

## Article

# The Unintended Consequences of COVID-19 Mitigation Measures on Mass Transit and Car Use

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**Abstract:** As the world adapts to COVID-19, the transport behaviour of commuters has been greatly modified. Governments and transit authorities will need strong, well-received mitigation measures and education campaigns to maintain the historically upward trend of sustainable mass transit usage following this pandemic. This study, from a survey of 1968 Canadians in early May 2020, reveals that, following the end of stay-at-home orders, commuters intend to use their cars more and mass transit less. Driving these behavioural changes are commuters' perceptions that mass transit use will negatively impact their health safety, peace of mind, and travel experience. The results also show that certain mitigation measures, such as more frequent cleaning and mandatory hand washing, are likely to reduce this decline, whereas e-monitoring and the use of health certificates will be detrimental to mass transit ridership through user perception. These results can help lessen the environmental impact of the public returning to work by encouraging their continued use of more environmentally friendly modes of transportation.

**Keywords:** COVID-19; public transport; travel behaviour; risk perception; mitigation measures; post-lockdown travel

## 1. Introduction

As the world wrestles with the SARS-CoV-2, or COVID-19, virus, many city dwellers appear to have greatly reduced or even discontinued their use of public transit for fear of being in an enclosed space with a crowd [1]. Conversely, some journalists and politicians are calling for authorities to seize this opportunity and align economic recovery efforts with a more sustainable future [2,3]. Turning away from public transportation can also lead to diminished social equity and financial adversity, as lower-income commuters tend to be more reliant on public transportation [4,5]. On the other hand, in the current situation, mass transit—in which physical distancing is difficult to maintain—is seen by some as one of the main conduits for the contagion of viruses [6]. In addition, the closing or curtailing of mass transit by local governments during stay-at-home orders has contributed to creating the impression that its usage is dangerous. As risk perception is at the heart of human behaviour [7], we investigated user perception of car and mass transit use to evaluate a potential impact of COVID-19 on expected transport behaviour post-lockdown and how mitigation measures can affect risk perception.

At the height of stay-at-home policies, global carbon emissions diminished by 17%, in part due to the reductions in transportation emissions [8]. Ensuring long-term improvements in transportation emissions and reducing the use of fossil fuels will play a significant role in the fight against climate change. The Canadian transportation sector, more specifically, accounts for 30% of the country's greenhouse gas emissions [9]. Investing in more sustainable means of transportation is a priority all

around the world, including for the Canadian government [10]. “The car is not the future of the city, there will never be enough money to make more roads, never enough parking spaces, never enough streets” [11]. While some politicians are using this crisis to discreetly remove some environmental protections [12,13], many others, notably at the city level, are keeping promises and implementing change [14,15]. When major crises happen and people’s lives are upended, there is an opportunity to change habits significantly [16].

To evaluate how major crises can affect public transit ridership, we can look to previous public health crises and terrorist attacks that affected trust in the safety of public transit and commuter behaviour. For example, following the terrorist attacks on the London metro in 2005, the use of private transport, such as cars and bicycles, increased. This was related to a reduction in the use of public transport of 20% over 10 weeks [17]. We can also look to the SARS epidemic, which caused significant fear in affected regions, such as Taiwan. Kuo-Ying Wang presented a detailed analysis of what he dubbed “fresh fear” (the immediate impact of new cases) and “residual fear” (the long-term impact). Fresh fear was directly linked to the number of cases reported that day and was accompanied by an immediate loss of ridership; it took 28 days for the residual fear to subside and ridership to return to original values. The ridership was back to its initial level the following year, though no explanation is given as to how public health measures influenced these behaviours [18]. Current health anxiety, what some are referring to as “coronaphobia” [19], is likely to have a similar impact in 2020 and beyond. Some observations of the impact of COVID-19 are becoming available in the scientific literature, showing diminished ridership on the New York City subway and potential modal transfer to the bike-sharing system [20]. Similarly, Tirachini and Cats present the lessened activity levels of public transit in many countries around the world from February to June 2020, in part due to generalized stay-at-home orders [5]. Finally, in Spain, we can see that public transit use was reduced significantly during quarantine [21], and that after reopening, traffic and cycling levels have increased while bus ridership has remained low [22].

However, as countries open up, risk perception will be a more important factor in transport behaviour. While mitigation measures, such as the use of masks and digital contact tracing, have been shown effective [23] to prevent the spread of the virus, how users perceive these measures will matter greatly in their transportation-related decision making. Indeed, behavioural science teaches us that to alleviate commuters’ health concerns and other perceived risks, the transportation industry will need to implement major changes as stay-at-home orders are gradually lifted, and before immunity, through vaccines or other means, has been attained.

To ascertain how Canadians intend to commute in the coming months, a study was conducted between 1 May and 10 May 2020, gauging the perceptions and intentions of Canadians in six cities across the country—Vancouver, Calgary, Toronto, Ottawa, Montréal, and Halifax—regarding their future use of a variety of means of transportation following the anticipated lifting of stay-at-home orders. This study specifically looked at how different health risk mitigation measures would impact commuters’ intended use of each type of transportation in order to ascertain each measure’s feasibility and acceptance, and ultimately inform decision-makers as they decide to implement a data-driven response to this public health challenge while still aiming to improve carbon footprints.

## 2. Materials and Methods

### 2.1. Respondents and Recruitment

Results are based on a survey in six major Canadian metropolitan regions. In total, 1968 Canadians completed the survey (1053 females, 915 males) between May 1 and 10 May 2020. They were recruited by a research firm using the largest online consumer panel in Canada. In order to have a (sub)urban and country-wide perspective, citizens from six major Canadian metropolitan areas were targeted (i.e., Vancouver: 631,486 inhabitants; Calgary: 1,239,220 inhabitants; Toronto: 2,731,571 inhabitants; Ottawa: 934,243 inhabitants; Montréal: 1,704,694 inhabitants; and Halifax: 403,131 inhabitants) [24].

