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What happens when post-secondary programmes go virtual for COVID-19? Effects of forced telecommuting on travel demand of post-secondary students during the pandemic

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ABSTRACT

The outbreak of coronavirus disease 2019 (COVID-19) spreads globally, disrupting every aspect of everyday activities. Countermeasures during the pandemic, such as remote working and learning, proliferated tele-activities worldwide during the COVID −19 pandemic. The prevalence of telecommuting could lead to new activity-travel patterns. It is in the interest of transport demand modellers to capture this developing trend of telecommuting using state-of-art travel demand forecasting techniques. This study develops a modelling framework using activity-based and agent-based microsimulation to forecast activity-travel demand considering telecommuting and the pandemic. For empirical application, the modelling framework investigates changes in travel behaviours in post-secondary students when all major post-secondary institutions in the Greater Toronto Area (GTA), Canada, decided to go virtual during the pandemic. The empirical investigation reveals that enforced telecommuting and the pandemic caused significant mobility drops and shifts in students' trip starting time patterns. While only considering the influence of telecommuting, the empirical exercise reveals noteworthy dynamics between telecommuting and the overall travel demand. Telecommuting could simultaneously reduce the need to commute but also induce discretionary travel. When telecommuting is enforced, students' overall trip rates drop by 14.2%, despite increasing trip rates for all discretionary activities except shopping/market. Moreover, the study demonstrates that it is beneficial to model at-home productive and maintenance episodes when telecommuting is prominent.

1. Introduction

Since its inception in late 2019, the coronavirus disease 2019 (COVID −19) has spread rapidly worldwide, causing irretrievable casualties and disrupting every aspect of everyday activities (Lipsitch et al., 2020; Vos, 2020; World Health Organization, 2020). As countermeasures to curb the spread of the pandemic, governments around the world closed international borders, offices, and schools, imposing travel restrictions and social distancing (UNESCO, 2020; World Bank, 2020). Consequently, tele-activities proliferated worldwide during the COVID −19 pandemic. For example, only one in twenty employees in the European Union (EU) reported telecommuting regularly before the pandemic (Eurofound, 2020). However, in 2020, more than a third of the employees in the EU

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reported telecommuting exclusively (Eurofound, 2020). Online learning also grew significantly during the pandemic. For instance, in 2020, the frequency of online learning in Greece increased by 53 % compared to pre-pandemic frequency (Mouratidis & Papagiannakis, 2021). A similar trend was also observed in North America. In the Greater Toronto Area (GTA), Canada, 54 % of students (both secondary and post-secondary) were studying from home completely in 2020, while 25 % adopted hybrid (in-person & virtual) learning arrangements (Wang et al., 2021).

Temporary closure of education facilities as preventive health and safety measures contributed to the trend. All major post-secondary institutions in the GTA, decided to move their courses online during the pandemic (University of Toronto, 2020; York University, 2020; Ryerson University, 2020; OCAD University, 2020; Ontario Tech University, 2020; Centennial College, 2020; Durham College, 2020; Sheridan College, 2020). The sudden shift to telecommuting led to a stark alteration in the daily activity-travel patterns of the post-secondary students. As of 2019, post-secondary institutions in the GTHA enrolled over 0.6 million learners, approximately 10 % of the population in the region. With all courses delivered online, the students became telecommuters, drastically changing their daily routines. As the immediate impact, travel and participation in out-of-home activities were significantly reduced during the COVID-19 pandemic (de Haas et al., 2020, Wang et al., 2021). In the long term, the prevalence of telecommuting could lead to new activity-travel patterns. Organizations, education institutions, workers, and students have been familiarized with telecommuting during the pandemic. Most of them also have positive attitudes toward continuing to telecommute in the future (de Haas et al., 2020; Mouratidis & Peters 2022). In post-pandemic time, new daily routines might emerge because of the flexibility offered by frequent telecommuting. Therefore, urban transport researchers must use state-of-art travel demand forecasting techniques to capture this developing telecommuting trend.

This study develops a comprehensive modelling framework to forecast demand concerning telecommuting and pandemic-influenced activity-travel behaviours. The framework uses an activity-based demand forecasting model (Habib, 2018a) and agent-based microsimulation to investigate activity-travel behaviours of post-secondary students under enforced telecommuting. Based on travel survey data collected in the Fall of 2019 and Fall of 2020, this study first empirically captures students' activity-travel behaviour, including their activity-types choices, activities locations choices, and activities durations choices then calibrates the model to fit the behaviours during the pandemic. Three scenarios are simulated using an agent-based microsimulation approach. In the first scenario, students commute to their campuses as usual. In the second scenario, students telecommute and attend online courses from their homes, considering various impacts and restrictions of the pandemic. In the last scenario, students telecommute and attend online courses but participate in discretionary activities at the pre-pandemic level. Differences between these scenarios are analyzed to decipher emerging telecommuting behaviour and its impact on daily activity-travel.

