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COVid-19 influenced households’ Interrupted Travel Schedules (COVHITS) survey: Lessons from the fall 2020 cycle

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ARTICLE INFO

Keywords: COVID-19 impacts on travel demand
Travel behaviour
Activity-travel pattern
Household travel survey

ABSTRACT

The spread of the novel coronavirus disease-2019 (COVID-19) since early in 2020 has affected every aspect of daily life, including urban passenger travel patterns. Lockdowns to control the spread of COVID-19 created unprecedented travel demand contexts that have never been seen in modern history. So, it is essential to benchmark trends of travel behaviour, especially people’s daily travel patterns that are necessary to develop a comprehensive understanding of the impacts of COVID-19. A multi-cycle benchmarking household travel study: the COVID-19 influenced Households' Interrupted Travel Schedules (COVHITS) Survey was implemented in the Greater Toronto Area with a random sample of over 4000 households. The results indicated a stark alteration in people’s daily activity-travel patterns due to COVID-19. The pandemic caused a substantial decline in mobility in the study area. The average weekday household trip rate dropped from 5.2 to 2.0 trips. Transit modal shares suffered severely during the pandemic, while private car dependency was enhanced. Overall, transit modal share dropped from 17.3% to 8.1% in the study area, while the modal share of private cars increased from 70.8% to 74.1%. Factors such as having to work from home, ownership of private cars, and household incomes influenced mobility levels of the people in the study area during the pandemic. While overlooked, travel demand analysis can reveal effective strategies to curb the spread of such contagious diseases. An econometric model and analysis of sample data reveal several potential strategies. These include: (1) working/learning from home should be implemented until the end of the pandemic; (2) transit agencies should provide as much transit frequency as possible (particularly for bus routes) during peak hours to avoid crowding inside transit vehicles and project a positive image of public transit; and (3) strict restrictions should be implemented in regions with lower confirmed COVID-19 cases, as they became attractive destinations during the pandemic.

1. Introduction

The ongoing spread of the novel coronavirus disease-2019 (COVID-19) has changed every aspect of urban life, and the travel demand of urban residents is no exception. Residents in the Greater Toronto Area (GTA), Canada, have been adapting their lifestyles in response to the COVID-19 pandemic. Since the outbreak of COVID-19 in Ontario in March 2020, various policy measures such as imposed work from home options, online learning, restricting business operations, and social distancing guidelines have been implemented to stop the spread of the virus.

Although these policies play vital roles in slowing down the spread of the virus, they also alter regular participation in activities and consequently change travel patterns of urban residents. It is essential to provide rigorous assessments of the impacts on urban passenger travel brought by policies implemented during the pandemic. Possible behavioural alteration should be carefully studied to facilitate better policy responses during the pandemic and inform long-range planning for the post-pandemic era. In the short-term, policy responses during the pandemic should serve two goals. First, to contain the spread of COVID-19, policymakers want to restrict movements and limit contact between people to the largest extent possible. Second, policymakers are also obligated to ensure the continued operation of economic activities during the pandemic. In addition, they should look after the welfare of the population, especially the vulnerable groups, during the pandemic. Because these two goals sometimes will conflict with each other, it is

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https://doi.org/10.1016/j.tranpol.2021.08.009
Received 14 July 2021; Accepted 16 August 2021
Available online 19 August 2021
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critical to analyze people’s daily activity-travel patterns under pandemic-related restrictions. These insights can be used to modify and design policy responses, which can help bridge the gap between the conflicting short-term policy goals mentioned above. In the long-term, some behavioural changes caused by the pandemic might become permanent in the post-pandemic era. For example, the mass adoption of telecommuting during the pandemic might change the landscape of home location choices, land use patterns, urban densification and out-of-home activity travel patterns compared to the pre-pandemic pattern. Such disruptions should be carefully studied. Policymakers need to act sooner rather than later to account for potential long-term impacts, given their implications for long-term planning.

This type of analysis cannot be performed without real-world datasets. Collecting revealed preference datasets to keep track of urban residents’ activity-travel patterns will become necessary. Thus, we implement a multi-cycle benchmarking household travel study: the COVHITS (COVID-19 influenced Households’ Interrupted Travel Schedules) Survey to assess the impact of COVID-19 on travel demand in four of the most populated regions in the Greater Toronto Area (GTA). Qi et al. (2020) recognized the need to utilize modern data collection techniques to capture travel behavioural changes during the pandemic. They recommended using stated-preference (SP) surveys and discrete choice modelling to capture causality in travel behaviour changes. Indeed, data collected through SP surveys can be used to analyze the causality of trade-offs between different alternatives. However, this study’s multi-cycled household travel survey can provide more comprehensive snapshots of people’s daily activity-travel patterns during the pandemic. The COVHITS survey captures individuals’ out-of-home activity type choices, destination location choices, activity duration choices, travel modal choices along with their personal and household characteristics. Investigators can use such datasets to conduct various econometric analyses, including discrete choice modelling.

Moreover, it can also be utilized to develop travel demand models for research and policy analysis in pandemic contexts (Goulias, 2013). This paper presents an in-depth analysis of data collected in the fall 2020 cycle of the COVHITS survey, focusing on changes in travel demand due to COVID-19 and the corresponding restrictions. It presents a comprehensive snapshot of activity-travel patterns during the pandemic in the study area. Econometric modelling exercises are conducted to capture the travel behaviour of residents in the study area. Insights derived from this study will provide valuable perspectives on curbing the spread of the COVID-19 through the lens of travel demand. It will also facilitate planning for the post-pandemic “new normal” in terms of urban transport.

The remainder of this paper is organized into seven sections. Section 2 reviews COVID-19 related literature in the field of transportation. Section 3 summarizes policies implemented in the GTA to account for the spread of COVID-19. Section 4 describes details of the COVHITS survey. Section 5 provides an in-depth descriptive analysis of activity-travel patterns revealed from the survey. Section 6 presents the result from the empirical investigation. Section 7 recommends short-term policies to better account for COVID-19 and any future outbreak of the transmissive virus, followed by recommendations of long-term policies that facilitate better planning for the post-pandemic era. Section 8 concludes the study by summarizing findings and lessons learned from the 2020 fall cycle of the COVHITS survey.

2. Literature review

COVID-19 and its impact on passenger travel demand have received growing attention from the transportation research community. Several studies focused on travel-related behaviours during the pandemic. Beck and Hensher (2020a, 2020b) conducted a multi-wave survey to investigate impacts on households’ travel and activities in Australia. Beck et al. (2020) also identified the popularity of work from home (WFH) during the pandemic. They also suggested policymakers leverage the benefits of WFH in the post-pandemic era. Shamshiripour et al. (2020) implemented a revealed preference-stated preference (RP-SP) survey in Chicago, USA. They concluded that the pandemic brought various changes in activity-travel behaviours. They identified the adoption of tele-activities (online shopping, learning, and working from home) due to the pandemic. They also identified the shift towards active modes (walking and cycling) during the pandemic. Parady et al. (2020) administered an online survey in Tokyo, Japan, to investigate urban residents’ voluntary out-of-home activity participation during the early stage of the pandemic. They found that people were voluntarily avoiding out-of-home dining and leisure activities since the early stage of the pandemic. Utilizing data obtained from 1052 residents of Japan, Kashima and Zhang (2021) also discovered that a significant portion of the Japanese population voluntarily altered their out-of-home activity participation behaviour during the early stages of the pandemic.

Besides traditional survey methods, researchers also utilized big data to track travel demand changes during the pandemic. Dandapat et al. (2020) used high-volume mobility data from Google and Apple to evaluate the effectiveness of lockdown imposed by local governments in India. They identified the effect of fatigue resulting from multiple iterations of the national lockdown. The first two lockdowns were very effective in reducing out-of-home activities. But the effectiveness diminished for the third and fourth lockdowns. Marsden et al. (2021) surveyed how travel behaviours have adapted in England and Scotland during the pandemic. Mortira et al. (2020) also used high-frequency data to analyze travel behaviour changes during the pandemic in 131 countries across the world. They identified that the impacts of local COVID-19 case counts and the strictness of restrictions on out-of-home activities differed across countries and development stages.

