Arriagada[2,3], Kimberly Montenegro[2], Alejandro Tirachini[4,1], and Marcela Munizaga[1,5]

[1]Faculty of Physical and Mathematical Sciences, Universidad de Chile, Santiago, Chile
[2]Transapp, Santiago, Chile
[3]University of Leeds, Leeds, United Kingdom
[4]Department of Civil Engineering & Management, University of Twente, Enschede, The Netherlands
[5]Institute of Complex Engineering Systems, Santiago, Chile

Short summary

In this paper, we go beyond the current state-of-the-art, by analysing the modal choice changes induced by the use of a mobile-phone app for real-time public transport information, and estimate the effects on motorised traffic levels (vehicle-kilometre travelled -VKT) and pollutant emissions. A survey was conducted through the nation-wide public transport app *Red* in Chile, and responded by 3681 travellers from 15 medium-sized cities. We find that urban buses gain 50% more users than it loses, and that the main competitors are shared taxis and ridesourcing services. Logit models show that public transport attracts short-distance travellers with a good perception of the safety of the transport system and without vulnerability conditions. Finally, Monte Carlo simulations show that the app reduces total VKT (probability $P = 0.98$), which implies saving up to 88 tonnes of CO_2 emissions per year. Finally, we discuss the policy and technology implications of our findings.

Keywords: Behaviour change;Sustainable transport; Real-time transport information; Travel app.

1 Introduction

Advanced Traveller Information Systems (ATIS) play an increasingly important role in the modernisation and improvement of public transport systems around the world. With the advent of new technologies, such as GPS devices and smartphones, ATIS platforms provide valuable real-time information to passengers, allowing them to plan their trips and make better decisions. This information can be about itinerary, vehicle arrival time at stops, service disruptions, and other important aspects.

In the absence of travel information, people form expectations about each relevant transport attribute on a trial-by-trial basis (Ben-Elia & Shiftan, 2010; Jha et al., 1998), which can be biased by abnormal experiences (Y. Tang et al., 2017) and endogenous beliefs (Vos et al., 2021). In contrast, real-time information allows to travellers to update their perception of public transport taking into account descriptive information. The effects of real-time information on behaviour and the underlying mechanisms are multiple, for which we developed a framework to summarise them (Figure 1). The literature indicates that ATIS improves the travel satisfaction associated with public transport and makes it a more attractive alternative (Dziekan & Kottenhoff, 2007; Watkins et al., 2011; Papangelis et al., 2016; Brakewood et al., 2014; Brakewood & Watkins, 2019).

In this context, numerous stated-preferences studies suggest that providing real-time information increases the demand for public transport (L. Tang & Thakuriah, 2007; Gooze et al., 2013; Politis et al., 2010; Ferris et al., 2010; Zito et al., 2011). However, all of them have focused on the effect on public transport passengers, without considering the interaction between different modes and how ATIS affect travellers' modal shift behaviour (Brakewood & Watkins, 2019).

The aim of this study is to evaluate the impact of real-time travel information on modal choice in 15 medium-sized Chilean cities. Unlike previous studies, we intend to assess the impact of this information not only on public transport demand but also on other modes of transport, including cars, bicycles, walking and ride-hailing services. This broader perspective will provide a comprehensive understanding of how real-time information affects different modes of travel, traffic

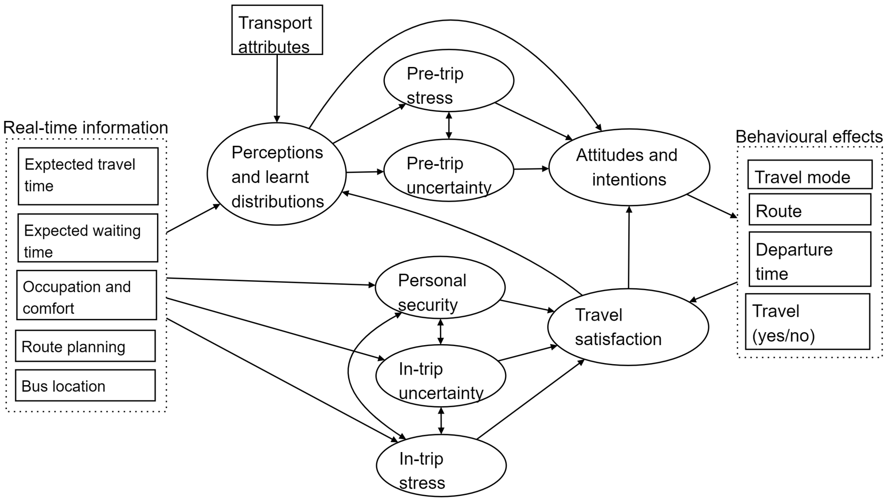

Figure 1: Framework representing the effects of ATIS on travel behaviour. Source: own elaboration.