The contribution of this study is twofold. This study sets the initial step to examine travel behaviours when telecommuting is forced on all post-secondary students in the GTA, Canada, during the pandemic. The estimated model reveals many behavioural insights, including trade-offs and heterogeneity in time allocation choices, effects of workplace arrangements on activity-type choices, the difference in travel mode choices between trip segments in home-based tours, etc. Insights from agent-based microsimulation reveals the influences of telecommuting and the pandemic on travel behaviours and demand. Experiences gained from this exercise will shed light on travel demand modelling and data collection methods approach in the post-pandemic era, where telecommuting became prominent. Secondly, the study examines the validity of using the agent-based model to investigate behavioural changes in events like the pandemic. While this study investigated enforced telecommuting, the modelling framework proposed in this study can be modified to investigate scenarios where telecommuting can be chosen based on preferences.

The remainder of the paper is organized as follows. First, **Section 2** presents literature reviews on telecommuting. Then, **Section 3** presents data sources and the modelling framework used in this study. Next, **Section 4** presents empirical results from the model. **Section 5** will present agent-based microsimulation results of the post-secondary student's enforced telecommuting. This section will also discuss insights drawn from this study and their implication for future modelling applications. Finally, **Section 6** will conclude the key findings and limitations of this study.

2. Literature review

This section discusses relevant literature on telecommuting by workers and students and their implications on travel behaviours.

2.1. Telecommuting by workers

Workers' telecommuting behaviour has received substantial attention in the scholarly literature. Andreev et al. (2010) reviewed and summarized about 100 studies on travel behaviour and tele-activities and found more than 50 % of the reviewed articles to focus on telecommuting for workers. These studies primarily investigated two aspects: factors that influence choices/frequencies of telecommuting and subsequent travel demand impacts. Bernardino and Ben-Akiva (1996) estimated structural equation models to investigate the joint probability of workers' telecommuting frequency and availability of telecommuting options. They found that telecommuting was positively associated with workers' productivity as well as their quality of life. Using ordered probit regression and unordered multinomial logit models, Drucker and Khattak (2000) found that having dependent children, gender as male, and having to pay for parking at the workplace significantly increase telecommuting frequencies. Singh et al. (2012) jointly investigated workers' options, choices, and frequency of telecommuting. Their findings largely agreed with Drucker and Khattak (2000). They found that the presence of dependent children increases the likelihood of telecommuting. They also found that female workers are less likely to telecommute. However, they are more likely to choose to telecommute if they can do so. Interestingly, they found that middle-aged individuals, 36 to 50 years old, are more likely to have the opportunity to telecommute. They attributed this finding to middle-aged individuals being more likely to hold "power" positions than younger individuals. This implies that telecommuting might have been considered a privilege instead of a norm when the investigation was conducted. Asgari et al. (2014) found that age and possession of driver's licenses positively affect worker's choices of telecommuting. Also, household size and nonflexible working schedules negatively influence telecommuting frequencies.

Literature also studied the impact of telecommuting on travel demand. Mokhtarian et al. (2004), Mokhtarian (1998), Hamer et al. (1991), and Choo et al. (2005) all found that telecommuting may reduce total vehicle-kilometres-travelled (VKT). Hamer et al. (1991) found that telecommuting might reduce total VKT by 17 % by eliminating the need to commute. Therefore, Kim et al. (2015) concluded that telecommuting was often considered a travel demand management (TDM) policy to manage traffic congestion and air pollution. Conversely, some studies suggested that telecommuting might complement travel demand (Mokhtarian et al., 2004; Zhu, 2013; Zhu & Mason, 2014; Kim, 2016). Mokhtarian et al. (2004) found that commute time saved by telecommuting might induce additional discretionary travel. Zhu and Mason (2014) also found that telecommuting might increase work and discretionary trips. Asgari and Jin (2017) investigated the relationship between activity-travel behaviours and telecommuting decisions. They identified the feedback effect between telecommuting and nonmandatory activity participation with structural equation modelling. They also found participation in discretionary activity led to a higher propensity to telecommute. Lavieri et al. (2018) proposed a comprehensive modelling framework to capture the interrelation between travel behaviours and virtual and in-person activities engagement. They highlighted the endogeneity problem between virtual and physical activity accessibility and their actual engagements. This reflected the intrinsic complexity of the substitution pattern between virtual and in-person activities. They found that young and wealthy individuals have the highest access to virtual activities. They also found that telecommuting would benefit time-squeezed working mothers who had to undertake family maintenance responsibilities. Moeckel (2017) proposed integrated land use and transport modelling suite to interactively simulate travel demand with telecommuting and land use pattern shifts. However, he only reported implementing the prototype model without discussing modelling results. More recently, Budnitz et al. (2020) found that telecommuters had a higher propensity to participate in additional discretionary trips. They highlighted the necessity of increasing the accessibility of discretionary destinations to optimize the benefits of telecommuting.