Studies have also tried to establish frameworks that will guide policymaking in response to future pandemics. Budd and Ison (2020) proposed the concept of “responsible” transport, where travellers account for the effects of their travel behaviours on themselves and others and will act responsibly. They believed that a transition from “smart” and “intelligent” transport to “responsible” transport has occurred due to the pandemic. However, Oum and Wang (2020) found in their study that individuals tend not to internalize the external risk of infections on others during the pandemic. So classical Pigouvian tax can be applied. Zhang et al. (2021) conducted a survey of 357 transportation experts from more than 60 countries. Their opinions regarding the preparedness for a public health crisis in transportation systems, measures are taken locally to curb the pandemic, impact of the pandemic in the transportation sector and their professional recommendations were collected and carefully analyzed. Li et al. (2021) analyzed the relationship between the initial spread of the COVID-19 and built environments. They found that the value of betweenness centrality and population density was positively associated with the infection rates. Their findings recognized the necessity of land use planning efforts to mitigate the spread of possible future pandemics in their early stages. Zhang (2021) found communication between governments and the public is vital during the early stage of the public health crisis. He suggested a LAST-ING (life [L], activities [A], space [S], timing [TING]) approach to mitigate the spread of possible future pandemics. Zhang (2020) also proposed a PASS approach to facilitate public policy design in response to future pandemics.

3. COVID-19 policy responses in the Greater Toronto Area (GTA)

On March 17, 2020, the Government of Ontario declared a state of emergency due to COVID-19 (Premier and President of the Council, 2020). The declaration of emergency locked down the GTA. Lockdown in a pandemic context refers to large-scale physical distancing and movement restrictions to slow disease transmission (World Health Organization, 2020). During the initial lockdown in Ontario, all non-essential businesses were closed. Workers were asked to work remotely if possible. All schools and post-secondary institutions in the
GTA transitioned to virtual learning. After locking down the GTA for more than a month, the provincial government announced a set of policies and guidelines to reopen the halted economy. On May 1, 2020, the Government of Ontario implemented a three-staged reopening plan (Government of Ontario, 2020a). The plan gradually relaxed restrictions. In stage one, only essential services were permitted to open. Stage two allowed the operation of some non-essential services under strict health and safety requirements. Shopping malls were allowed to open. Dining at restaurants & bars was only permitted if it was outdoors. All outdoor recreation facilities were allowed to operate. Gathering for ceremonies such as weddings and funerals were allowed for up to ten people. Personal care services such as haircuts were also allowed to operate with proper health and safety protocols. Stage three was the most relaxed. It permitted nearly all businesses to operate with health and safety protocols. There are three levels of governance in Ontario: provincial, regional, and municipal. This three-stage system was applied on the regional level so that the stage of each region depends on its status of COVID-19. In October 2020, due to the rising COVID-19 case counts, the Government of Ontario introduced a modified stage 2 into the scheme. The modified stage closed high-contact locations such as gyms, casinos, cinemas, and conference centers (Government of Ontario, 2020a). Later, the Government of Ontario adjusted the three-stage system into a five-stage system. The new system included lockdown as a standalone stage (Government of Ontario, 2020b). Aside from that, the goals of three-stage and five-stage systems were similar. Both the three-staged and five-staged systems tried to contain the spread of COVID-19 while minimizing impacts on economic activities and social welfare. Regardless of their stringency, all of the restrictions implemented in the GTA have the potential to affect the decision to participate in out-of-home activities, and by extension, travel patterns.

4. The survey for data collection

The 2020 COVHITS survey (referred to as the COVHITS survey in this paper) was conducted to collect passenger travel demand data after the first round of COVID-19 lockdown in the study area. The main objective of the survey was to collect observed weekday passenger travel patterns during the pandemic. In the post-pandemic world, and eventual return to pre-pandemic normalcy is expected. The survey was expected to serve as a reference to assess such return to normalcy.

The survey was an online household travel survey that collected socioeconomic characteristics of both the household and each member of the household. The survey also collected single weekday travel diaries for all household members aged six years or older. The survey study area included the four most populated regions in the Greater Toronto Area (GTA): the City of Toronto and the Regional Municipalities of York, Peel, and Halton (see Fig. 1). The survey was administered to a random sample of people belonging to commercial survey panels. It was programmed using an online travel survey platform: Travel and Activity Internet Survey Interface (TRAISI) (Chung, 2018). The final dataset contains 3721 households with 6948 reported weekday trips.

4.1. Data collection window during the pandemic

Selecting the data collection period was a crucial consideration for the COVHITS survey. Passenger activity-travel patterns were dramatically disturbed by COVID-19. The study aimed to capture relatively stable activity-travel behaviours under the influence of the pandemic. The survey was conducted between October 20, 2020, and November 20, 2020. This time period was selected based on the following considerations. Firstly, the data should be collected during the time of year where the local large-scale regional household travel is conducted. Typically, the Transportation Tomorrow Survey (TTS), a household travel survey that surveyed 5% of the population in the GTA every five years since 1986, is conducted during the fall – a time when travel patterns were more stable compared to other time of the year (Data Management Group, 2018a). Collecting data in the same period as TTS would facilitate a direct comparison of travel behaviour between the COVHITS and TTS datasets.

Secondly, rigid restrictions on participating in out-of-home activity should not be in place during the data collection period. In other words, the study area should not be locked down during the data collection period. The complete closure of businesses, shopping facilities, and restaurants would forcefully reduce passenger travel demand. As indicated in Fig. 2, all regions in the study area were at least in modified stage 2 of reopening during the data collection period. As discussed in section 2, modified stage 2 of reopening or higher stages permitted most out-of-home activities with limits on the capacity of facilities.

Thirdly, data should be collected when activity-travel demand remained relatively stable. Residents in the study area should have sufficient time to develop stable behaviours under the influence of the pandemic. Fig. 2 shows a fluctuation in mobility in the study area since the initial lockdown in March 2020. The initial outbreak of COVID-19 and subsequent lockdown in March 2020 reduced mobility in the study area dramatically. As indicated in Fig. 2, the dramatic disturbance was reflected by a sudden drop in driving, walking and transit trips reported by Apple Mobility Reports (Apple, 2020).

However, mobility has been trending upwards after early April. Beck and Hensher (2020b) also identified similar upward trends in mobility after the initial lockdown in Australia. The upward trend peaked during the beginning of September when all regions within the study area were in stage 3 of the reopening plan, which featured the most relaxed restrictions. The trend started to move downward again since the beginning of September. The reason might be twofold: first, people returned to work after the summer break; also, the daily COVID-19 cases in Ontario started rising again, indicating possible arriving of the second wave of COVID-19. However, after mid-October, the downward mobility trend started to flat (see Fig. 2). A relatively flat change in
mobility demand indicated that residents in the study area might have developed their strategies/habits in travelling and participating in daily activities while coping with the pandemic.

Considering all factors discussed above led to an ideal data collection window between October and November 2020. Data collected within this one month provide a snapshot of relatively stable pandemic-influenced passenger travel patterns under moderate restrictions in the study area. The dataset also had sufficient comparability with regards to the benchmark dataset: the Transportation Tomorrow Survey (TTS).

4.2. Weight adjustment approach

To improve the representativeness of the data, samples collected in the COVHITS survey were weight-adjusted to match distributions of selected socioeconomic attributes in the study area. The COVHITS survey had a relatively small sample size compared to regional travel surveys. Therefore, it is at risk of being skewed towards specific population segments (e.g., smaller household size and younger people). Also, samples from each region were pooled and further weight-adjusted to represent the population distribution across four regions in the study area. The bi-proportional Iterative Proportional Fitting (IPF) approach was used to estimate weight adjustment factors. The IPF approach is a weighting approach that cycles through various control variables until the resulting weighting factors yield convergence against targeted distributions of said control variables. In this study, two socioeconomic control variables were used at the household and person levels. At the household-level, the distribution of household size in each region was used as the target. At the person-level, the distribution of age in each region was used as the target. All individuals within the same household will carry the same weighting factor, identical to the household level’s weighting factor. The distribution of the target variables came from the 2016 Canadian Census (Statistics Canada, 2017a, 2017b). The bi-proportional IPF procedures used in this study will be described in detail below (Data Management Group, 2018b).