levels, and traffic externalities, such as carbon emissions. This article addresses the following research questions: (A) Does ATIS have an effect on the choice of travel mode? (B) What are the determinants of adopting or leaving public transport conditional on the use of an ATIS? and (C) Is there a benefit in terms of decreasing VKT and the associated pollutant emissions?
To address the research questions, we analyse the effect of *Red Movilidad Regional* (*Red* for short), the first mobile application for transport information in cities other than Santiago in Chile. We conducted a survey on the app, obtaining 3681 responses. We identify the modal substitution effect by asking participants for their latest trip and how they would have travelled if the app was not available. We analyse the factors that influence the adoption of public transport and simulate the effect of *Red* on the variation in total VKT and associated emissions. To our knowledge, our research is the first to estimate the benefits of providing information in real time to travellers, in terms of increasing the demand for sustainable modes, reducing total motorised traffic levels (VKT), and reducing the associated pollution.

2 Methodology

Modal substitution estimation

In order to identify the behavioural change triggered by the application, we asked participants if they would have used another mode in case the *Red* application had not been available. The mode stated to have been used in the hypothetical situation where the application was not available is considered the **counterfactual mode**. Then, let us call y^f_{nj} to an indicator function that is 1 if the subject n chose the mode j in the latest trip and 0 if not. On the other hand, y^c_{ni} is 1 if the individual n chooses the mode i as counterfactual and 0 if not. This allows us to define the total number of trips in mode i substituted by trips in mode j (V_{ij}) as follows:

$$V_{ij} = \begin{cases} \sum_{n=1}^{N} y^f_{nj} \cdot y^c_{ni} & \forall i \neq j \in C \\ 0 & \text{other case,} \end{cases} \tag{1}$$

where C is the consideration set of size J and N is the number of individuals. Here, it is important to consider that one of the alternatives is *not to make the trip.* From the above, we can define a travel mode substitution matrix S_{JxJ}, with diagonal 0 and each component ij denotes the number of users who substituted a trip in a mode i by a trip in a mode j. Then, the total trips captured by a mode j (V^f_j) are given by the column sums of the above matrix, and the total of trips that left the mode i (V^c_i) are given by the row sums of the above matrix. Then, the net variation of the trips in mode j', i.e. the substitution rate, is given by the difference between the trips atracted and the trips that left the mode j':

$$\Delta V_{j'} = V_{j'}^{f} - V_{j'}^{c} \tag{2}$$

In this study, the consideration set C is comprised by: not making the trip, car, car passenger, bicycle, walking, taxi, *colectivos* (shared taxis running on fixed routes), bus, ride-hailing, and train.

Mode shift models for behavioural change analysis

In order to assess whether ATIS have an impact on mode choice, we used the Random Utility Maximisation (RUM) framework to model travellers' decisions to use or not use public transport. This approach allows us to understand which users were attracted to public transport once they began using *Red* and which users left public transport and adopted other modes.

We assumed that once people started using Red, they faced a decision: whether to continue travelling in the same mode or not. Then, we estimated two binomial logits. The first (**public transport adoption**) captures the choice of to shift to public transport or not. On the other hand, the second model (**public transport abandonment**) refers to the choice of leaving public transport for any other mode. In both models, we specify the utility U_n^{shift} associated with changing the counterfactual decision, as linear-additive function explained by the travel attributes of the trip and demographics characteristics of the individual. The details of the formulation is not provided here for extensions limitation.