2.2. Telecommuting for post-secondary students

Despite the abundance of literature on workers' telecommuting, there is a lack of research on students' telecommuting, particularly among those who attend post-secondary institutions. Mouratidis et al. (2021) reviewed more than 200 scholarly articles on the impacts of Information and Communication Technologies (ICT) on travel behaviour. Although their discussion involved online education enabled by ICT, they found very limited transportation-related studies, specifically investigating telecommuting by students. Habib (2020) specifically looked at influential factors in post-secondary students' choice of telecommuting. He found that living further away from campuses might increase students' frequency of telecommuting. He also found that regular bicycle riders and transit pass owners are less likely to telecommute frequently. Most recently, Mouratidis and Peters (2022) investigated the factors affecting the frequency of telecommuting (for study) during the COVID-19 pandemic. They found higher population density and transit accessibility lead to a lower frequency of online learning. Likewise, they found that being female and living with parents or partners are negatively associated with the frequency of telecommuting to study. All studies mentioned in this section used equilibrium models to study telecommuting for workers and students. Their methodology might not be appropriate in catastrophic events like the COVID-19 pandemic, where in-person activities are suddenly strongly discouraged. To model situations like the pandemic, a flexible methodology is needed to handle a far more comprehensive range of nonlinear behaviours and responses to various behavioural rules (e.g., enforced telecommuting and various health and safety measures restricting travel) that have never been implemented before the pandemic. Therefore, this study undertakes agent-based modelling with microsimulation of decision-makers interacting with rules implemented during the pandemic.

On the other hand, literature in education has thoroughly studied online learning by post-secondary students (Swan, 2003; Nguyen, 2015; Ni, 2018; Shukor et al., 2015). Shukor et al. (2015) found that students can perform well by studying online, but they have to spend more effort to be successful online learners. Ni (2018) found that post-secondary students taking online courses might be more likely to drop out of courses. However, for those who persisted, their grades are independent of the media of instruction (e.g., taking online or in-person courses). These positive findings suggest the possibility of more frequent adoption of online learning by post-secondary students after the pandemic if given the option. At the same time, offering online options can benefit institutions and post-secondary learners. Gallagher and Palmer (2020) believed that offering online options can reduce faculty workloads and student tuition.

All the discussions above indicate the possibility that universities might continue to provide online courses after the pandemic. Students might be able to choose the medium of learning based on their preferences. This urges the need to study telecommuting by post-secondary students from the perspective of travel demand. Specifically, it highlights the need to develop comprehensive activity-travel demand forecasting models considering telecommuting. Study of post-secondary students' telecommuting behaviour is particularly important as they will eventually join the workforce. Such behaviour may have a long-term influence on their future travel behaviour as workers. This study initiated the effort by developing a modelling framework capable of handling enforced telecommuting during the pandemic for post-secondary students. The following section will present the data used in this study and explain the modelling framework.

3. Modelling framework & data sources

3.1. Modelling framework to forecast pandemic-influenced activity-travel behaviours

The modelling framework is based on activity-based travel demand modelling and agent-based microsimulation. The framework captures individuals' pre-pandemic activity-travel behaviour first, and then forecast their pandemic-influenced behaviours based on benchmarking observation and behavioural rules implemented during the pandemic in agent-based simulation. Fig. 1 shows the diagrammatic flow of the modelling framework. First, individual's activity-travel behaviours are observed through periodically planned and conducted large scale travel surveys. Then, individuals' activity-travel behaviour is captured using activity-based travel demand models. After that, agent-based microsimulation is used to replicate the activity-travel pattern to establish the base scenario.