First, base weights were developed at the household level. Based on the size of the household, households in each region received base weights calculated by:

$$\text{weights}_{\text{household, region}} = \frac{\text{Census target distribution of household size}_{\text{region}}}{\text{Unweighted distribution of household size}_{\text{region}}}$$

(1)

Then, base weights calculated were assigned to each household and individuals within households. Within each IPF iteration, adjustment factors were calculated by capturing the difference between the control distribution of age within each region and the weight-adjusted distribution of age within each region.

$$\text{weights}_{\text{person, region}} = \text{weights}_{\text{household, region}} \cdot \text{if from same household}$$

(2)

$$\text{age adjustment factors}_{\text{person, region}} = \frac{\text{Census target distribution of age}_{\text{region}}}{\sum_{i=1}^{n} \text{weights}_{\text{person, region, age stratum}}}$$

(3)

Since age adjustment factors were at the person-level, the household-level adjustment should be the average of adjustment factors across all individuals in the household. For a household that had $n$ persons, the adjustment factor was calculated by:

$$\text{household adjustment factor}_{\text{household}, i, \text{region}} = \frac{\sum_{j=1}^{n} \text{age adjustment factors}_{\text{person, region}}}{n}$$

(4)
Then the weighting factor of each household was updated by:

\[ \text{weights}_{\text{household, regions}} = \text{household adjustment factors}_{\text{household i, regions}} \times \text{weights}_{\text{household, regions}} \]  

(5)

Since each household had different adjustment factors, each household would have its unique weighting factor. The household size adjustment factors were calculated by:

\[ \text{household size adjustment factors}_{\text{regions}} = \frac{\text{Census target distribution of household size}_{\text{regions}}}{\sum_{n=1}^{N} \text{weights}_{\text{household, regions, age stratum}}} \]  

(6)

Then, if the household size adjustment factors obtained from equation (6) met the convergence criteria, the IPF procedure will stop. If not, the next IPF iteration would begin from Equation (2) after updating household weights with adjustment factors.

Table 1 presents the summary statistics of the normalized estimated weighting factors. Samples in Toronto and Peel had relatively larger weighting factors than other regions. This indicated samples in Toronto and Peel were more skewed than control socioeconomic distributions. This also deemed the necessity to perform weight adjustment. All descriptive analysis in section 4 will be based on weight-adjusted COVHITS survey samples.

5. Descriptive analysis

This section presents an in-depth analysis of changes in passenger travel demand in the study area due to COVID-19 and the corresponding restrictions. Descriptive statistics reflecting activity-travel patterns were compared between the COVHITS survey and the benchmark survey. The Transportation Tomorrow Survey (TTS) was used as a benchmark in this study representing passenger travel demands in the pre-COVID normal condition. TTS is a regional household travel survey that surveyed 5% of the population in the COVHITS survey study area since 1986 (Data Management Group, 2018c). The latest cycle of the TTS conducted in 2016 was used in this study.

Before any analysis, discrepancies on sampling frames between two datasets must be removed to identify changes in passenger travel demands attributed to the pandemic. The COVHITS survey collected detailed travel diaries for all six year or older individuals. The TTS collected travel diaries for individuals who were eleven years of age or older (Data Management Group, 2018c). Therefore, individuals in the COVHITS dataset who are younger than eleven years old were removed from the analysis.

5.1. Socioeconomic characteristics

Socioeconomic characteristics have been shown to affect activity-travel behaviours (Yasmin et al., 2017). Thus, the distribution of socioeconomic attributes between the COVHITS survey and 2016 TTS should be similar so that changes in travel patterns between the two datasets can be firmly attributed to the pandemic. Key socioeconomic characteristics in both datasets have been presented in Tables 2 and 3. At the person level, age, gender, employment status, student status, driver’s license ownership, and transit pass ownership matched reasonably well between the two datasets. At the household level, household size, vehicle availability, income, the average number of persons, workers, and licensed drivers matched well. The only discrepancy was observed for dwelling types. 58% of households in the COVHITS survey reported living in single and semi-detached houses, compared to 46% of households in 2016 TTS. At the same time, the COVHITS survey only had 22% of households living in apartments, compared to 44% in 2016 TTS. 2016 TTS dwelling types matched well to the Canadian census (Statistics Canada, 2017a, 2017b). The reason for this discrepancy might be the

Table 1
Estimated weighting factors for COVHITS survey.

| Region       | Mean | Std Dev | Min. | Max. | 25th | 50th | 75th | 99th |
|--------------|------|---------|------|------|------|------|------|------|
| Toronto      | 20.4 | 17.2    | 1.0  | 187.4| 9.6  | 17.6 | 23.0 | 87.3 |
| York         | 6.5  | 5.3     | 1.0  | 40.1 | 3.6  | 5.7  | 7.7  | 28.1 |
| Peel         | 74.4 | 81.8    | 1.0  | 783.9| 31.2 | 52.6 | 89.5 | 461.0|
| Halton       | 4.0  | 3.3     | 1.0  | 52.6 | 2.3  | 3.1  | 4.1  | 15.1 |

Table 2
Personal socioeconomic attributes in the COVHITS survey and 2016 TTS

|                  | 2016 TTS | COVHITS |
|------------------|----------|---------|
| Age              |          |         |
| 0-10             | 12%      | 12%     |
| 11-15            | 6%       | 6%      |
| 16-25            | 13%      | 13%     |
| 26-45            | 29%      | 29%     |
| 46-64            | 26%      | 26%     |
| 65+              | 14%      | 13%     |
| Median           | 38       | 39      |
| Gender           |          |         |
| Female           | 51%      | 52%     |
| Male             | 49%      | 48%     |
| Employment Type  |          |         |
| Full-time worker | 46%      | 45%     |
| Part-time worker | 7%       | 7%      |
| Student          | 23%      | 27%     |
| Licensed driver  | 69%      | 68%     |
| Transit pass holder | 20%  | 15%     |

|                           |           |         |        |         |
|---------------------------|-----------|---------|--------|---------|
|                           | Male      | Female  | Male   | Female  |
| Employment Type           |           |         |        |         |
| Full-time worker           | 46%       | 34%     | 45%    | 35%     |
| Part-time worker           | 7%        | 10%     | 7%     | 10%     |
| Student                    | 23%       | 22%     | 27%    | 26%     |
| Licensed driver            | 69%       | 61%     | 68%    | 64%     |
| Transit pass holder        | 20%       | 22%     | 15%    | 14%     |

Table 3
Normalized weighting factors for household size and age distribution

|                  | Mean | Std Dev |
|------------------|------|---------|
| Toronto          | 20.4 | 17.2    |
| York             | 6.5  | 5.3     |
| Peel             | 74.4 | 81.8    |
| Halton           | 4.0  | 3.3     |

|                  | Mean | Std Dev | Min. | Max. | 25th | 50th | 75th | 99th |
|------------------|------|---------|------|------|------|------|------|------|
| Toronto          | 20.4 | 17.2    | 1.0  | 187.4| 9.6  | 17.6 | 23.0 | 87.3 |
| York             | 6.5  | 5.3     | 1.0  | 40.1 | 3.6  | 5.7  | 7.7  | 28.1 |
| Peel             | 74.4 | 81.8    | 1.0  | 783.9| 31.2 | 52.6 | 89.5 | 461.0|
| Halton           | 4.0  | 3.3     | 1.0  | 52.6 | 2.3  | 3.1  | 4.1  | 15.1 |

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difference in sampling methods used in the two surveys. The 2016 TTS randomly recruited samples from a regional database of mailable addresses (Data Management Group, 2018a). The 2020 COVHITS survey randomly recruited samples from online commercial survey panels, which might contain a greater share of house dwellers compared to the study area.

5.2. Working/studying from home practiced during the pandemic

The COVID-19 had a profound impact on how workers and students work and study. The survey collected worker’s workplace arrangements before and during the pandemic. Four options were given to the respondents: working from home only (WFH only), work outside from home and work from home sometimes (Hybrid), work outside from home only (WOFH only) and no fixed location. Before the pandemic, only 14.5% of employed workers in the study area worked from home completely. 60% worked outside of the home, and 18.5% had hybrid arrangements, indicating they sometimes worked from home. Fig. 3 shows the flow of workplace arrangements under the influence of COVID-19. In the COVHITS survey, almost one-third of workers who worked outside of home before the pandemic shifted to work from home due to the closure of their workplace. Consequently, 45.6% of employed workers in the study area worked from home before the pandemic shifted to work from home. Consequently, 45.6% of employed workers worked outside of home before the pandemic shifted to work from home. COVID-19 caused a large drop in urban passenger mobility in the study area, as reflected in the COVHITS survey. As observed from the COVHITS survey, the average weekday trip rate was 2.0 trips per household in the study area (see Table 4). The trip rate was 5.2 trips per household in the 2016 TTS. Immobility (in which no trips are made) was one of the main possible reasons for such large drops in trip rates. In the COVHITS survey, two-thirds of the study area population did not make any trips. Table 4 shows that the proportion of individuals who reported no trips on the survey day increased from 22% to 62%.

Consequently, daily personal trips dropped to 0.84 in COVHITS, compared to 2.2 trips in the 2016 TTS. Reduction in commuting trips might be one of the main contributors to such a dramatic mobility drop. In the study area, commuting trips per worker dropped from 0.83 trips per day to 0.35 trips per day as working from home eliminated the need to commute.