These cities were chosen as they are dense urban areas with public transportation means easily accessible to the population. Quota sampling was used to obtain a comparable number of respondents per region. See Table 1 for participant demographics. Quota sampling was used to obtain a comparable number of respondents per region. See Table 1 for participant demographics. Respondents had to indicate their usage frequency for eight different transportation modes for commuting (i.e., Subway, Bus, Suburban Train, Taxi and Ridesharing, Personal Car, Bicycle, Motorcycle, and Carpooling) as of February 2020. Then, they were asked if their commuting habits would change for each transportation mode once the stay-at-home measures were lifted. They were presented with a list of definitions for seven COVID-19 contagion mitigation measures, asked to what extent each measure would affect their usage when the stay-at-home measures were lifted and, how they would impact their perceived risks for one specific transportation mode that they frequently used.

**Table 1.** Demographic data of the sample of respondents.

| Age                                                                                    | Calgary | Halifax | Montreal | Ottawa | Toronto | Vancouver | Total |
|----------------------------------------------------------------------------------------|---------|---------|----------|--------|---------|-----------|-------|
| 18–20                                                                                  | 23      | 12      | 16       | 16     | 11      | 18        | 96    |
| 21–30                                                                                  | 44      | 48      | 80       | 34     | 43      | 66        | 315   |
| 31–40                                                                                  | 73      | 47      | 59       | 42     | 57      | 59        | 337   |
| 41–50                                                                                  | 51      | 55      | 64       | 51     | 83      | 55        | 359   |
| 51–60                                                                                  | 45      | 69      | 46       | 58     | 58      | 48        | 324   |
| 61–70                                                                                  | 60      | 69      | 40       | 75     | 55      | 52        | 351   |
| 71–80                                                                                  | 26      | 27      | 19       | 44     | 21      | 25        | 162   |
| 81–88                                                                                  | 2       | 1       | 3        | 10     | 2       | 6         | 24    |
| Total                                                                                  | 324     | 328     | 327      | 330    | 330     | 329       | 1968  |
| <b>Transport Means</b>                                                                 |         |         |          |        |         |           |       |
| Bus                                                                                    | 40      | 41      | 41       | 41     | 41      | 41        | 245   |
| Suburban Train                                                                         | 40      | NA      | 40       | 41     | 41      | 41        | 203   |
| Subway                                                                                 | 40      | NA      | 41       | 41     | 41      | 41        | 204   |
| Other (not included in this study)                                                     | 204     | 287     | 205      | 207    | 207     | 206       | 1316  |
| Total                                                                                  | 120     | 41      | 122      | 123    | 123     | 123       | 1968  |
| <b>Access to Car</b>                                                                   |         |         |          |        |         |           |       |
| No                                                                                     | 38      | 50      | 71       | 56     | 63      | 65        | 343   |
| Yes                                                                                    | 286     | 278     | 256      | 274    | 267     | 264       | 1625  |
| Total                                                                                  | 324     | 328     | 327      | 330    | 330     | 329       | 1968  |
| <b>Employment Status</b>                                                               |         |         |          |        |         |           |       |
| No change: employed or self-employed                                                   | 132     | 147     | 146      | 127    | 164     | 134       | 850   |
| No change: student                                                                     | 21      | 16      | 26       | 20     | 17      | 20        | 120   |
| No change: homemaker                                                                   | 15      | 10      | 8        | 8      | 15      | 13        | 69    |
| No change: retired                                                                     | 63      | 81      | 57       | 124    | 61      | 60        | 446   |
| No change: unemployed                                                                  | 17      | 11      | 10       | 7      | 10      | 12        | 67    |
| Change: from employed or self-employed to not employed                                 | 55      | 35      | 49       | 31     | 45      | 54        | 269   |
| Change: student whose part-time job was either eliminated, suspended, or reduced hours | 15      | 11      | 19       | 7      | 12      | 21        | 85    |
| Other change                                                                           | 6       | 17      | 12       | 6      | 6       | 15        | 62    |
| Total                                                                                  | 324     | 328     | 327      | 330    | 330     | 329       | 1968  |

Table 1. Cont.

| Age                            | Calgary | Halifax | Montreal | Ottawa | Toronto | Vancouver | Total |
|--------------------------------|---------|---------|----------|--------|---------|-----------|-------|
| <b>Scholarity</b>              |         |         |          |        |         |           |       |
| Elementary                     | 0       | 2       | 3        | 2      | 3       | 0         | 10    |
| High School (8–12 years)       | 73      | 68      | 60       | 48     | 42      | 66        | 357   |
| College (13–15 years)          | 87      | 108     | 103      | 81     | 70      | 85        | 534   |
| University Certificates        | 28      | 19      | 30       | 22     | 19      | 31        | 149   |
| University Undergraduate       | 95      | 91      | 83       | 107    | 135     | 105       | 616   |
| University Master's            | 34      | 36      | 40       | 61     | 58      | 35        | 264   |
| University Doctorate           | 7       | 4       | 8        | 9      | 3       | 7         | 38    |
| Total                          | 324     | 328     | 327      | 330    | 330     | 329       | 1968  |
| <b>Family Income</b>           |         |         |          |        |         |           |       |
| \$39,999 or less               | 53      | 79      | 67       | 41     | 37      | 58        | 335   |
| Between \$40,000 and \$79,999  | 74      | 88      | 96       | 86     | 99      | 116       | 559   |
| Between \$80,000 and \$119,999 | 77      | 74      | 87       | 88     | 75      | 57        | 458   |
| \$120,000 or more              | 72      | 58      | 45       | 77     | 75      | 63        | 390   |
| Not reported                   | 48      | 29      | 32       | 38     | 44      | 35        | 226   |
| Total                          | 324     | 328     | 327      | 330    | 330     | 329       | 1968  |

## 2.2. Survey

At the beginning of the survey, respondents had to indicate their usage frequency (ranging from Never (1) to Everyday (7)) for eight different transportation modes for commuting (i.e., Subway, Bus, Suburban Train, Taxi and Ridesharing, Personal Car, Bicycle, Motorcycle, and Carpooling) as of February 2020. Then, they were asked if their commuting habits would change in terms of frequency (from Large Decrease (−3) to Large Increase (+3)) for each transportation mode once the stay-at-home measures were lifted.