The effect of information on traffic: simulating the VKT variation

We adapt and extend the methodology proposed by Tirachini & Gomez-Lobo (2020), which simulated the variation in VKT generated by the use of a ride-hailing application. This section details our adaptation of that methodology, which allowed us to estimate the global variation in VKT caused by the use of *Red* and the associated pollutant emissions. First, we estimate ΔVKT_j, which is the net variation in VKT for the mode j:

$$\Delta VKT_j = \frac{L_j^* \Delta V_j}{O_j}, \tag{3}$$

where ΔV_j is the net variation in trips in mode j as obtained in the Equation 2, L_j^* is the corrected mean distance of a trip in mode j and O_j is the mean occupation of that mode. Then, the total variation in the VKT (ΔVKT) is given by the sum of the variation in VKT for each mode. The average variation in VKT of a trip made with the *Red* application can be estimated by dividing ΔVKT by the number of trips made with the application V_{app}. This can be interpreted as the marginal variation in total VKT when an individual uses the *Red*. Finally, the total average variation of VKT can be written as follows:

$$\begin{aligned}\Delta\overline{VKT} =& \frac{\overline{L}_c(1+\theta)(1+\tau_c)}{O_c}\frac{\Delta V_c}{V_{app}} + \frac{\overline{L}_t(1+\mu_t)(1+\tau_t)}{O_t}\frac{\Delta V_t}{V_{app}} + \frac{\overline{L}_{RH}(1+\mu_{RH})}{O_{RH}}\frac{\Delta V_{RH}}{V_{app}} + \\ & \frac{\overline{L}_b\beta(1+\tau_b)}{O_b}\frac{\Delta V_b}{V_{app}} + \frac{\overline{L}_{cp}(1+\theta)(1+\tau_c)}{O_{cp}}\frac{\Delta V_{cp}}{V_{app}} + \frac{\overline{L}_{col}(1+\mu_t)(1+\tau_t)}{O_{col}}\frac{\Delta V_{col}}{V_{app}}\end{aligned} \tag{4}$$

where the subindexes denote the mode: car as driver (c),taxi (t), ride-hailing (RH), bus (b), car as passenger (cp), and *colectivo* (col). The correction factors (θ, τ_i, μ_i) were extracted from Tirachini & Gomez-Lobo (2020). We used this result to estimate the variation in emissions, using the emissions factors per mode estimated in Osses et al. (2022).

3 Results

Modal substitution

Among the 2881 participants who used *Red* in their latest trip, 286 reported that without the application they would have made the trip in a different way. This is, the effect on the behaviour change associated with the use of *Red* is 9.927%. Figure 2 shows graphically the travel substitution matrix. This graph summarises the directions of behavioural change among those users whose behaviour was affected by the application. It shows on the left-hand side the substituted mode and on the right-hand side the chosen mode. The annotations indicate the percentage relative to the 286 participants whose behaviour changed.

254 participants would have made the trip in a different mode and 34 would not have made the trip. That is, the application had an effect on inducing close to 1% of the demand, which was mostly attracted by public transport. 5.6% of the users left the private car either as a driver or as passenger. Every participant who left the private car as a driver (3.5%) switched to public transport. In addition, 97.6% of people who left ride-hailing modes shifted to public transport, as well as 93.36% of those who left the *colectivo* and 94.86% of those who left the train. On the other hand, users who left public transport were attracted by the *colectivo* (31.35%), ride-hailing (10.45%), train (13.62%), private car (14.09%) and walking (28.19%).