5.4. Purpose of trips

Travelers in the study area were making fewer discretionary trips due to COVID-19. The proportion of trips travelled for work, and school purposes remained stable. Fig. 4 shows that 22.7% and 6.8% of trips were made for work and school in the COVHITS survey, respectively. The proportions in 2016 TTS were 22.5% and 6.8% for work and school, respectively. These trips were made for committed activity purposes. At the same time, it was observed that the proportion of shopping trips increased from 8.0% to 13.1%. The increase was reasonable because shopping trips, especially for groceries, were characterized as essential trips during the pandemic. However, trips made for discretionary purposes (restaurant, visiting, recreation, health, services, worship, and others) decreased from 20.2% to 13.3%. The drop in discretionary trips can be explained from two perspectives. First, people had more flexibility for discretionary activities. Observation from the COVHITS survey suggested that residents in the study area reduced their participation in out-of-home discretionary activities because of COVID-19. Secondly, local governments implemented policies that effectively added additional costs on participating in out-of-home discretionary activities. Restrictions on the number of people gathering, capacity limits for stores and facilities, and social distancing rules, would affect people’s decisions. Local governments in the study area also encouraged their residents to avoid non-essential travels to save lives. This might add another layer of moral responsibility on people and lead to less non-essential out-of-home activities.

5.5. Modal shares of trips

In terms of modal share, driving and active modes gained popularity, whereas transit modal share decreased unanimously for all trip purposes in the study area. Considering all trip purposes, the modal share of driving increased from 58.2% (in 2016 TTS) to 65.3% (in COVHITS) in the study area (see Fig. 5). Work and shopping trips had the highest dependence on driving during the pandemic. 77.2% of working and 70.8% of shopping trips were made by driving. School trips experienced the highest increase in modes involved private vehicles. Pre-COVID, 33.1% of school trips in the study area were made by private vehicles (both driving or as passengers). In COVHITS, the private vehicles’ modal share increased to 43.2% for school trips made in the study area. Active modes (walk and cycle) gained modal shares for all purposes, except

Table 3 Household socioeconomic attributes in the COVHITS survey and 2016 TTS

| Household Income       | 2016 TTS  | COVHITS  |
|------------------------|-----------|----------|
| $0 - $14,999           | 5%        | 3%       |
| $15,000 - $39,999      | 14%       | 12%      |
| $40,000 - $59,999      | 14%       | 14%      |
| $60,000 - $99,999      | 21%       | 28%      |
| $100,000 - $124,999    | 10%       | 16%      |
| $125,000 and above     | 18%       | 20%      |
| Decline/don’t know     | 18%       | 8%       |

Household Averages

| Persons                | 2.7       | 2.7     |
| Workers                | 1.4       | 1.6     |
| Licensed drivers       | 1.8       | 1.9     |
work trips. Overall, the study area experienced an increase from 9.4% (in 2016 TTS) to 16.0% (in COVHITS) for the walk & cycle modal shares for daily weekday trips. A similar trend had also been identified in Australia by Beck and Hensher (2020a).

Transit suffered a loss in modal share during the pandemic. Overall, the transit modal share dropped from 17.3% (in 2016 TTS) to 8.1% (in COVHITS) for all travel purposes in the study area. The most significant drop came from school trips. Fig. 5 shows that transit model share decreased from 30.6% (in 2016 TTS) to 10.1% (in COVHITS) due to COVID-19. Crowded vehicles, cleanliness, and hygiene remained the biggest concern for travelers regarding the use of transit (Beck and Hensher, 2020a; Mashrur et al., 2020). Breaking down transit usage in more detail, transit users used transit differently during COVID-19. For transit trips served by Toronto Transit Commission (TTC), 51.8% were made by surface routes, and 48.2% were subway trips before the pandemic. In the COVHITS survey, surface transit trips accounted for 64.2% of all TTC trips captured, and subway trips decrease to 35.8%.

### 5.6. Trip length by modes

The COVHITS survey revealed that people used private vehicles for longer trips. The average trip length of driving and auto passenger trips generated by residents in the study area increased from 6.4 km (in 2016 TTS) to 11.5 km (in COVHITS) and from 4.3 km (in 2016 TTS) to 6.1 km (in COVHITS), respectively. The distribution of driving and auto passenger trip length became flatter in the COVHITS survey, compared to the 2016 TTS (see Fig. 6). This indicated that residents in the study area changed their habits when using private vehicles during the pandemic. Since driving and auto passenger trips accounted for 74.1% of all weekday trips in the study area, this indicates that COVID-19 had altered travel patterns in the study area; specifically, residents were making longer trips in their cars.

The average transit trip distance also increased from 7.0 km (in 2016 TTS) to 12.2 km (in COVHITS) in the study area. Fig. 6 shows that the increase in average transit trip distance resulted from an increase in longer-distance transit trips (20 km & 30 km) in the COVHITS survey compared to the 2016 TTS. However, despite the increase in average trip length, the distributions of transit trip length between the COVHITS survey and 2016 TTS still followed similar shapes. Transit still served trips with various distances during the pandemic. Although some travelers tried to avoid transit during the pandemic, people still used transit services to meet different travel needs.

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### Table 4

Average trip rates and number of trips per person in the study area.

|                      | 2016 TTS | COVHITS |
|----------------------|----------|---------|
| Average trips per weekday (age 11+) |          |         |
| Household             | 5.2      | 2.0     |
| Person                | 2.2      | 0.84    |
| Work trips per worker | 0.83     | 0.35    |
| Number of trips per person (age 11+) |          |         |
| 0                     | 22%      | 62%     |
| 1                     | 1%       | 2%      |
| 2                     | 49%      | 30%     |
| 3                     | 8%       | 4%      |
| 4                     | 11%      | 2%      |
| 5+                    | 8%       | 1%      |

---

Fig. 3. Flow of workplace arrangement before and during COVID-19.
5.7. Start time of trips by purposes

The morning peak period (6–9 a.m.) of the trips generated by respondents in the COVHTIS survey was flattened, indicating a more evenly distributed trip generation pattern across the day than before the pandemic. Fig. 7 shows fewer trips departed between 6 a.m. and 9 a.m. in the COVHTIS survey, compared to the 2016 TTS. More trips departed between 12 p.m. and 3 p.m. in the COVHTIS survey than in the 2016 TTS. Patterns in the departure times for home, work, and school trips in COVHTIS were similar to the 2016 TTS. The key drivers for the changes...
Fig. 6. Distribution of trip length by modes in the study area.

Fig. 7. Distribution of trip start time by purposes in the study area.
in the departure times of shopping/grocery and other discretionary trips. In 2016 TTS, the departures time for both purposes followed a double-peaked pattern, peaking twice a day during the morning (6 a.m.–9 a.m.) and afternoon peak hours (3 p.m.–6 p.m.). However, in the COVHITS survey, departure times for both purposes only peaked once during the midday (12 p.m.–3 p.m.) period. It was possible that working/studying from home gave people greater flexibility in scheduling non-mandatory activities during the day.

5.8. Duration of out-of-home activities

The COVHITS survey reported an average out-of-home work duration of 476 min, close to the 484 min reported in the 2016 TTS. Work duration is usually exogenously determined, so it should not vary between the COVHITS survey and the 2016 TTS. Out-of-home school duration varied significantly between COVHITS and the 2016 TTS. Fig. 8 shows that the distribution of school duration peaked at 480 min (8 h) in 2016 TTS, which is consistent with regular school hours. In the COVHITS survey, the distribution of school duration peaked twice at 300 min and 480 min, respectively. As discussed in section 4.2, some secondary schools in the study area adapted hybrid in-class & online models. The hybrid class model contained half-day in-person school and half-day virtual learning. Thus, the change in out-of-home school duration was well captured by the COVHITS survey.

The duration of shopping/grocery activities followed similar distribution between the COVHITS survey and the 2016 TTS (see Fig. 8). However, the average duration of shopping/grocery activities increased from 84 min to 105 min. It was possible that social distancing practiced at stores and shopping facilities elongated the duration of these activities since people were more likely to wait in lines. During the pandemic, people tended to spend longer time on other activities (e.g., sports/recreations, visiting family/friends, etc.) out-of-home discretionary activities. The average duration increased from 98 min (in 2016 TTS) to 132 min (in COVHIS). This increase might be in response to working/studying from home. After spending an excessive amount of time at home, residents in the study area might have been inclined to spend more time outside of their homes.