The pandemic-influenced activity-travel behaviours are forecasted from two sources. Firstly, the empirical model estimated using pre-pandemic behaviours is calibrated using benchmarking observation collected during the pandemic. Specifically, alternative-specific-constants (ASCs) are calibrated based on the market share observed during the pandemic (Ortúzar & Willumsen, 2009, P235). This approach is adopted to account for the lack of large-scale travel surveys during catastrophic events like the pandemic. Activity-based travel demand models are often data hungry (Goulias et al., 2013). In an event like the pandemic, there is a dilemma between data collection to fit activity-based travel demand models for new behaviours and the risk of conducting large-scale travel surveys during an uncertain time. Therefore, the proposed modelling framework offers a feasible solution by calibrating a pre-pandemic model using a small-scale benchmarking survey during the pandemic. Although small-scale benchmarking surveys will not provide enough sample size to estimate activity-based models (especially for specific sub-population, like university students), statistics such as market shares of activity types can serve the purpose of calibrating existing models. The calibration will account for changes in individuals' preferences caused by the pandemic. For example, after calibration, certain out-of-home activities such as dining in restaurants will become less favorable during the pandemic. Secondly, behavioural rules are implemented in the agent-based simulation stage. This approach allows the microsimulator to generate corresponding activity-travel patterns brought by policies that have been implemented during the pandemic, such as enforced student telecommuting. It can also be used to test new and possible costly policies before they are implemented.

3.2. Implementing enforced telecommuting in agent-based simulation

This study implements behavioural rules to enforce student telecommuting during the pandemic.Fig. 2 illustrates the implementation of enforced telecommuting in agent-based simulation. To enforce telecommuting, students' out-of-home school episodes are treated as at-home study episodes instead. Fig. 2 shows an example of a pre-pandemic activity-travel schedule of a student studying at school, shopping, and then returning home. Implementation of enforced telecommuting would bring several changes to this activity-travel schedule. First, the need for commuting to campus will be eliminated. This can be directly associated with the substitution effect of telecommuting summarized in the literature (Hamer et al., 1991; Mokhtarian, 1998; Mokhtarian et al., 2004; Choo et al., 2005).

Moreover, location choices for out-of-home discretionary activities might also be influenced. Telecommuting will alter travel

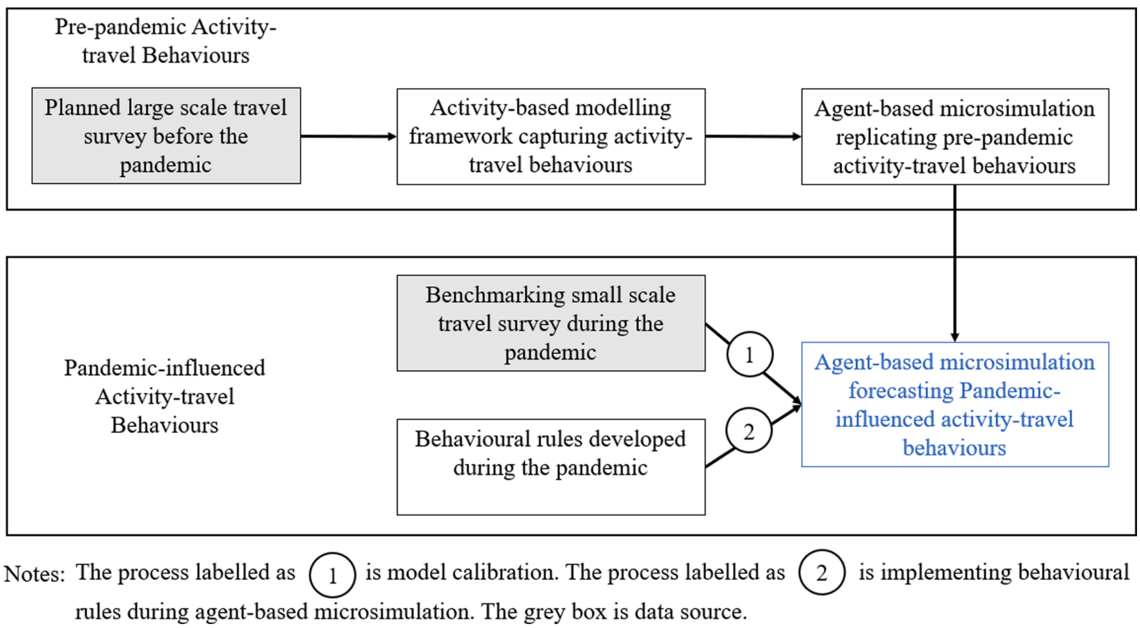

Fig. 1. Modelling framework to forecast pandemic-influenced activity-travel behaviour.