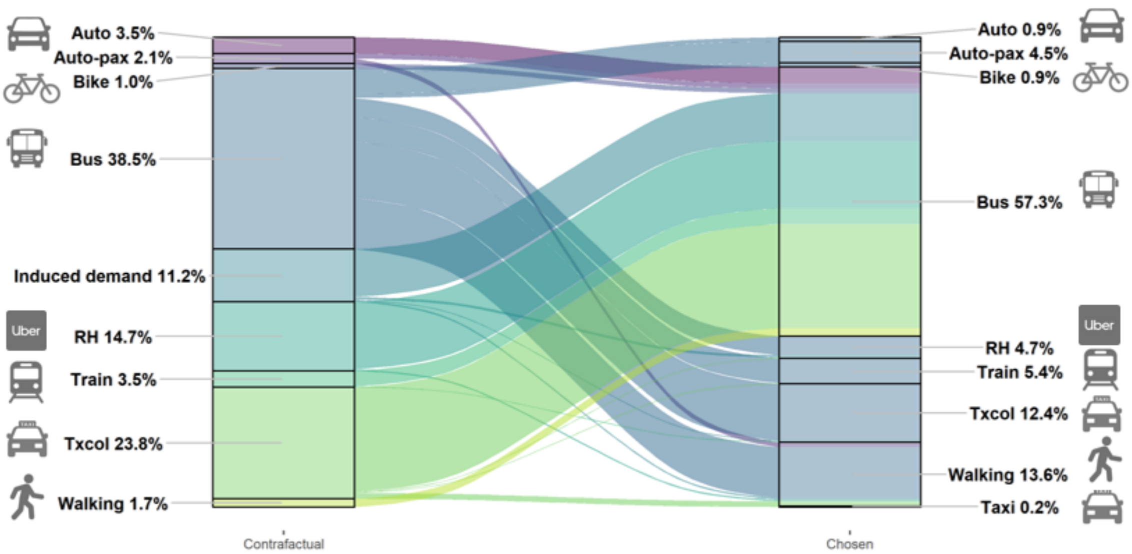

Figure 2: Graphic representation of the estimated modal substitution.

As observed, the main competitors for public transport in the sample studied are ride-hailing and *colectivos*. Both are private modes that have been previously shown to compete with public transport (Tirachini, 2020). The results in this section show that one of the main effects of providing real-time information to public transport passengers is the substitution of private transport modes by public transport.

Mode shift models

We made two models, a bus adoption model and a bus abandonment model (binomial logits). Table 1 shows the estimation of the models. In summary, public transport attracted users whose security perception improved because of the use of the app and short travel times. High-income, vulnerable participants (those who reported having a disability, having some difficulty travelling compared to other passengers, or regularly travelling with someone who has a disability) and long-travel-time users tended to leave public transport. Planning the trip in advance (at least one hour before) made behaviour change more likely. This effect was significant in getting people off public transport.

Monte Carlo simulation of the VKT variation

The VKT variation was simulated following Tirachini & Gomez-Lobo's (2020) parameterisation, with $20,000$ independent draws for each random parameter. The result shows a significant increase in the contribution of VKT of the bus and car passenger, while a reduction in the VKT of ride-hailing, *colectivo* and car as driver. In terms of mean vari-

Table 1: Bus adoption and abandonment model results.

	Bus adoption model Other mode $\rightarrow$ Bus		**Bus abandonment model** Bus $\rightarrow$ Other mode	
Variable	Estimate	Std. Error	Estimate	Std. Error
Constant	1.858***	0.619	-3.648***	0.301
Male	-0.313	0.372	0.083	0.21
Age<34	0.509	0.369	-0.293	0.212
Having a car	-0.291	0.365	-0.119	0.216
High income	0.463	0.392	0.387*	0.231
Private transport user	-0.401	0.46	0.391	0.29
Waiting time perception	-0.184	0.4	-0.306	0.225
Security perception	1.467***	0.351	0.004	0.217
Satisfaction with transport system	0.18	0.351	0.078	0.209
Vulnerability	-0.412	0.496	0.892***	0.237
Planning	1.034	0.707	1.067***	0.307
Travel time	-0.099***	0.022	0.031***	0.008
AIC	221.14		846.22	
BIC	263.21		916.71	
Adj. Rho2	0.3515		0.7678	
N	245		2636	

$p - valor :^{*} < 0.1;^{**} < 0.05;^{***} < 0.01$

ations, the VKT of ride-hailing and *colectivos* decrease 3.7 and 2.4 times the increase of the bus' VKT, respectively.

As shown in Figure 3, the net mean variation of the VKT among *Red* users is negative in 99.25% of the scenarios, with an expected value of $-0.099[km/trip]$. It is important to note that the variation of VKT is negative in the different settings of the modal subsitution rates, the occupation rates, and the mean length of the trip. This result is highly consistent due to the relatively high subsitution of ride-hailing and *colectivo* trips. The cases in which $\Delta VKT > 0$, are possibly explained by scenarios with low bus occupation rates or with a long bus travel distance.

Furthermore, we can estimate the variation of greenhouse gases and air pollutants emissions. We estimate the total variation in CO_2 as a function of the mean occupation of the bus. For this, we used the factors in Osses et al. (2022) and the estimated variation of VKT by mode. Figure 4a shows the mean variation ($\Delta EMIS$, black line) in function of bus occupation, the standard deviation (shadowed area), and the probability that the variation is negative ($P(\Delta EMIS < 0)$, red line). In the observed data, the mean occupation was 26.11 passengers, which would give a negative variation with probability 0.98.