5.9. Destination location choices by trip purposes

Destination location choices were analyzed by comparing the percentage of trips destined for each traffic zone in the COVHITS survey and the 2016 TTS. Changes in work trip destination choices varied by regions within the study area. In the COVHITS survey, work trips destined for the City of Toronto reduced significantly compared to 2016 TTS (see Fig. 9). At the same time, work trips destined for other regions in the study area endured fewer changes between the COVHITS survey and the 2016 TTS. The differences might result from the different employment types between the City of Toronto and other regions. The City of Toronto predominantly contains white-collar jobs, which permitted remote working during the pandemic. On the contrary, employment types in other regions were more industrial-oriented, requiring employees to work on-site (Statistics Canada, 2020a, 2020b). For example, as home to several car manufacturers and regional freight transport centers, Peel and Halton regions had similar work trip destination patterns before and during the pandemic (see Fig. 9). School trip destination choices were reduced unanimously in the study area. Unlike the 2016 TTS, school trip destination choices were concentrated in a few hotspots in the COVHITS survey. Enforced virtually learning eliminated school trips made to post-secondary institutions (see section 4.2). Subsequently, hotspots identified in Fig. 9 correspond to the locations of elementary and secondary schools.

Destination choices patterns for shopping/grocery trips also changed between the COVHITS survey and the 2016 TTS. In the COVHITS survey, shopping/grocery trips within the study area tended to concentrate in a few zones compared to a more evenly distributed pattern in the 2016 TTS (see Fig. 9). Hotspot zones for shopping/grocery destination choices were zones where shopping malls and big-box retailers were located. Small businesses were struggling during COVID-19. Anecdotal evidence in news media sources also showed that small businesses struggled during the pandemic (Xing, 2020). There were plausible reasons for people’s preference for bigger retailers during the pandemic. Supermarket chains and big-box retailers had attractive goods and services during the pandemic. They offered one-stop solutions for not only groceries (which were essentials during the pandemic) but also all manners...
of goods and services.

In contrast, small businesses often provided a finite selection of goods or services. It was also possible that people had more positive perceptions towards big chain stores than small businesses. During the pandemic, big-box retailers were subjected to health and safety inspections from local governments (DeClerq, 2021). In the COVHITS survey, destination choices for other discretionary trips also concentrated in few zones compared to a more evenly distributed pattern during the 2016 TTS (see Fig. 9). In the COVHITS survey, destination location choices for zones within the City of Toronto reduced significantly. Instead, choices shifted to York and Halton regions, where the number of COVID-19 cases were lower (see Table 8 for average

Fig. 9. Trip destination location choices by purposes in the study area. Fig. 9 (continued). Trip destination location choices by purposes in the study area.
COVID-19 cases for each region). Some emerging hotspot zones in the COVHITS survey were zones that included outdoor recreational facilities such as parks, conservation areas, golf courses, and forests.

5.10. Online shopping during the pandemic

COVID-19 changed how people shop. While being locked at home, people started to shop more online. Statistics Canada stated that e-commerce sales in Canada doubled in May 2020 compared to May 2019 (Aston et al., 2020). The COVHITS survey collected information on households’ in-store and online shopping frequency during the pandemic. These data indicated that, in the study area, 50% of households experienced ordering meals online (see Table 5), with 23% of the households ordering food online at least once a week. Also, 46% of households experienced ordering groceries online, with 25% ordering groceries online at least once a week. Purchasing food and groceries are...
Empirical investigation

To further investigate the effects of various factors on urban travel movement in the study area, a zero-inflated negative binomial (ZINB) regression model was estimated for weekday trip frequency made by households. ZINB models have been widely used in transportation to model the frequency of trips (Deka and Fei, 2019; Mitra et al., 2019). As discussed in section 4.3, mobility in the study area experienced a significant drop during the pandemic. The sample had many households that made no trips at all on a typical weekday. Thus, the two behaviours should be investigated simultaneously. The ZINB model is useful in this regard because it is comprised of two components. The first model component captures the effects that affected the decision to stay at home by households (the zero-inflation model). The other model component captures the factors that affected the number of trips travelled by a household, once the household decided to travel (the count model).

The detailed formulation of the ZINB model is presented below (Long, 1997). Each observation for household i has two possible cases. In the first case, the household made no trips at all on a given weekday. In the second case, the household travelled. The probability of case 1 will be denoted as \( \pi_i \) and the probability of case 2 will be \( 1 - \pi_i \). \( \pi_i \) follows logistic distribution, which can be described as:

\[
\pi_i = \frac{1}{1 + e^{-\alpha \beta}} \quad \text{(7)}
\]

where, 
\( \beta \) is socioeconomic or any variable of interest for household \( i \) in the zero-inflation model. 
\( \alpha \) is estimated coefficient for the zero-inflation model.

Therefore, the probability of observing household \( i \) making \( y_i \) trips on a weekday will follow:

\[
\Pr(y_i) = \begin{cases} 
\pi_i + (1 - \pi_i)g(y_i) & \text{if } y_i = 0 \\
(1 - \pi_i)g(y_i) & \text{if } y_i > 1 
\end{cases} \quad \text{(8)}
\]

where \( g(y_i) \) will follow the negative binomial distribution given by:

\[
g(y_i) = \Pr(Y = y_i | \mu_i; \alpha) = \frac{\Gamma(y_i + 1)}{\Gamma(\alpha + y_i) \Gamma(1 + 1/\alpha)} \left( \frac{\alpha \mu_i}{1 + \alpha \mu_i} \right)^{\alpha} \frac{\mu_i^y}{y_i!} \quad \text{(9)}
\]

\( \mu_i = \exp(\xi_i) \quad \text{(10)} \)

where, 
\( \xi_i \) is the dispersion factor.
\( \xi \) is socioeconomic or any variable of interest for household \( i \) in the count model. 
\( \gamma \) is estimated coefficient for the zero-inflation model. 

Thus, the log-likelihood function for the dataset that has \( n \) households will follow:

\[
LL = \sum_{i=1}^{n} \left[ \sum_{y=0}^{y_i} \ln(\pi_i) + (1 - \pi_i) \ln\left( \frac{\alpha \mu_i}{1 + \alpha \mu_i} \right)^{\alpha} \right] + \ln\Gamma(y_i + 1) - \ln\Gamma(\alpha + y_i) = \ln(1 - \frac{1}{1 + \alpha \mu_i}) \quad \text{(11)}
\]

The log-likelihood function is in closed form and can be estimated using classical maximum likelihood estimators. This study used a package in R software for estimation (Zeileis et al., 2008).

6.1. ZINB modelling results

Table 6 presents the ZINB model results for weekday trip frequency per household under the influence of COVID-19. The count model captured the probability that households make a specific number of trips. The zero-inflation model captured the probability that a household making no trips at all (staying at home) on a typical weekday during the pandemic. Various model specifications were tested, and the final model selected yields the best goodness-of-fit. Most parameters estimated in the final model are statistically significant at 95% confidence level. The parameters pertaining to the overall model, including log-likelihood, Akaike Information Criterion (AIC), number of observations, are shown at the bottom of the table.

Table 6 shows that the following factors were associated with trip frequency the household. First, larger household size would encourage more trips. It is expected because a larger household size implies more workers and students obligated to participate in their committed activities outside of their home. A larger household size indicated more household maintenance tasks that every household must perform periodically. With online shopping, travelling for these activities will be replaced by delivery trips. Such behavioural changes might bring significant impacts on urban travel patterns. Extensive future research is required to understand the impact on urban travel patterns from the increased adoption of online shopping, especially grocery shopping and food delivery.
Table 6

ZINB model of weekday trip frequency per household during COVID-19.