Following that, they were presented with a list of seven mitigation measures and their definitions, identified by the authors from local public health reports at the time. These are measures that transportation organizations could put in place to reduce the risk of contagion: Physical Distancing (two meters apart), Cleaning Practices (increased vehicle cleaning frequency and communication), Age-Related (separating passengers who are 60 years and older from other passengers), Mask and Hand Sanitizing (mandatory mask-wearing and using hand disinfectant), Temperature Monitoring (temperature taking before boarding the vehicle), Health Certificate (mandatory certificate before boarding), Electronic Monitoring and Alerting (mobile phone or GPS data to anonymously monitor COVID-19 infections and movements, and to alert individuals).

Then, they were asked to what extent each measure would affect their usage when the stay-at-home measures were lifted (ranging from 100% decrease to 100% increase) for one specific transportation mode (e.g., bus) that they frequently used. They were also asked to which extent each mitigation measure would impact their perceived risks (i.e., health safety (physical risk), peace of mind (psychological risk), price (financial risk), travel duration (time risk), the way people think about them (social risk), and experience as a user (performance risk)) for the same transportation mode. The survey concluded with demographic questions.

## 2.3. Statistical Analysis

Graphs were produced with Tableau 2019.4. The marginal R<sup>2</sup> was calculated with R version 3.6.1, using package MuMIn version 1.43.15. All other statistical analyses were performed with SAS

software 9.4. All the models were controlled by the following variables: age, sex, status, education, city, language family size, family income, and access to a car. Respondents ( $n = 1968$ ) answered questions about their expected change in use of all the transportation means (except for subway and suburban train in Halifax where neither is available) following the end of stay-at-home orders. The data is therefore longitudinal. The response variable, expected change in usage, is ordinal with seven levels ( $-3, -2, -1, 0, 1, 2, 3$ ). To analyze the expected use of the transportation means, we used linear random intercept models to estimate the least squares mean of the usage. More precisely, we regressed the expected use of transportation means, controlled by the demographic variables.

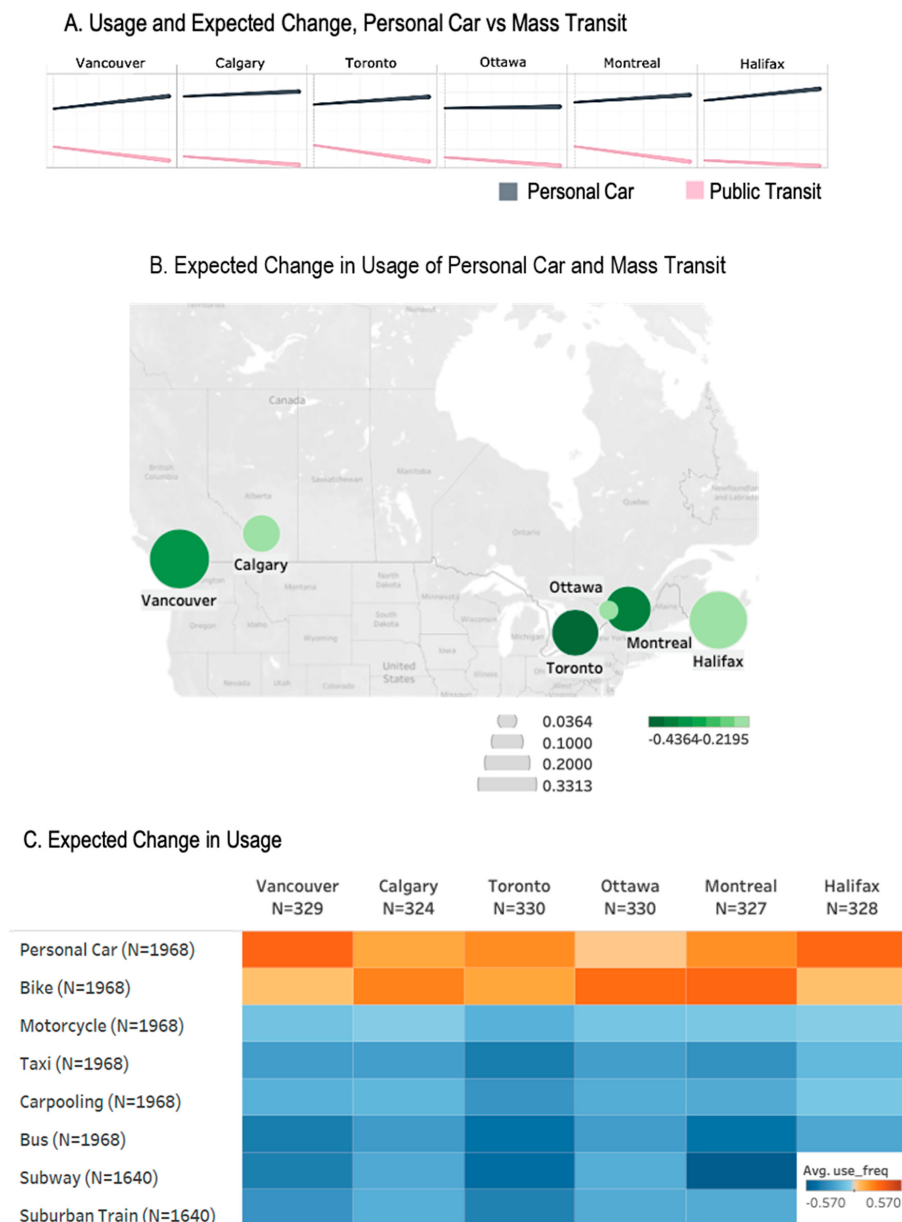
A random intercept model was used to capture the unobserved subject-specific effect by the subject-specific intercepts, as the data is longitudinal. The least squares mean is the mean estimated by such a linear model. Least squares mean is a better estimate of the population mean than the arithmetic sample mean because it is adjusted for the control variables. A positive least squares mean indicates the expected use increases and a negative value indicates a decrease. A test of the estimated mean being significantly different from zero was performed for each mean. This was a one-sample  $t$ -test for location, testing if the least mean square = 0, performed by SAS software.

We performed this test for personal car use and mass transit use for all the cities combined, as well as for each of the six cities. For the analysis by city, the  $p$ -values were adjusted for multiple testing using the method of Holm–Bonferroni, where a family of tests was all the tests for one transportation mean. For example, a raw  $p$ -value of 0.02, which is the second-lowest in a family of 10 tests, was adjusted as  $0.02 \times 9 = 0.18$ .