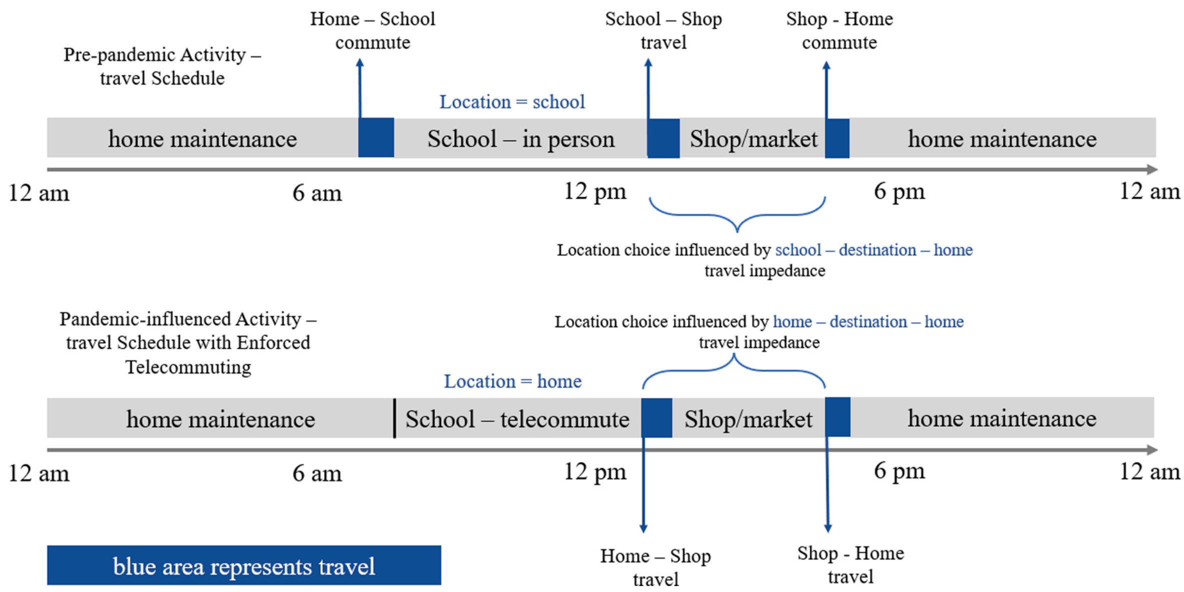

Fig. 2. Diagrammatic illustration of modelling enforced student telecommuting.

impedance in location choices for students having a mandatory activity (school) in their schedules. For out-of-home discretionary activity location choices, the travel impedance will change from school-destination-home to home-destination-home. All of the changes discussed above will directly impact the student's activity-travel demand.

3.3. Activity-based modelling framework to capture activity-travel behaviours

This study applies a zero-inflated comprehensive utility-based system of activity-travel options modelling (CUSTOM) random utility-maximizing (RUM) econometric framework to capture pre-pandemic behaviours of post-secondary students in the Greater Toronto Area (GTA). Zero-inflation is used to account for a significant proportion of post-secondary students in our study area reported staying at home on a random day. The CUSTOM framework models individual's full-day activity-travel schedules (Habib, 2018a). The approach models home-based tour formation while allowing for the evolution of non-home-based tours at any stage of the scheduling process. Detailed mathematical formation of CUSTOM can be found in Habib (2018a). Fig. 3a presents the workflow of CUSTOM. The scheduling process begins with the choices of staying at home all day or participating in out-of-home activities. If the individual

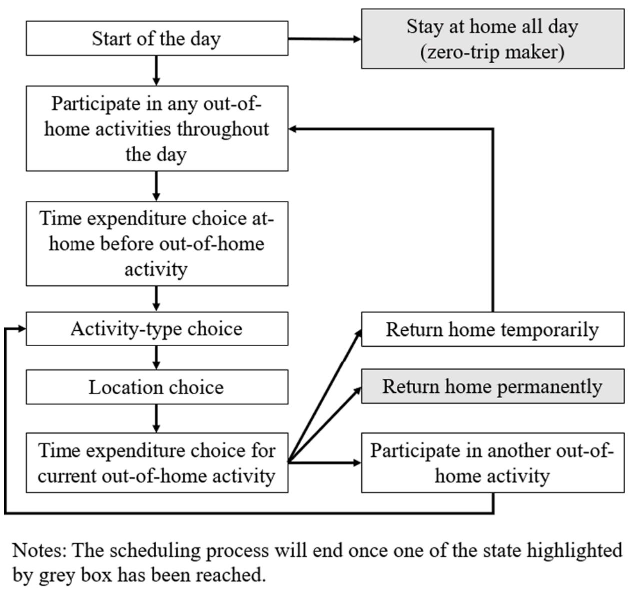

Fig. 3a. Activity-scheduling process of CUSTOM.

decides to participate in out-of-home activities, the start time of the first trip will be determined by the time expenditure choice component. Then activity type, location, and time spent for the activity will be determined. Following the first activity, the individual will have the option of participating in another out-of-home activity, returning home temporarily to make another trip later, or returning home permanently for the remainder of the day. The scheduling process will end until return home permanently is chosen.