| Count model | Estimate | S. E. | Household size | Intercept |
|-------------|----------|-------|----------------|-----------|
|             | 1.63     | ***   | None           |          |

|     | Estimate | S. E. | Household income | Intercept |
|-----|----------|-------|------------------|-----------|
| None |          |       | $0 - $39,999     | -0.16 *** 0.06 |
| 1 member | 0.14 *** | 0.04 | $40,000 - $79,999 | -0.25 *** 0.06 |
| 2 members | 0.27 *** | 0.05 | $80,000 - $99,999 | -0.12 *** 0.04 |
| 3 or more members | -0.40 | 0.29 | $100,000 - $149,999 | -0.14 *** 0.04 |
|             |          |       | > $150,000       | -0.09 * 0.04 |

| Number of household members who are 65 years or older | Reference |
|-----------------------------------------------------|-----------|
| None |          |       | 1 member | 0.14 *** 0.04 |
| 2 members | 0.27 *** | 0.05 | 3 or more members | -0.40 | 0.29 |

| Number of workers who must travel to work | Reference |
|------------------------------------------|-----------|
| None |          |       | 1 worker | 0.05 |
| 2 workers | 0.26 *** | 0.04 | 3 or more workers | 0.47 *** 0.07 |

| Number of students in the household | Reference |
|-----------------------------------|-----------|
| None |          |       | 1 student | 0.36 *** 0.05 |
| 2 students | 0.53 *** | 0.07 |
| 3 or more students | 1.09 *** 0.19 |

| Number of licensed drivers | Reference |
|----------------------------|-----------|
| None |          |       | 1 driver | -0.71 *** 0.18 |
| 2 drivers | -1.20 *** | 0.19 | 3 or more drivers | -1.91 *** 0.23 |

| Household dwelling types | Reference |
|--------------------------|-----------|
| None |          |       | Townhouse | -0.27 * 0.12 |
| 3 or more vehicles | -1.14 *** 0.22 | |

| Number of work-from-home workers | Reference |
|----------------------------------|-----------|
| None |          |       | 1 worker | 0.51 *** 0.09 |
| 2 workers | 0.94 *** | 0.13 | 3 or more workers | 1.00 * 0.39 |

| Number of household members who are 65 years or older | Reference |
|-----------------------------------------------------|-----------|
| None |          |       | 1 member | 0.05 | 0.13 |
| 2 members | 0.71 *** | 0.15 | 3 or more members | -0.12 1.16 |
| logit of daily COVID-19 cases in household’s region | 0.44 *** 0.12 |

Log likelihood = -5987
AIC = -12,052
Degree of freedom = 38
N = 3719

Notes: Level of significance: *** 0.001 ** 0.01 * 0.05 . 0.1. Akaike Information Criterion (AIC) is calculated as 2(LL-k), where LL is the log-likelihood and k is the number of estimated parameters including intercept.

Also, they tend to need to seek out health services more often than younger individuals. So, they needed to travel despite the risk of COVID-19. They contributed to a significant portion of travel demand during the pandemic. 13.3% of weekday trips reported in the COVHITS were travelled by individuals 65 years or older, compared to 11.4% in 2016 TTS. Aside from socioeconomic variables, a variable that described the severity of COVID-19 in the household region was included in the model. The result shows that more daily new cases in the households' regions would negatively affect trip frequencies travelled by households.

The following factors were identified as associated with the household’s decision to stay at home (make no trips at all) on a typical weekday during COVID-19. Firstly, ownership of private cars matters. Households having no access to private vehicles were more likely to stay at home during the pandemic. At the same time, having no licensed driver in the household would also discourage the decision to make trips. This confirmed the observation that private vehicles gained popularity during the pandemic (see section 4.5). Dwelling types also influenced the decision to stay at home. Households living in single and semi-detached houses were more likely to stay at home than other households in smaller dwellings. Detached houses offer more space to household members, which might reduce dwellers’ tendency and desire to travel. As for student status, if an individual was the only student in the household and he/she had to attend virtual learning, the likelihood of staying at home decreased. Isolation and lack of social activities are by-products of virtual learning and remote working. Understandably, school-age children might seek out-of-home activities if they did not have peers in the same household. However, working-age adults behaved differently. Working from home effectively increased the probability of staying at home during weekdays. Having one or two elderly members at home would encourage staying at home, compared with having no elderly members. This fit the expectation that seniors should be more inclined to avoid leaving their homes, given their vulnerability. However, as discussed above, seniors would tend to make more trips to fulfill their needs for groceries, meals, and health services once they decided to leave their home. Lastly, higher new daily COVID-19 cases would encourage people to stay home. Both the count and zero models identified this behaviour. These results indicated that residents in the study area adjusted their travel behaviour according to the severity of COVID-19 in their community.

6.2. Binary logit model on the active trip making

To provide more policy insights, the relationship between travelling by active modes during the pandemic and various socio-economic and land use characteristics was carefully examined. A binary logit model was estimated for travelling with active modes (Yes = 1, No = 0) at the household level ( Hosmer and Lemeshow, 2000 ). Estimation of parameters, standard errors, along with odd ratios were presented in Table 7. Various model formulations were tested, and the final model selected yields the best goodness-of-ﬁt. All parameters estimated in the final model are statistically significant at a 95% conﬁdence level. The parameters pertaining to the overall model, including log-likelihood, McFadden’s R², Akaike Information Criterion (AIC), the number of observations, are shown at the bottom of the table. For socio-economic variables, the results indicated that household size, number of vehicles, number of workers, and having more than three licensed drivers in the households would negatively affect the likelihood of using active modes. This suggested that active modes were less preferred for working trips and for households having access to vehicles during the pandemic. On the other hand, living in an apartment, having students in the household, and earning more than $150,000 annually would positively affect the likelihood of using active modes. It is surprising that the number of adult bikes was not statistically significant with the likelihood of travelling with active modes. The reason might be that walking dominates active trips (6.7% of the active trips were made by bikes).

For land-use characteristics, the possibility of travelling by active
students in Toronto even their schools are not located in the same zone as their households. Thus, the correlation between the number of schools in the same zone where the household is located and the number of active trips made became insignificant. On the other hand, commuting by active modes for students in suburban regions like Halton might be too burdensome considering its low-density land-use pattern. As a result, the correlation was also insignificant.

Aside from student commuting, land use characteristics also affect the likelihood of using active modes for recreational purposes during the pandemic. Interestingly, the supply of parks and recreation areas produced opposite effects between Toronto and York Region. Larger parks and recreation areas will increase the likelihood of using active modes in Toronto but will decrease the likelihood in York Region. The average areas for zones in Toronto and York Region are 1.00 km² and 4.36 km², respectively. Also, parks and recreational facilities are usually well located in residential areas in Toronto. On the other hand, parks and recreational facilities in York Region are usually located away from residential areas designed to convenient accessibility be private vehicles. As a result, Torontonians might be more likely to use walking and biking for recreational purposes, but York Region residents might prefer other modes.

7. Policy implications

The above analysis provided a snapshot of weekday activity-travel patterns of residents in the GTA during COVID-19. The COVHITS survey results indicated that COVID-19 altered how residents live and travel in the study area. Governments implemented various policies to curb the spread of COVID-19 (see section 3). These policies coincided with reduced mobility and caused disturbances in travel patterns. Unfortunately, on January 12, 2021, ten months after the declaration of the first state of emergency, the Government of Ontario declared a second provincial emergency due to COVID-19, officially noting the occurrence of a second wave of the pandemic (Office of the Premier, 2021). The COVHITS survey was collected in between the first and second waves of the COVID-19 pandemic. Thus, empirical experiences and lessons learned should be carefully utilized to curb the second wave of COVID-19 and any future public health crisis involving a transmissible virus. The discussion will be divided into two parts. In the first part, policies and possible improvements for immediate responses to the pandemic will be discussed. Aside from dealing with direct threats during the pandemic, the post-pandemic world might look different. Preparation and planning for the “New Normal” will also be discussed.

7.1. Short-term policy implication during the pandemic

Various policies implemented by local governments aimed to reduce mobility during the pandemic have proven to be effective. Thus, it is recommended to consistently implement these successful policies such as working and studying (especially for post-secondary institutions) from home until COVID-19 is no longer a public health threat. Although there are no definitive answers about when the COVID-19 pandemic will end, experts suggested that the time when herd immunity is achieved by mass vaccination might mark the end of the pandemic (Charumilind, 2021). The timing of herd immunity through vaccination might differ by region based on various factors. Factors affecting mass vaccination include the amount of vaccine supply secured, supply-chain readiness, sentiment towards the vaccine among the local population, and the effectiveness of the vaccine against variants (Charumilind, 2021). Local governments should consider the aforementioned factors while maintaining or easing policies such as work and study from home. The literature had quantitively identified the positive correlation between mobility and the spread of COVID-19 (Maria et al., 2020). Thus, restricting mobility is critical to curbing the spread of COVID-19 or any other future transmissible virus outbreak (World Health Organization, 2020). The COVHITS survey had identified

Table 7
Binary logit models of travelling by walking and biking during the pandemic.