The linear random intercept model with one IV can be expressed as  $y_{ij} = (u_j + \beta_0) + \beta_1 x_{ij} + \varepsilon_{ij}$ , where  $y_{ij}$  is the  $i$ th observation of participant  $j$ . This model allows the intercept ( $u_j + \beta_0$ ) to vary by participant while keeping the slope ( $\beta_1$ ) for the independent variable ( $x_{ij}$ ) the same for all the participants. As each respondent replied to multiple questions, unmeasured characteristics of participants may render the responses clustered by participant. For example, an optimist participant may answer all the questions more optimistically. The participant-specific intercept is used to capture such unmeasured characteristics so that the effect of the IV can be correctly estimated.

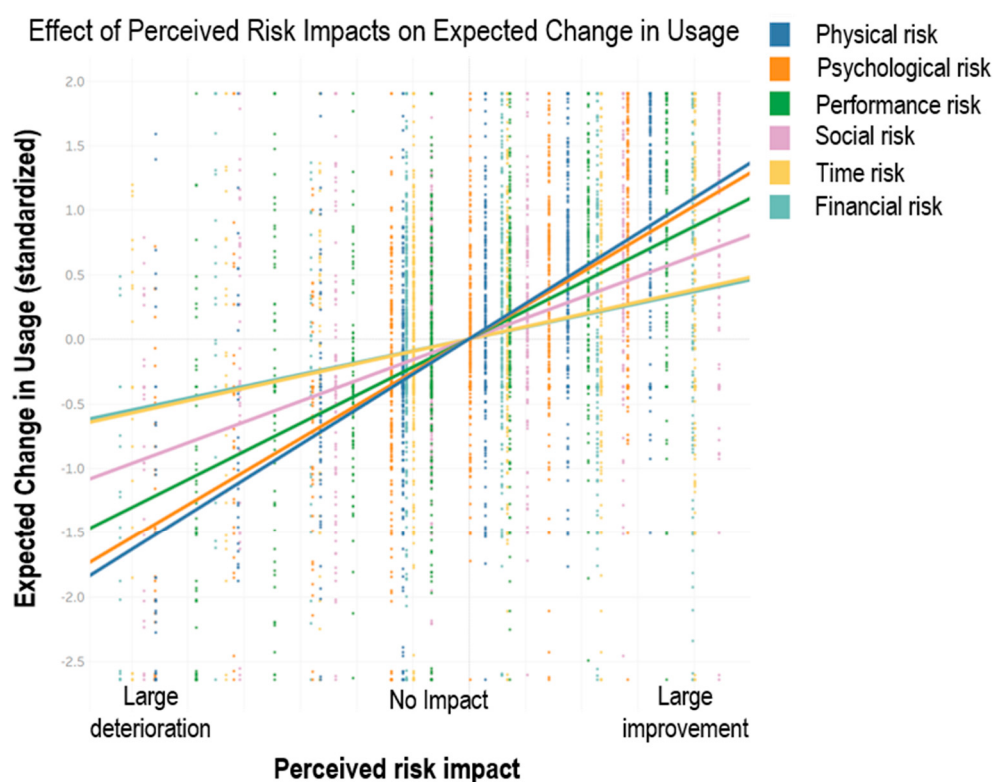
### 3. Results

Using a linear regression model with random intercepts to estimate the least squares mean of the expected usage for each type of transportation, our results show that, following the end of stay-at-home orders, Canadians intend to use their cars significantly more than they did in February 2020, as can be seen in Figure 1. In addition, they project a substantial decrease in their use of mass transit means, such as buses and subways. This trend is observable in all major cities across the country, although it is more significant in Vancouver and Halifax for increased car use, and Toronto and Montreal for decreased mass transit use. These findings are in line with reports from other countries around the world where car usage is increasing [25]. Even respondents who reported never using their cars to commute expect to use personal cars for commuting in the future. Cycling also shows an increase across the country (increase is significantly different from 0 at  $p < 0.0001$ ). Differences in weather conditions between February and May may partly explain those results, however, this behaviour is not likely to be maintained during winter in Canada.