CUSTOM considers interrelationships among modelling components. This arrangement realistically captures dynamics between modelling components in the activity-travel scheduling process. Fig. 3b shows the feedback mechanisms in CUSTOM. For each scheduling cycle, the time remaining for the current cycle is determined by the time expenditure choice of all previous scheduling cycles. Further, the remaining time budget determines feasible locations available for the current scheduling cycle through the Potential Path Area (PPA). Likewise, CUSTOM also considers feedback between modelling components. Activity-type choice considers expectation from the location choice of the chosen activity. Also, the time expenditure choice of the current episode considers the expectation of activity-type choice in the next cycle.

The joint likelihood function in CUSTOM is closed form. So the model can be estimated using classical gradient searching algorithms, such as BFGS gradient searching algorithm in GAUSS (Aptech Systems, 2016). For any scheduling cycle j, CUSTOM calculates the probability to return home permanently ($Pr(H_j)$), the probability to return home temporarily ($Pr(HT_j)$), the probability of choosing various types of out-of-home activities ($Pr(Act_j)$), the probability of their corresponding location choices ($Pr(l_j)$), and the probability of time expenditure choice in the previous scheduling cycle ($Pr(t_{j-1})$). Therefore, the likelihood of the scheduling cycle j is:

$$L_j = \left(Pr(H_j)^{\delta_H} Pr(HT_j)^{\delta_{HT}} Pr(Act_j)^{\delta_{Aj}} Pr(l_j)^{\delta_l}\right)^{\delta_{Act}} Pr(t_{j-1}) \tag{1}$$

where,

δ_H	is 1 if choose to return home permanently, 0 otherwise.
δ_{HT}	is 1 if choose to return home temporarily, 0 otherwise.
δ_{Act}	is 1 if choose to proceed to next out-of-home activity, 0 otherwise.
δ_{Aj}	is 1 if choose a specific activity type, A_j, 0 otherwise.
δ_l	is 1 if choose a location, 0 otherwise.

For each record, k, with J total activity scheduling cycle per day, the likelihood of observing each record staying home or participating in any out-of-home activities with activity type, location, and time expenditure choice is:

$$L_k = \left(Pr(A_{stay})\right)^{\delta_{stay}} \left(Pr(A_{out}) \prod_{j=1}^{J} L_j\right)^{\delta_{out}} \tag{2}$$

where,

$Pr(A_{out})$	is the probability of an individual deciding to participate in any out-of-home activities.
$Pr(A_{stay})$	is the probability of an individual deciding to stay home for the entire day. It is $1 - Pr(A_{out})$.
δ_{stay}	is 1 if decide to stay home for the entire day, 0 otherwise.
δ_{out}	is 1 if decide to participate out-of-home activities, 0 otherwise.

Finally, the joint likelihood with a total number of K records is:

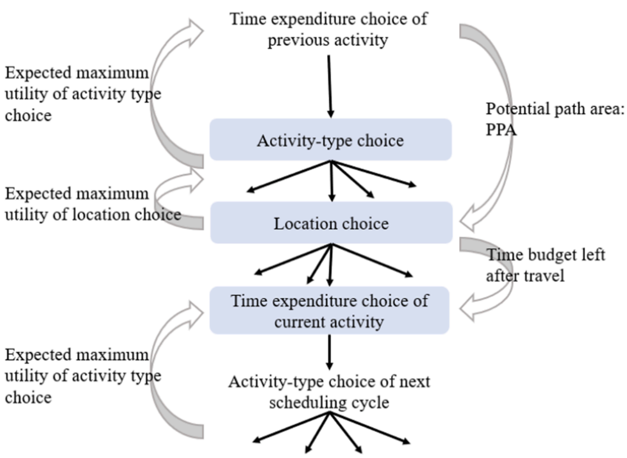

Fig. 3b. Feedback and interrelationship between modelling components in CUSTOM.

$$L = \prod_{k=1}^{K} L_k \tag{3}$$

3.4. Data sources

The Greater Toronto Area (GTA) is the study area for this investigation. The GTA is the largest Canadian urban region located in Ontario, Canada. By 2019, the GTA had over 6.4 million estimated population residing in five regional municipalities: the City of Toronto, Regions of Peel, York, Durham, and Halton (Statistics Canada, 2019). In 2019, there were five major universities with around 184,000 students and several colleges operating in the GTA (Ontario Council of University Libraries, 2019). Fig. 4 shows the study area and major post-secondary campus locations in the region.