However, as shown in Figure 4b the variation is negative for 87.17% of the simulated scenarios, and the mean variation is $-11.24[gCO_2/trip]$ ($p - value < 0.001$). That is, each trip made using the application to check real-time information saves on average 11.24 gCO_2. Taking this into account, it is possible to estimate the yearly variation of the emissions. To this purpose, let us assume that the total of active users per day is constant and equal to $20,000$, and that on average each one of them makes one trip per day. Under these assumptions, **the estimated variation of CO_2 is** $TEMIS = -82.074[tonsCO_2/year]$.

4 Conclusions

In this paper, we analyse the results of a survey responded by 3681 users of *Red Regional de Movilidad* (Red), the official mobile application for public transport information in

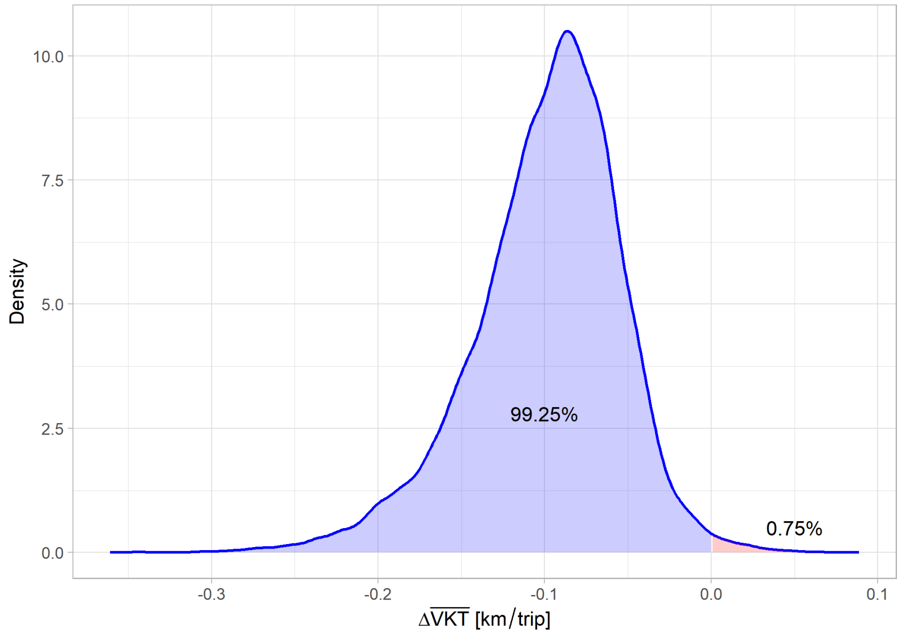

Figure 3: Simulation of VKT variation conditional on the use of Red.