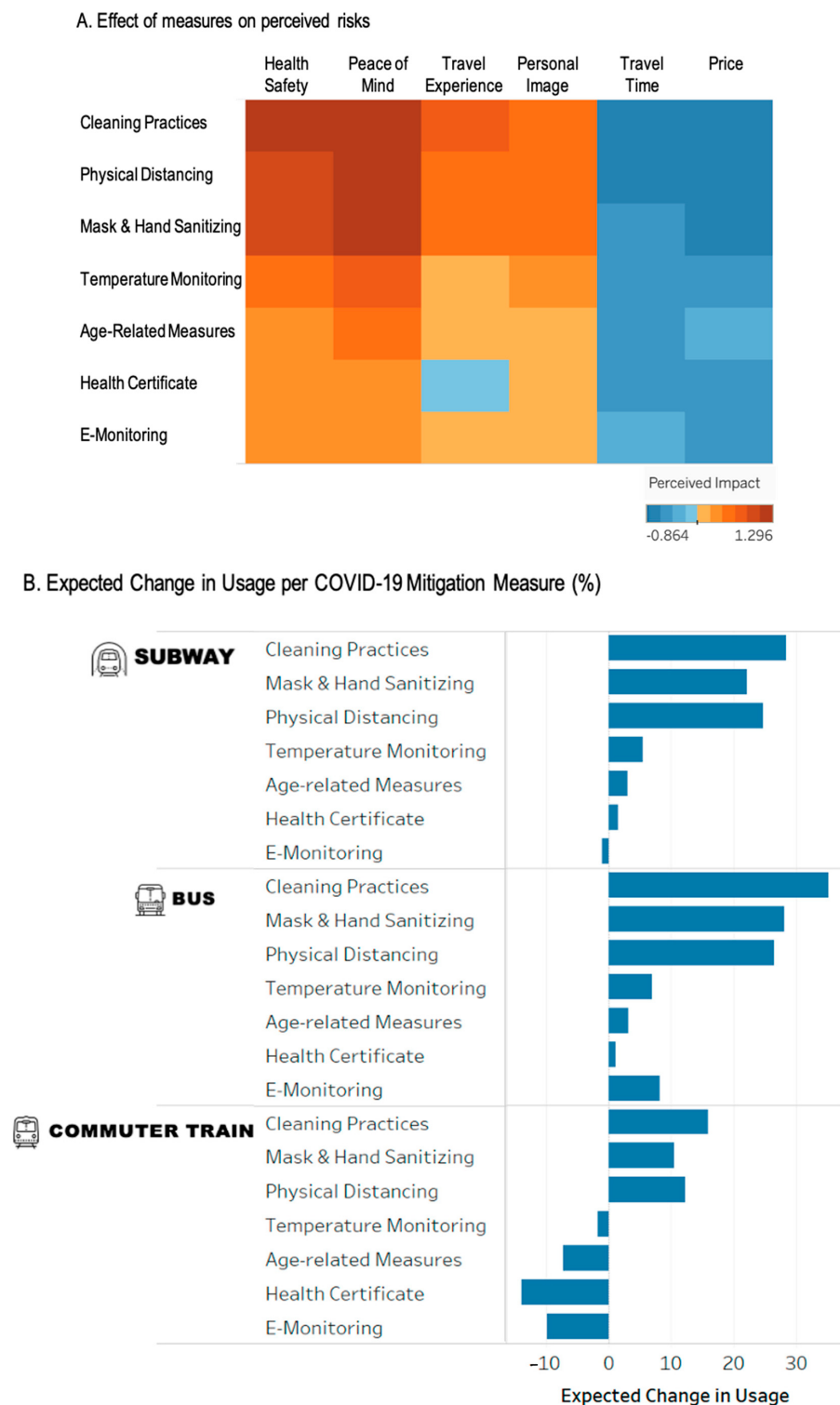
**Figure 1.** Expected changes in usage of means of transportation for commuting. Respondents indicated how frequently they used each means of transport for commuting in February 2020 and how their use of each would increase or decrease following the end of stay-at-home orders. Mass transit is a sum of bus, subway, and suburban train. (A) shows the increase in car use (orange line) and the decrease in mass transit use (blue line) for each city; for each line separately, magnitude is plotted vertically, while the line slope reflects the degree of intended change. (B) shows the expected change in the use of mass transit (where the darker the colour, the greater the decrease) and the use of a personal car (where the larger the circle, the greater the increase). (C) shows the expected change in use of each transportation means by city. Expected personal car use increases significantly in Vancouver ( $p = 0.0056$ ) and Halifax ( $p = 0.0002$ ); a change is also observed in Toronto ( $p = 0.052$ ) and Montreal ( $p = 0.053$ ). Expected mass transit use decreases significantly in Ottawa ( $p = 0.017$ ), Vancouver ( $p = 0.016$ ), Toronto ( $p = 0.0003$ ), and Montreal ( $p < 0.0001$ ). Linear regressions with random intercept comparing least squares means of expected change in usage reveal that car usage increases significantly more in Calgary than in Toronto, Ottawa, and Vancouver ( $p = 0.014$ ,  $p = 0.0014$ , and  $p < 0.0001$ , respectively). In addition, the increase is higher in Montreal and Halifax than in Vancouver ( $p < 0.0001$ ,  $p = 0.0017$ ).

Consumer behaviour research has shown that before making a decision, ranging from which store to visit to how to shop, people evaluate the risk associated with each alternative. The most salient types of perceived risk include the following six components: financial risk, performance risk, physical risk, psychological risk, social risk, and time-related risk [26–28]. To assess the impact of these risks in the context of mass transit, respondents indicated how each risk (adapted respectively as price, travel experience, health safety, peace of mind, personal image, and travel time) would affect their usage of each means of transportation. Results show that physical (health safety), psychological (peace of mind), and performance (travel experience) risks are the primary drivers of commuters' reluctance to use mass transit (Figure 2). Regression results show that these three risks explain 34% of the variation in commuters' planned usage.



**Figure 2.** Regression results, indicating how much each of the commuters' perceived risks will impact their expected usage of mass transit, thus showing the relative weight of each perceived risk in their decision-making process.

A variety of COVID-19 mitigation measures could be put in place, which may also decrease a traveller's perceived risks and increase their likelihood of using a more sustainable means of commuting. Figure 3 shows how each mitigation measure considered in this study (temperature monitoring, physical distancing, mask and hand sanitizing, use of health certificates, e-monitoring, cleaning practices, and age-related measures) impacts each of the perceived risks and the usage of each type of public transportation. Specifically, linear regressions to estimate the least squares means of each type of perceived risk by mitigation measures show that cleaning practices, physical distancing, and mandatory hand sanitizing and mask-wearing would compel commuters to use the bus. On the contrary, e-monitoring and being asked to present a health certificate may have the unintended consequence of turning people away from using buses, subways, and suburban trains.



**Figure 3.** This figure shows the impact of each mitigation measure on perceived risks and usage. (A) shows that Cleaning Practices, Physical Distancing, and Masks and Hand Sanitizing have the greatest impact on physical risk (perceived health safety) and psychological risk (peace of mind). Closer inspection of (B) indicates that E-Monitoring and Health Certificates can have a negative impact on usage, particularly for suburban trains. Cleaning Practices, on the other hand, appear to be perceived as reassuring and increase expected usage by 28% for subways and 35% for buses.

Responses for mass transit were used for the second part of analysis, including data for bus ( $n = 245$ ), subway ( $n = 204$ ) and suburban train ( $n = 203$ ). Each respondent answered questions about their expected change in use of their chosen mass transit means as a consequence of the implementation of each of the seven COVID-19 mitigation measures (see Table 2). The data is therefore longitudinal. To test the effect of perceived risks on the expected change in use of the transportation means, we used a multiple linear regression with a random intercept model including all the six perceived risks, controlled by the same variables as described in the previous section, Result 1, of this appendix.