|                      | Estimate | S. E. | O.R. (95% C.I.) |
|----------------------|----------|-------|-----------------|
| Intercept            | 0.65     | *     | 0.32 1.92 (1.03, 3.61) |
| Household size       |          |       |                 |
| 1 person             | –1.19    | ***   | 0.24 0.30 (0.19, 0.49) |
| 2 persons            | –0.76    | ***   | 0.19 0.47 (0.32, 0.69) |
| 3 or more persons    |          |       |                 |
| Number of vehicles   |          |       |                 |
| None                 | –1.56    | ***   | 0.22 0.21 (0.14, 0.32) |
| 1 vehicle            | –2.02    | ***   | 0.25 0.13 (0.08, 0.22) |
| 3 or more vehicles   | –2.45    | ***   | 0.34 0.09 (0.04, 0.17) |
| Living in apartments | 0.54     | ***   | 0.16 1.72 (1.25, 2.36) |
| Number of workers    |          |       |                 |
| None                 | –0.75    | ***   | 0.18 0.47 (0.33, 0.68) |
| 1 worker             | –0.68    | ***   | 0.20 0.51 (0.35, 0.75) |
| 3 or more workers    | –0.52    | .     | 0.30 0.59 (0.33, 1.06) |
| Number of students   |          |       |                 |
| None                 | –0.49    | *     | 0.22 0.61 (0.44, 0.94) |
| 1 student            | 0.34     | .     | 0.18 1.41 (0.99, 2.00) |
| 2 students           | 1.10     | ***   | 0.21 3.02 (2.01, 4.54) |
| 3 or more students   | 1.38     | ***   | 0.34 3.96 (2.01, 7.64) |
| Having three or more licensed drivers | –0.49 | * | 0.22 0.61 (0.44, 0.94) |
| Household incomes > $150,000 | 0.37 | * | 0.18 1.45 (1.07, 2.06) |
| Land use characteristics of zones where the household is located | | | |
| Log odds² institutions | | | |
| York Region          | 0.06     | *     | 0.03 1.06 (1.01, 1.11) |
| Peel Region          | 0.04     | *     | 0.02 1.04 (1.00, 1.08) |
| Log of m² of parks & recreation | | | |
| Toronto              | 0.04     | *     | 0.02 1.04 (1.01, 1.07) |
| York Region          | –0.04    | .     | 0.02 0.97 (0.93, 1.01) |
| Log likelihood       | –817.93  |       |                 |
| Log likelihood of null model | –944.83 | | |
| McFadden’s R²        | 0.13     |       |                 |
| AIC                  | 1673.9   |       |                 |
| N                   | 2042     |       |                 |

Notes: (1) Level of significance: * = 0.01, ** = 0.05, *** = 0.1 (2) McFadden’s R² is calculated as 1 – (LL/LLnull), where LL is the log-likelihood and LLnull is Log likelihood of null model (3) Akaike Information Criterion (AIC) is calculated as –2(LL-k), where k is the number of estimated parameters including intercept.
that work trips, especially those designated in the City of Toronto, were significantly reduced by remote working. Moreover, school trips have been significantly reduced across the entire study area because of virtual learning. Therefore, working and studying from home should be consistently implemented with a clear message from governments until the end of the pandemic. Consistency is critical. Dandapat et al. (2020) reported diminished effectiveness of lockdown after repeated rounds of lockdown and reopening. According to the “PASS” transport policymaking framework proposed by Zhang (2020), to help manage a public health crisis, policies must avoid being inconsistent and unstable, especially for those requiring large-scale public corporation. Evidence from the COVHITS survey showed that the public in the study area has demonstrated a considerable degree of behavioural change due to these policies. Therefore, it is up to the government to keep implementing policies with a direct and clear message to the public.

Transit suffered during the pandemic. Transit modal share dropped from 17.3% to 8.1% due to COVID-19. The drop in modal share, coupled with an overall reduction in travel demand, led to a significant decrease in transit ridership during the pandemic. Also, travelers changed how they used transit during the COVID-19. Surface routes served more trips than subways. Surface routes served 64.3% of TTC trips in the COVHITS survey, compared to 51.8% before COVID-19. As initial responses to COVID-19, transit providers in the GTA first cut service frequency on most surface routes in May 2020 and did not restore service frequency until January 2021 (Spurr, 2020; Toronto Transit Commission, 2021). This resulted in dangerously crowded buses on popular TTC routes during the pandemic (Connor, 2020).

In contrast, the Chicago Transit Authority (CTA) took a different approach to COVID-19 (Chicago Transit Authority, 2020). Since the beginning of the pandemic, CTA tried to maintain maximum service frequency on their bus and rail services to ensure social distancing onboard. The CTA approach might be more effective in ensuring both transit riders’ and operators’ health and safety during the pandemic. It is recommended for future pandemic responses to provide as much transit frequency as possible instead of cutting services. The financial cost of providing such service frequencies during the pandemic should also be considered.

Maintaining a responsible and reliable image of public transit during the pandemic is critical. A positive image will prevent permanent transit ridership loss in the post-pandemic era. Transit agencies should provide sufficient, reliable, and also flexible services during the pandemic. Fig. 10 provided the purposes of trips made by transit, segmented by the time of day. It is clear that most riders predominantly utilized transit for essential purposes (e.g., home, work, school, shopping/grocery) during the pandemic. Except from 9 p.m. to midnight, essential trips account for at least 87% of the transit demand throughout the day. This indicated transit riders were heavily reliant on transit to fulfill their basic needs during the pandemic. Marsden et al. (2021) reported a similar trend in England and Scotland that 60% of transit riders were reliant on public transport for certain trips during the pandemic. Transit agencies should recognize such reliance on public transit from segments of the population. Transit providers could give attention to routes connecting residential zones to local employment centers, schools, and shopping centers. Also, transit service could be flexible during the pandemic. Fig. 11 presented the transit trip departure time during the pandemic. It is clear that transit demand peaked during 6–9 a.m. and 3–6 p.m. Instead of cutting service frequency indiscriminately during the pandemic, high-frequency services could be provided during these peak periods, while reduced services could be provided during off-peak periods.

Local governments should tighten restrictions on shopping malls, restaurants, recreational facilities, etc., in regions where COVID-19 case counts are relatively low. During the pandemic, facilities in regions with fewer case counts became increasingly attractive destinations of trips. Such an increase in demand might lead to health and safety concerns. During the pandemic, it was observed that residents adjusted their destination choices for shopping and discretionary activities. They tended to visit regions with lower COVID-19 case counts. For example, among all regions in the COVHITS study area, Peel and Halton regions had the lowest average COVID-19 case counts during the data collection period (see Table 8) (Public Health Ontario, 2021). As a result, 10.7% of shopping/grocery and discretionary trips originated in the City of Toronto destined in York Region (this proportion was 6.1% before COVID-19). At the same time, the proportion of shopping/grocery and discretionary trips that both originated and destined in York Region increased from 79.2% to 84.2%. This indicated that more Toronto and York residents chose York Region as their destination during the pandemic. A similar trend can also be observed for Halton Region. Fig. 9 (from section 4.9) confirms that the York and Halton Regions were the most popular destinations for shopping and discretionary trips during the pandemic. One apparent reason could be that residents in the study area perceived less risk in these regions. The current region-based approach to public health restrictions implemented by local governments allowed relaxed restrictions in regions with lower COVID-19 case counts. Relaxed restrictions in these regions might be attractive to people, and consequently, precautionary measures should be taken. Despite lower COVID-19 cases in local communities, stricter policies on

![Fig. 10. Purposes of transit trips by time of day during the COVID-19 pandemic.](image-url)
shopping malls, restaurants, and recreational facilities, etc., should still be implemented to discourage non-essential out-of-home activities.

7.2. Long-term transport policy for the new normal

Active modes, such as walking and cycling, gained significant popularity during the pandemic. Overall, the modal share for walking and cycling increased from 9.4% to 16.0% in the study area. Policy-makers should aim for capitalizing on this momentum to make this into a long-term trend. Several other studies on the topic also suggest that long-term policy attention be paid to active modes (Budd and Ison, 2020; Marsden et al., 2021; Qu et al., 2020). Modelling results in section 6.2 recognized the trend in adopting active modes by students during the pandemic. From a policy perspective, the trend should be encouraged even post-pandemic. Students are the next generation of society. They will shape the many aspects of the future world. Numerous studies in psychology have shown that early life experiences can have a lasting effect on individuals' behaviours in adulthood (Kuijper and Johnstone, 2019). Therefore, sufficient infrastructure investments and policy supports should be implemented to facilitate a safe and efficient experience for students to commute by active modes. However, from an efficiency point of view, policies and investments can be devised to focus on moderately dense regions such as York and Peel instead of Toronto and Halton. Active commuting to school in Toronto might be already well established, and further investment might produce diminishing returns. Also, land use characteristics in Halton might make the active commute for most students infeasible.