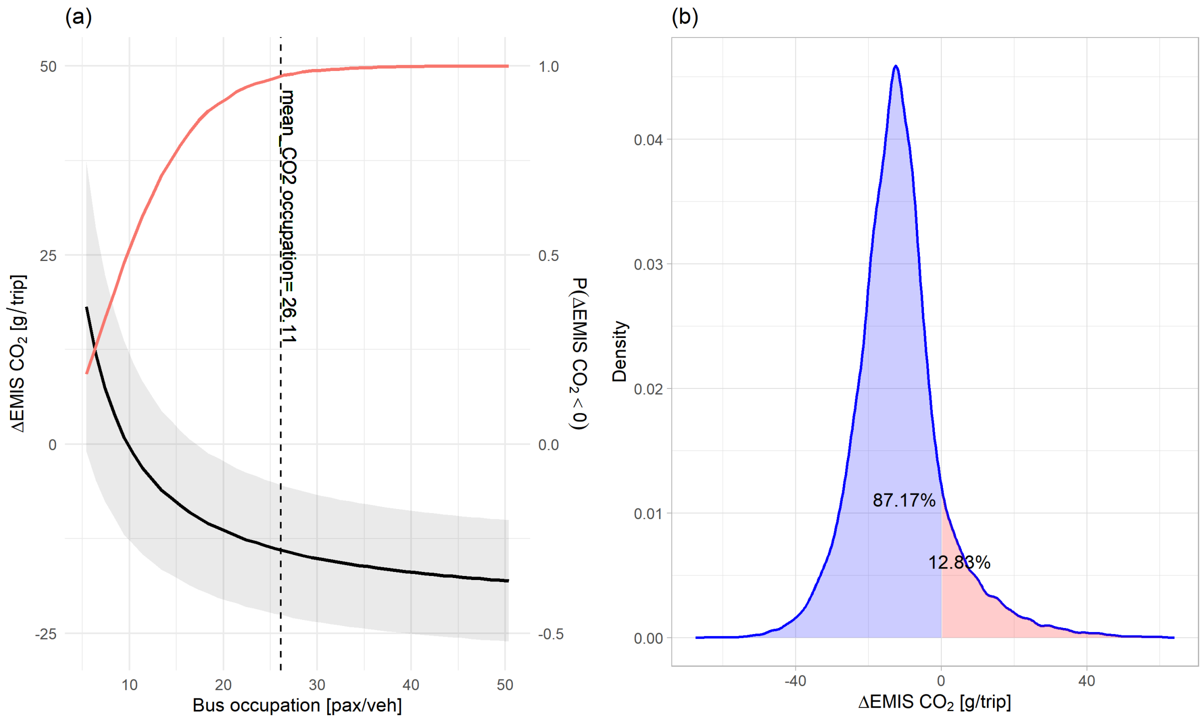

Figure 4: (a) The black line shows the mean CO_2 variation in function of the bus occupation, the shadowed area is the standard deviation, and the red line shows the probability of $P(\Delta EMIS < 0)$. (b) The distribution of $\Delta EMIS\, CO_2$ considering random values for the bus occupation.

15 medium-sized cities in Chile. In these cities, this is the first application to provide real-time information about public transport.We addressed three research questions: A) Do ATIS have an effect on the choice of travel mode? (B) What are the determinants of adopting or leaving public transport conditional on the use of an ATIS? and (C) Are there benefits in terms of decreasing vehicle kilometres travelled (VKT) and the associated pollutant emissions?

Regarding the first research question, we found that the use of *Red* changed the behaviour of 9.97% of the users. The main behavioural change detected was the substitution of ride-hailing and *colectivos* by public transport. Despite public transport lost some demand due to the use of Red, it gained 3 passengers for every 2 lost passengers.
The main determinant of the adoption of public transport was the perception of security. That is, users whose security perception improved due to the use of the application were more likely to adopt public transport. Despite waiting time by its own being not significant on explaining this behavioural change, the security perception can be correlated to the waiting time (more waiting time implies more exposure time). On the other hand, users with a longer travel time were less likely to adopt public transport. In fact, users with a long travel time were more likely to leave public transport. In addition, participants with some vulnerability condition were more likely to leave public transport.
Lastly, our simulations of the variation of VKT showed a negative effect in 99.25% of the simulated scenarios. It means that a trip made with *Red* contributes, on average, 0.099 km less than a trip made without the application. Then, according to these results, the use of *Red* had an important benefit on traffic, contributing to the decrease in total VKT of the system. In addition, this effect implies a reduction in pollutants emissions. Specifically, greenhouse gasses decrease $-88.184[tonsCO_2/year]$. This variation is negative in 85.2% of the scenarios. It is positive in the cases where the occupation of buses is sufficiently low. However, the decrease in trips in private modes is not large enough to observe a decrease in other air pollutants, as, for example, NO_x.
This study closes the gap on the real effect of ATIS on travel behaviour and traffic. Our results support the previous literature, confirming that, by using real-time information, people perceive shorter waiting times and higher security perception. For the first time, we quantify the benefit that ATIS brings in terms of VKT and reduction in pollution.

Acknowledgements

The authors thank DTPR for their cooperation in the design, testing, and implementation of the survey. We would like to thank Felipe Hernández of Transapp for developing the process for sending notifications with the survey used for this study.