**Table 2.** Effect of Perceived Risks on Expected Change in Use of Mass Transit.

| Effect             | Estimate | Standard Error | DF   | t Value | Pr > t  | Marginal R2 Partition |
|--------------------|----------|----------------|------|---------|---------|-----------------------|
| Physical risk      | 0.3639   | 0.0196         | 3169 | 18.54   | <0.0001 | 0.1532                |
| Psychological risk | 0.2215   | 0.0211         | 3172 | 10.51   | <0.0001 | 0.1054                |
| Performance risk   | 0.1503   | 0.0186         | 3171 | 8.09    | <0.0001 | 0.0839                |
| Social risk        | 0.0111   | 0.0173         | 3164 | 0.64    | 0.5216  | 0.0358                |
| Financial risk     | −0.0107  | 0.0165         | 3132 | −0.65   | 0.5183  | 0.0156                |
| Time risk          | −0.0226  | 0.0158         | 3171 | −1.43   | 0.1515  | 0.0126                |

We calculated the marginal  $R^2_{\text{GLMM}}$  defined by Nakagawa and Schielzeth [29] for this model. The marginal  $R^2_{\text{GLMM}}$  measured the proportion of variance explained by the fixed effect as a proportion of the sum of all the variance components. We then partitioned the marginal  $R^2_{\text{GLMM}}$  of the model to each of the six perceived risks following the procedure proposed in [30] for the partitioning. This method was proposed for dominance analysis but can be used for  $R^2$  partitioning, as pointed out by [31]. It is a stepwise regression approach. At each step, a new predictor was added to the model. The increase of the model's  $R^2$  was recorded as the new predictor's contribution to the model's  $R^2$ . As the additional contribution of a variable depends on all the variables entered to the model prior to it, each variable was made to enter the model at all the possible positions (i.e., first through sixth position) with all possible combinations of the other variables entered before it. We then calculated the average contribution of each position. The variable's partition was then the average of the contributions over all the positions.

Clearly, physical risk, psychological risk, and performance risk are the risk components that explain the expected usage of all means of transportation. Adding up the marginal R2 partition, we see that these three risks explain 34% of the variation in commuters' planned usage. The effects of the control variables are not presented but available on request.

The same data was used for the final part of the analysis. To evaluate the effect of COVID-19 mitigation measures on the expected change in use of mass transit means, we used linear random intercept models to estimate the least squares means of the usage. More precisely, we regressed the expected change of use on mitigation measures, controlled by the demographic variables. The least squares means were the means estimated by this model, using the same as above. To compare the effect of the mitigation measures, we performed a pairwise comparison of the least squares means between the measures. The  $p$ -values were adjusted for multiple testing using the method of Holm–Bonferroni, where a family of tests is all the tests for one response variable. For example, a raw  $p$ -value of 0.02, which is the second-lowest in a family of 10 tests, was adjusted as  $0.02 \times 9 = 0.18$ .

#### 4. Discussion

In summary, our results show that commuters are certainly wary of using mass transit and appear to prefer the use of private cars. This change in their transport habits will be driven primarily by their perceptions of risk for their health safety and their peace of mind. However, certain mitigation measures, such as physical distancing and cleaning, will help them feel more at ease with the use of mass transit.

Reversing the trend in recent years of commuters' increasing use of mass transit, it appears that the current COVID-19 crisis is likely to make commuters use private vehicles rather than shared means of transportation. This is in line with the current need for better control of one's immediate environment and for avoiding shared spaces with potentially contagious strangers. Mitigation measures, like separating people by age or requiring health certificates that could be perceived to discriminate or exclude certain people, do not seem to be reassuring. As these measures could potentially separate groups or families, or even entirely prevent certain people from travelling, response to such measures has been negative overall. On the contrary, measures that apply to all travellers indiscriminately, such as hand sanitizing and mask-wearing, or physical cleaning of the environment, appear to increase the likelihood that people will use the same means of transportation that they used prior to COVID-19. In addition, recent trends also appear to indicate that buses may be more attractive than subways for New Yorkers [32] as there is no need to go inside a subway station to board. This is in agreement with our interpretation that more obviously visible mitigation measures are more attractive for commuters.

As nations around the world are reorganizing their transportation infrastructure to put in place mitigation measures to protect commuters, technological tools have become increasingly attractive. Many have suggested the use of cell phone data to track local outbreaks and ensure contact tracing [33,34], however, this type of mitigation measure did not yield positive reactions among respondents. Participating commuters indicated that the use of e-monitoring would discourage them from using suburban trains and subways. Health certificates would not encourage them to use buses or subways, and would even discourage them from using suburban trains. This result appears to be in line with published concerns over the ethics of privacy, autonomy, equity, accuracy, and accountability [35–37]. Digital epidemiology, especially digital contact tracing, has been proven effective in Taiwan and South Korea in recent months, but the ethical concerns have been debated extensively in the media [38–40], likely contributing to the apparent discomfort of Canadian commuters. Thus, the implementation of e-monitoring is likely to have unintended consequences on the use of mass transit and, in turn, may lead to an unintended, though likely, increase in personal car use and, by extension, carbon emissions [41,42]. Reductions in mass transit usage may also lead to detrimental effects on health [43] and on residential land use [44]. Hence, governments and transit authorities wishing to employ digital epidemiology should think about alleviating the concerns riders may have regarding such approaches by adopting appropriate policies and, in tandem, incorporating strong educational campaigns. Addressing the concerns of mass transit users has proven to be effective in the past, as the Washington DC region demonstrated in the 2010s with its effective campaign to re-earn the public's trust and increase ridership after a series of fatal rail accidents [45]. However, a meta-analysis of behavioural interventions related to household action on climate change shows that behavioural interventions, such as informational campaigns, only last while they are in effect [46], suggesting that post-pandemic interventions may need to be lengthy and targeted. Multipronged behavioural change campaigns have also been identified as more effective [47]. We advise reading the very relevant insights into how social and behavioural science could be used to guide such interventions, put together by Bavel, Baker, Boggio, et al. [7].

As time goes on, new avenues of research will open up to help refine our recommendations. Already, a second iteration of our survey will be sent out in the fall of 2020. The Canadian government released a tracing application along with an advertising campaign to inform people of the low risk to privacy of this application [48]. It will be interesting to measure the perceptions of commuters following the adoption of this application. Other future research should compare user intentions with ridership reports to see whether intentions and behaviour are well correlated and which mitigation measures do impact actual use. In addition, future research will have the opportunity to look at new and creative means of reducing risk that are being implemented by transit authorities, such as increased ventilation.

## 5. Conclusions

During the current pandemic, fear has understandably played a large role in how people conduct themselves in their daily lives. This is understandable in that it helps protect both individuals and the greater population. However, when the time is appropriate, in order for society to return to normal, fear will need to give way to reasoned caution. This is especially true when it comes to returning to pre-pandemic levels of mass transit ridership, which is not likely to happen unless there is restored confidence in the safety of public transportation. Lessening the environmental impact of the public returning to work depends on the continued use of more environmentally friendly modes of transportation.