3.4.1. StudentMoveTO survey

In this study, the 2019 StudentMoveTO (SMTO) survey is used as a large-scale survey to estimate CUSTOM. The 2019 STMO survey is a web-based student travel survey targeting post-secondary students in the Greater Toronto and Hamilton Area (GTHA) (Habib, 2018b; StudentMoveTO, 2019). The 2019 SMTO adapted an institutional sample frame with participating institutions: the University of Toronto, York University, Ryerson University, OCAD University, McMaster University, Ontario Tech University, Centennial College, Durham College, Mohawk College, and Sheridan College. The survey was one of the largest travel surveys worldwide, targeting post-secondary students. A total of 9,183 samples were collected with completed travel diaries. A subset of 2019 SMTO was used for this study. Records from McMaster University and Mohawk College are excluded from the analysis because their campuses are located outside of the GTA, the study area. Records with weekend travel dairy are also excluded because this study specifically focuses on students' weekday travel patterns. As a result, 4,315 records are selected into the subset for this study.

The descriptive statistic of the subset is presented in Table 1. The average age is 23.0 years old, closely matching the Canadian average of 22.8 years for university students and 21.6 years for college students (Statistics Canada, 2010). It is also skewed to the age group of 22 and younger, as expected. Female students comprise 63.64 % of the sample, recognizing the increasing female representation in higher education. The 2015 Graduating Student Survey collected data across 36 Canadian universities, revealing that 60 % of graduating students were female in Canadian institutions (Prairie Research Associates, 2015). About two-thirds of the students are driver's license holders. Over 93 % of the samples are full-time students. Only 7.9 % of the students are full-time workers. 43 % of the sample reported having part-time jobs. 34 % of the students allocate between \$100 - \$200 to their monthly travel budgets. As students heavily rely on transit, it is comparable to the price of a monthly transit pass (\$156) in the City of Toronto (Toronto Transit Commission, 2020). One-third of the students live alone or with roommates, and the rest live with families. Besides, around two-thirds of the students live in households with one or more vehicles. More than 50 % of the respondents refused to provide household income information; however, for those who provided household income levels, the income distribution matched with income distribution reported in the Canadian Census for the Toronto Metropolitan Area. Both have a median of \$60,000-\$99,999 (Statistics Canada, 2017a; Statistics Canada, 2017b).

3.4.2. COVHITS survey

A subset of the 2020 COVid-19 influenced Households' Interrupted Travel Schedules (COVHITS) survey was used as the

Esri, CGIAR, USGS | City of Toronto, Province of Ontario, Esri, HERE, Garmin, METI/NASA, USGS, EPA, NPS, USDA, NRCan, Parks Canada

Fig. 4. Map of the Greater Toronto Area with campuses locations.

Table 1
Descriptive statistics of post-secondary students in GTA.

Variables	2019 SMTO	2020 COVHITS
Age		
mean	23.0	23.8
22 and below	63.6 %	68.0 %
23–29	25.4 %	21.3 %
30 or older	10.9 %	10.7 %
Gender		
Female	66.4 %	63.0 %
Male	33.6 %	34.3 %
Driver's license holders	61.1 %	71.4 %
Student status		
Full time	93.8 %	
Part time	4.74 %	
Continuing education	1.46 %	
Employment status		
Full time	7.91 %	4.20 %
Part time	43.4 %	11.1 %
Not employed	48.7 %	
Monthly travel budget		
<$100	29.9 %	
$100-$200	34.1 %	
$200-$300	15.9 %	
$300-$400	9.47 %	
>$300	10.7 %	
Household size		
1 *(live alone + live with roommates)*	31.3 %	
2	11.6 %	
3	14.7 %	
4	21.6 %	
5 or more	20.8 %	
Living arrangements		
Live with family/parents	57.2 %	
Live with partner	10.0 %	
Live with host family or at friend's house	2.34 %	
Live alone	8.60 %	
Live with roommates	21.9 %	
Number of vehicles		
0	32.9 %	
1	28.0 %	
2	25.2 %	
3 or more	14.0 %	
Household income		
< $15,000	4.59 %	
$15,000-$39,999	9.57 %	
$40,000-$59,999	8.99 %	
$60,000-$99,999	12.8 %	
$100,000-$124,999	5.31 %	
$125,000 and above	8.46 %	
Decline/don't know	50.3 %	