References

Ben-Elia, E., & Shiftan, Y. (2010). Which road do I take? A learning-based model of route-choice behavior with real-time information. *Transportation Research Part A: Policy and Practice*, *44*(4), 249–264. Retrieved from http://dx.doi.org/10.1016/j.tra.2010.01.007 doi: 10.1016/j.tra.2010.01.007

Brakewood, C., Barbeau, S., & Watkins, K. (2014, 11). An experiment evaluating the impacts of real-time transit information on bus riders in Tampa, Florida. *Transportation Research Part A: Policy and Practice*, *69*, 409–422. doi: 10.1016/j.tra.2014.09.003

Brakewood, C., & Watkins, K. (2019, 5). A literature review of the passenger benefits of real-time transit information. *Transport Reviews*, *39*(3), 327–356. doi: 10.1080/01441647.2018.1472147

Dziekan, K., & Kottenhoff, K. (2007). Dynamic at-stop real-time information displays for public transport: effects on customers. *Transportation Research Part A: Policy and Practice*, *41*(6), 489–501. doi: 10.1016/j.tra.2006.11.006

Ferris, B., Watkins, K., & Borning, A. (2010, 4). OneBusAway: Results from Providing Real-Time Arrival Information for Public Transit. In *Chi 2010: Bikes and buses* (pp. 1807–1816). Atlanta: Association for Computing Machinery.

Gooze, A., Watkins, K., & Borning, A. (2013, 12). Benefits of real-time transit information and impacts of data accuracy on rider experience. *Transportation Research Record*(2351), 95–103. doi: 10.3141/2351-11

Jha, M., Madanat, S., & Peeta, S. (1998). Perception updating and day-to-day travel choice dynamics in traffic networks with information provision. *Transportation Research Part C: Emerging Technologies*, *6*(3), 189–212. Retrieved from https://www.sciencedirect.com/science/article/pii/S0968090X98000151 doi: https://doi.org/10.1016/S0968-090X(98)00015-1

Osses, M., Rojas, N., Ibarra, C., Valdebenito, V., Laengle, I., Pantoja, N., … Gómez, B. (2022, 3). High-resolution spatial-distribution maps of road transport exhaust emissions in Chile, 1990-2020. *Earth System Science Data*, *14*(3), 1359–1376. doi: 10.5194/essd-14-1359-2022

Papangelis, K., Velaga, N. R., Ashmore, F., Sripada, S., Nelson, J. D., & Beecroft, M. (2016, 3). Exploring the rural passenger experience, information needs and decision making during public transport disruption. *Research in Transportation Business and Management*, *18*, 57–69. doi: 10.1016/j.rtbm.2016.01.002

Politis, I., Papaioannou, P., Basbas, S., & Dimitriadis, N. (2010). Evaluation of a bus passenger information system from the users' point of view in the city of Thessaloniki, Greece. *Research in Transportation Economics*, *29*(1), 249–255. doi: 10.1016/j.retrec.2010.07.031

Tang, L., & Thakuriah, P. (2007). *Relationship of Attitudes Toward Road and Transit Capital Investments and Propensity to Ride Transit Given Traveler Information* (Tech. Rep.).

Tang, Y., Gao, S., & Ben-Elia, E. (2017). An exploratory study of instance-based learning for route choice with random travel times. *Journal of Choice Modelling*, *24*(April), 22–35. Retrieved from http://dx.doi.org/10.1016/j.jocm.2017.03.004 doi: 10.1016/j.jocm.2017.03.004

Tirachini, A. (2020). Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation*, *47*(4), 2011–2047. doi: 10.1007/s11116-019-10070-2

Tirachini, A., & Gomez-Lobo, A. (2020, 3). Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile. *International Journal of Sustainable Transportation*, *14*(3), 187–204. doi: 10.1080/15568318.2018.1539146

Vos, J. D., Singleton, P. A., Gärling, T., Vos, J. D., & Singleton, P. A. (2021). From attitude to satisfaction : introducing the travel mode choice cycle. doi: 10.1080/01441647.2021.1958952

Watkins, K. E., Ferris, B., Borning, A., Rutherford, G. S., & Layton, D. (2011). Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders. *Transportation Research Part A: Policy and Practice*, *45*(8), 839–848. doi: 10.1016/j.tra.2011.06.010

Zito, P., Amato, G., Amoroso, S., & Berrittella, M. (2011, 1). The effect of Advanced Traveller Information Systems on public transport demand and its uncertainty. *Transportmetrica*, *7*(1), 31–43. Retrieved from https://doi.org/10.1080/18128600903244727 doi: 10.1080/18128600903244727