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## References

1. Dandapat, S.; Bhattacharyya, K.; Annam, S.K.; Saysardar, K.; Maitra, B. Impact of COVID-19 Outbreak on Travel Behaviour: Evidences from early stages of the Pandemic in India. *SSRN Electron. J.* **2020**. Preprint. [CrossRef]
2. Rosenbloom, D.; Markard, J. A COVID-19 recovery for climate. *Science* **2020**, *368*, 447. [CrossRef] [PubMed]
3. Countries should seize the moment to flatten the climate curve. *Economist*. 21 May 2020. Available online: <https://www.economist.com/leaders/2020/05/21/countries-should-seize-the-moment-to-flatten-the-climate-curve> (accessed on 26 November 2020).
4. Gutiérrez, A.; Miravet, D.; Domènech, A. COVID-19 and urban public transport services: Emerging challenges and research agenda. *Cities Health* **2020**, 1–4. [CrossRef]
5. Tirachini, A.; Cats, O. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. *J. Public Transp.* **2020**, *22*, 1. [CrossRef]
6. Harris, J. *The Subways Seeded the Massive Coronavirus Epidemic in New York City*; National Bureau of Economic Research: Cambridge, MA, USA, 2020.
7. Bavel, J.J.V.; Baicker, K.; Boggio, P.S.; Capraro, V.; Cichocka, A.; Cikara, M.; Crockett, M.J.; Crum, A.J.; Douglas, K.M.; Druckman, J.N.; et al. Using social and behavioural science to support COVID-19 pandemic response. *Nat. Hum. Behav.* **2020**, *4*, 460–471. [CrossRef] [PubMed]
8. Le Quéré, C.; Jackson, R.B.; Jones, M.W.; Smith, A.J.P.; Abernethy, S.; Andrew, R.M.; De-Gol, A.J.; Willis, D.R.; Shan, Y.; Canadell, J.G.; et al. Temporary reduction in daily global CO<sub>2</sub> emissions during the COVID-19 forced confinement. *Nat. Clim. Chang.* **2020**, *10*, 647–653. [CrossRef]
9. Greenhouse Gas Sources and Sinks: Executive Summary 2020—Canada.ca. Available online: <https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/sources-sinks-executive-summary-2020.html#toc3> (accessed on 25 May 2020).
10. Sustainable Canada Dialogues. *Springing Canada Forward: Open Letter to Prime Minister Justin Trudeau on Climate-Literate Stimulus Priorities*. 2020. Available online: [http://www.sustainablecanadadialogues.ca/pdf\\_2020/Open\\_letter\\_to\\_Trudeau\\_on\\_Investment\\_priority\\_sent.pdf](http://www.sustainablecanadadialogues.ca/pdf_2020/Open_letter_to_Trudeau_on_Investment_priority_sent.pdf) (accessed on 25 May 2020).
11. Étienne Leblanc. L'après-COVID-19: «Une occasion sans précédent de réinventer nos villes»|Coronavirus. Étienne Leblanc. 16 May 2020. Available online: <https://ici.radio-canada.ca/nouvelle/1702735/apres-covid-19-coronavirus-villes-avenir-demain-reinventer-repenser-villes> (accessed on 26 November 2020).

12. Popovich, N.; Albeck-Ripka, L.; Pierre-Louis, K. The Trump Administration Is Reversing 100 Environmental Rules. Here's the Full List. *New York Times*. 11 May 2020. Available online: <https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html> (accessed on 26 November 2020).
13. King, A. Environmentalists slam Ontario for suspending oversight regulation amid pandemic. *CBC News*. 2020. Available online: <https://www.cbc.ca/news/canada/toronto/ontario-temporarily-suspends-environmental-oversight-law-citing-covid-19-1.5541875> (accessed on 26 November 2020).
14. C40 Cities. *11 Mayors Unite to Lead Global Mayors COVID-19 Recovery Task Force*; C40 Cities: New York, NY, USA, 2020.
15. Goering, L. Milan's mayor says 'people are ready' for green change in postpandemic Italy. *Globe Mail*. 2020. Available online: <https://www.theglobeandmail.com/world/article-milans-mayor-says-people-are-ready-for-green-change-in-postpandemic/> (accessed on 26 November 2020).
16. Linley, P.A.; Joseph, S. Positive Change Following Trauma and Adversity: A Review. *J. Trauma. Stress* **2004**, *17*, 11–21. [CrossRef]
17. Ayton, P.; Murray, S.; Hampton, J.A. Terrorism, Dread Risk and Bicycle Accidents. *Judgm. Decis. Mak.* **2019**, *14*, 280–287.
18. Wang, K.-Y. How Change of Public Transportation Usage Reveals Fear of the SARS Virus in a City. *PLoS ONE* **2014**, *9*, e89405. [CrossRef]
19. Asmundson, G.J.G.; Taylor, S. How health anxiety influences responses to viral outbreaks like COVID-19: What all decision-makers, health authorities, and health care professionals need to know. *J. Anxiety Disord.* **2020**, *71*, 102211. [CrossRef] [PubMed]
20. Teixeira, J.F.; Lopes, M. The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. *Transp. Res. Interdiscip. Perspect.* **2020**, *6*, 100166. [CrossRef]
21. Aloï, A.; Alonso, B.; Benavente, J.; Cordera, R.; Echániz, E.; González, F.; Ladisa, C.; Lezama-Romanelli, R.; López-Parra, Á.; Mazzei, V.; et al. Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability* **2020**, *12*, 3870. [CrossRef]
22. Orro, A.; Novales, M.; Monteagudo, Á.; Pérez-López, J.-B.; Bugarín, M.R. Impact on City Bus Transit Services of the COVID-19 Lockdown and Return to the New Normal: The Case of A Coruña (Spain). *Sustainability* **2020**, *12*, 7206. [CrossRef]
23. Chu, D.K.; Akl, E.A.; Duda, S.; Solo, K.; Yaacoub, S.; Schünemann, H.J.; Chu, D.K.; Akl, E.A.; El-harakeh, A.; Bognanni, A.; et al. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: A systematic review and meta-analysis. *Lancet* **2020**, *395*, 1973–1987. [CrossRef]
24. Statistics Canada. *Municipalities in Canada with the Largest and Fastest-Growing Populations between 2011 and 2016*; Statistics Canada: Ottawa, ON, Canada, 2017.
25. IBM. *IBM Study: COVID-19 Is Significantly Altering U.S. Consumer Behavior and Plans Post-Crisis*; IBM: Armonk, NY, USA, 2020.
26. Peter, J.P.; Ryan, M.J. An Investigation of Perceived Risk at the Brand Level. *J. Mark. Res.* **1976**, *13*, 184–188. [CrossRef]
27. Kaplan, L.B.; Szybillo, G.J.; Jacoby, J. Components of perceived risk in product purchase: A cross-validation. *J. Appl. Psychol.* **1974**, *59*, 287–291. [CrossRef]
28. Festjens, A.; Bruyneel, S.; Diecidue, E.; Dewitte, S. Time-based versus money-based decision making under risk: An experimental investigation. *J. Econ. Psychol.* **2015**, *50*, 52–72. [CrossRef]
29. Nakagawa, S.; Schielzeth, H. A general and simple method for obtaining R<sup>2</sup> from generalized linear mixed-effects models. *Methods Ecol. Evol.* **2013**, *4*, 133–142. [CrossRef]
30. Azen, R.; Budescu, D.V. The Dominance Analysis Approach for Comparing Predictors in Multiple Regression. *Psychol. Methods* **2003**, *8*, 129–148. [CrossRef]
31. Nathans, L.L.; Oswald, F.L.; Nimon, K. Interpreting multiple linear regression: A guidebook of variable importance. *Pract. Assess. Res. Eval.* **2012**, *17*, 1–19.
32. Goldbaum, C.; Hu, W. Why New York Buses Are on the Rise in a Subway City. *New York Times*. 2020. Available online: <https://www.nytimes.com/2020/07/06/nyregion/mta-buses-nyc-coronavirus.html> (accessed on 26 November 2020).