Modelling results in section 6.2 also recognized the positive relationship between recreational activities and active trip making in Toronto. Walk and bike-friendly land use characteristics in Toronto might contribute to it. Sufficient policy supports from the local government in the City of Toronto might play another critical role. The City of Toronto initiated the ActiveTO campaign to support walking and biking during the pandemic (City of Toronto, 2020). The campaign contained two major components. The first component closed some streets and dedicated them to walking and cycling. The second component was infrastructure investment. Temporary bicycle lanes were implemented on eight corridors (23.9 km in total) in Toronto. In the long run, some temporary cycling lanes could be turned into permanent infrastructure if they are proved to be well-utilized by cyclists.

Private vehicles gained popularity due to COVID-19. The pandemic broke the declining trend of private vehicle usage, which lasted for decades in the study area. From 1996 to 2016, the modal share of private cars dropped from 76.1% to 70.8% in the study area of COVHTIS (Data Management Group, 2018c). The literature also shows most developed countries shared similar trends of stagnation and decline in private vehicle usage in the past decades (Vij et al., 2017). However, due to COVID-19, the modal share of cars rebounded. This change in direction
should receive sufficient attention from policymakers and researchers. It is critical to identify whether the change in car usage is a demand shock, dissipating after the pandemic, or if the change reverses the decline of car usage and marks another era of auto-dependency. COVID-19 might also change long-term behaviours. Shakib et al. (2020) surveyed the Greater Toronto Area (GTA) to capture potential changes in residential location choice behaviour due to COVID-19. They found that 25% of households that used to consider proximity to transit an essential factor for their residential location choices no longer held the same thoughts. Similarly, nearly 30% who considered proximity to the workplace to be important changed their mind because of COVID-19 and subsequent remote working. Although their survey did not confirm the trend of suburbanization due to COVID-19, changes in factors mentioned above suggested some degree of behaviour alteration. Changes in real estate prices in the GTA also suggest the trend of reversing urban densification. Despite the overall rise in home prices during the pandemic, suburban regions in GTA experienced more dramatic price surge (21%-48%) compared to the City of Toronto (16%), which served as the high-density urban core in the GTA (Properly, 2021).

Beck and Hensher (2020b) also suggested the possibility of reversing urban densification in Australia because of COVID-19. A combination of revered urban densification and auto-dependency might lead to undesirable post-COVID scenarios in terms of traffic congestion and greenhouse gas emissions. Policymakers should take advantage of the propensity to work/study from home established during the pandemic. The negative consequences discussed above can be mitigated by encouraging telecommuting. Beck and Hensher (2020b) also suggested a similar approach. At the same time, investments in inter-regional transit services connecting suburban regions and the core regions can also be considered. Giving the fact that infrastructure investments typically required longer time span and substantial supporting evidence, this calls for the transportation planning community to take the lead. Discussions and substantial analyses on future travel demands can be conducted by future studies enabling evidence-based decision-making.

8. Conclusion

The COVHITS Survey provided a snapshot of daily life during the COVID-19 pandemic for residents in the four most populated regions in the Greater Toronto Area (GTA). The survey indicated a significant alteration in people’s daily activity-travel patterns due to COVID-19. A substantial drop in mobility was caused by COVID-19 and various countermeasures implemented by governments. Auto-dependency was enhanced with 74.1% of trips were travelled by car. People also drove longer distances, increasing from an average of 6.4 km (before COVID-19) to 11.5 km. Morning peak hours were diminished because of remote working and learning. Instead, people started to travel for discretionary activities during the midday period, which generated a more extended afternoon peak hour.

Overall, modelling results show that higher daily COVID-19 cases encouraged people to stay at home and make fewer trips. Elderly adults (65 years of age or older) still travelled considerably during the pandemic. They must. Unlike younger people, they were less familiar with e-shopping, which has boomed during the pandemic. So, they still travelled for shopping, picking up food, and receiving health services. These three purposes made up 55.9% of their out-of-home activities during the pandemic. Ownership of private cars largely determined a household’s decision to stay at home during the pandemic. Households without cars tended to stay at home. Wealthy families enjoyed more flexibility in terms of mobility tools and activity destination choices. As a result, household incomes influenced mobility during the pandemic.

Finally, we also recommended policies to better account for the pandemic and prepare for a “New Normal”. First, effective measures such as working/studying from home should be consistently implemented until the end of the pandemic. Instead of cutting services, transit agencies should provide services as frequently as possible to protect travelers and operators. Within a metropolitan area, stricter restrictions should also be implemented in regions with relatively lower COVID-19 case counts. Residents in areas with greater restrictions tended to visit regions with fewer confirmed COVID-19 cases during the pandemic. Such a shift in activity-travel patterns might create additional demands for facilities in these regions. For the “new normal”, policymakers should encourage the popularity of active modes by sufficient policy and investment supports. Temporary infrastructure implemented to support active transport during the pandemic can be made permanent if demand exists. Most importantly, the possible trend of auto-dependency and reserve of urban densification should receive attention from policymakers and researchers. Strategies should be carefully proposed and implemented to mitigate potential negative consequences from these emerging trends due to COVID-19.

As with any study, there are several limitations to this study. First, this study is conducted using a commercial survey panel. Typically, large-scale household travel surveys utilize sample frames randomly drawn from the population (Data Management Group, 2018a). However, such projects are extremely extensive and operationally challenging, especially during the pandemic. On the other hand, commercial survey panels are more flexible and accessible. Garrow et al. (2018) compared models estimated from data collected through an internet-based market research panel and a traditional market research firm. They found no statistical difference between trip characteristics from two data collection channels. They claimed data collected from internet-based market research panels could serve the purpose of travel demand analysis. However, they also found that cost sensitivities differed with data collected through traditional sources revealed a higher value of time. This suggested that trip characteristics, such as departure time, modes, destination location choices, and correlation between trip-marking behaviour and socio-economic status identified by this study might be valid. However, caution should be used while interpreting effects such as the value of time, elasticity and odd ratios considering the characteristics of online survey panels.

Second, proxy household travel surveys are known for trip under-reporting. Badoe and Stuart (2002) found that home-based work and school trips were well reported by proxy-respondents, whereas short-distance discretionary trips were likely to be omitted. During the pandemic, working and studying from home reduced the demand for out-of-home work and school trips. However, the demand for certain discretionary trips still persisted and might constitute a large portion of households’ travel demand. It is possible that restriction on households’ mobility observed in this study is overestimated. Short-distanced discretionary trips, mainly conducted by walking and cycling, might be underreported. So, mobility during the pandemic was not as restricted as observed in this study.

Third, the COVHITS survey was conducted in an extraordinary context. Shortly after the survey commerce, the study area entered the second round of lockdown. At this stage, it is hard to conclude whether changes captured in the 2020 fall cycle of the COVHITS survey will be translated into permanent changes when time dissipates. It is also possible that new behaviours and activity-travel patterns will emerge because of the second wave of COVID-19. Thus, continuous efforts are needed to monitor the situation. More data points are needed to draw decisive conclusions. The second cycle of COVHITS will be conducted in 2021 to capture another cross-section of activity-travel patterns in the study area. Also, this study only provides activity-travel analysis on an aggregate level. Heterogeneity existed in the population. More disaggregate analysis should be performed with more sophisticated techniques to account for individual preferences and heterogeneity.

There are several areas for future research. First, multiple waves of COVHITS surveys should be conducted. Multiple observation points should be collected. Critical trends observed in the first wave, such as diminished morning peak hours, the popularity of telecommuting, auto-dependency, preference of active modes, and declines in transit demands, should be evaluated longitudinally. The trajectory of those
trends should be examined and forecasted to facilitate planning decisions. Second, the pandemic’s impacts on shared mobility should be carefully studied. Before the pandemic, shared mobility was regarded as one of the prominent futures of the transportation system. But there is tremendous and increasing uncertainty nowadays due to the pandemic. Hensher (2020) discussed several possibilities of Mobility-as-a-Service (MaaS) post-pandemic. He admitted the caveat that sharing space in vehicles with strangers might be less welcomed because of the pandemic. Quantitative evidence is needed to capture consumers’ decision-making process after experiencing the COVID-19 pandemic. Indeed, as a collective conclusion made by more than 300 experts in transportation, the existence of uncertainties and unknowns about the pandemic’s impact should be recognized (Zhang et al., 2021). Future research efforts should shed some light on such uncertainties.

Acknowledgement

The COVHITS Survey was sponsored by and conducted on behalf of a consortium of regional municipalities, the provincial government and its agency, and a transit operator in the Greater Toronto Area. These are City of Toronto; Metrolinx; Ministry of Transportation, Ontario; Regional Municipalities of Halton; Regional Municipality of Peel; Regional Municipality of York; Toronto Transit Commission. We would like to thank their support and insightful advice. We would like to thank insightful comments from Dr. Junyi Zhang and two reviewers to improve the quality of the paper.

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