33. Buckee, C.O.; Balsari, S.; Chan, J.; Crosas, M.; Dominici, F.; Gasser, U.; Grad, Y.H.; Grenfell, B.; Halloran, M.E.; Kraemer, M.U.G.; et al. Aggregated mobility data could help fight COVID-19. *Science* **2020**, *368*, 145–146. [CrossRef] [PubMed]
34. Ferretti, L.; Wymant, C.; Kendall, M.; Zhao, L.; Nurtay, A.; Abeler-Dörner, L.; Parker, M.; Bonsall, D.; Fraser, C. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* **2020**, *368*, eabb6936. [CrossRef] [PubMed]
35. Johns Hopkins Project on Ethics and Governance of Digital Contact Tracing Technologies. In *Digital Contact Tracing for Pandemic Response*; Kahn, J.P. (Ed.) Johns Hopkins University Press: Baltimore, MD, USA, 2020; ISBN 9781421440613.
36. Mello, B.M.M.; Wang, C.J. Ethics and governance for digital disease surveillance. *Science* **2020**, *368*, 951–954. [CrossRef] [PubMed]
37. Morley, J.; Cowls, J.; Taddeo, M.; Floridi, L. Ethical guidelines for COVID-19 tracing apps. *Nature* **2020**, *582*, 29–31. [CrossRef] [PubMed]
38. Coronavirus: Security flaws found in NHS contact-tracing app. *BBC News*. 2020. Available online: <https://www.bbc.com/news/technology-52725810> (accessed on 26 November 2020).
39. Ollstein, A.M.; Ravindranth, M. Getting it right: States struggle with contact tracing push. *POLITICO*. 2020. Available online: <https://www.politico.com/news/2020/05/17/privacy-coronavirus-tracing-261369> (accessed on 26 November 2020).
40. Fowler, G.A. North and South Dakota’s Care19 coronavirus contact tracing app violates its own privacy policy. *Washington Post*. 2020. Available online: <https://www.washingtonpost.com/technology/2020/05/21/care19-dakota-privacy-coronavirus/> (accessed on 26 November 2020).
41. Oxley, T.; Elshkaki, A.; Kwiatkowski, L.; Castillo, A.; Scarbrough, T.; ApSimon, H. Pollution abatement from road transport: Cross-sectoral implications, climate co-benefits and behavioural change. *Environ. Sci. Policy* **2012**, *19–20*, 16–32. [CrossRef]
42. Woodcock, J.; Edwards, P.; Tonne, C.; Armstrong, B.G.; Ashiru, O.; Banister, D.; Beevers, S.; Chalabi, Z.; Chowdhury, Z.; Cohen, A.; et al. Public health benefits of strategies to reduce greenhouse-gas emissions: Urban land transport. *Lancet* **2009**, *374*, 1930–1943. [CrossRef]
43. Patterson, R.; Panter, J.; Vámos, E.P.; Cummins, S.; Millett, C.; Lavery, A.A. Associations between commute mode and cardiovascular disease, cancer, and all-cause mortality, and cancer incidence, using linked Census data over 25 years in England and Wales: A cohort study. *Lancet Planet. Health* **2020**, *4*, e186–e194. [CrossRef]
44. Wu, H.; Levinson, D.; Sarkar, S. How transit scaling shapes cities. *Nat. Sustain.* **2019**, *2*, 1142–1148. [CrossRef]
45. How Mobility Messaging Can Inject Confidence Into a COVID-Changed Society—Mobility Lab. Available online: <https://mobilitylab.org/2020/05/18/how-mobility-messaging-can-inject-confidence-into-a-covid-changed-society/> (accessed on 1 June 2020).
46. Nisa, C.F.; Bélanger, J.J.; Schumpe, B.M.; Faller, D.G. Meta-analysis of randomised controlled trials testing behavioural interventions to promote household action on climate change. *Nat. Commun.* **2019**, *10*, 1–13. [CrossRef]
47. Stern, P.C. A reexamination on how behavioral interventions can promote household action to limit climate change. *Nat. Commun.* **2020**, *11*, 1–3. [CrossRef] [PubMed]
48. COVID Alert Is Canada’s Free Exposure Notification App. Available online: <https://www.canada.ca/en/public-health/services/diseases/coronavirus-disease-covid-19/covid-alert.html> (accessed on 11 November 2020).

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