benchmarking survey reflecting pandemic influenced behaviour. The COVHITS survey is the core household travel survey of a systematic data collection effort in the GTA to monitor the impact of the COVID-19 on travel demand (Habib et al., 2021). The 2020 COVHITS survey randomly drew participants from commercial survey panels. The first wave of the COVHITS survey was conducted in the GTA in the Fall of 2020 (Wang et al., 2020). The survey collected household and personal characteristics and travel diaries from 3,721 households. This study selected a subset of 597 post-secondary students with 323 trips for model calibration.

Key statistics between 2019 SMTO and 2020 COVHITS are compared in Table 1. Overall, the two datasets closely match age and gender, which are the two most important demographic statistics. The average age is 23.0 and 23.8 years old in 2019 SMTO and 2020 COVHTIS, respectively. Moreover, 63.6 % of the samples from 2019 SMTO are aged 22; 68.0 % from 2020 COVHTIS fall into the same category. This indicates two samples contain a similar proportion of undergraduate students. Proportions of genders also match closely. 63.0 % of the samples from 2020 COVHITS are female. This is in line with the 2019 SMTO and the general trend that 60 % of students in Canadian universities are female (Prairie Research Associates, 2015). There is a discrepancy in driver's licenses between the two datasets. 71.4 % of the samples in 2020 COVHITS are driver's license owners, but the proportion is only 61.1 % in 2019 SMTO. The discrepancy could come from the difference in sample frames. The 2019 SMTO survey randomly invites students enrolled in targets institutions.

Therefore, the survey effectively covers student bodies (e.g., international students) less likely to own valid driver's licenses locally.

On the other hand, the 2020 COVHITS is drawn samples from local commercial survey panels. The panelists are more likely to be long-term residents of the study area, and it is more likely for them and their household members to own locally valid driver's licenses. Interestingly, employment status is also different between the two datasets. More than 50 % of students in 2019 SMTO are employed (7.9 % full-time & 43.4 % part-time); however, only around 15 % of students in 2020 SMTO are employed (4.2 % full-time & 11.1 % part-time). This reflects the job loss caused by the pandemic during the initial outbreak stages. Moreover, 93.1 % of the samples in 2020 COVHITS did not report any school-related trips. This observation confirms the enforced telecommuting assumption taken by this study. For consistency, records that reported school-related trips are removed from calibration.

4. Empirical modelling results

CUSTOM framework is used to capture post-secondary students' activity scheduling, time allocation, and location choices behavior. In the empirical model, the activity-type choice sets consider the following activities:

- The first out-of-home activity of the day
  1. Work
  2. School
  3. Shop/market
  4. Restaurant/coffee/bar
  5. Recreation/sports
  6. Other (including visiting friends, services, pick up/drop off, etc.)
- The subsequent activity of the day
  1. Work
  2. School
  3. Shop/market
  4. Restaurant/coffee/bar
  5. Recreation/sports
  6. Other (including visiting friends, services, pick up/drop off, etc.)
  7. Return home temporarily
  8. Return home permanently

The model estimation results are summarized in Table 2-1. Of all estimated parameters, 128 are statistically significant at 95 % confidence level. In addition, 7 parameters with lower significance are kept for the purpose of comparison and guiding future efforts. All parameters are at least within the 85 % confidence limit to ensure reliability. Detailed explanations regarding each parameter with lower statistical significance will be discussed in their corresponding sections. The rho-squared value against the constant-only model is 0.17, which is a reasonable goodness-of-fit. The goodness-of-fit is also compared with an equiprobable null model. The null model predicts equally likely probabilities for discrete choice components and constant marginal utility for time expenditure choice components. The rho-squared value against the null model is 0.40. It is a considerable high goodness-of-fit considering the complexity of the discrete–continuous model. Similar goodness-of-fit using the CUSTOM framework was reported in the literature (Habib & Hui, 2017; Habib, 2018a).

4.1. Choice of participating in out-of-home activities or staying home all day

Table 2-2 presents the parameter estimation results for the decision to participate in out-of-home activities or staying home all day. The dependent variable is the probability of participating in out-of-home activities. The systematic utility for deciding to participate in out-of-home activities is a function of the student's age, institution types, number of dependent children, and monthly travel budget. Younger students under 22 are inclined to stay at home compared to mature students. On the other hand, students with dependent children are more likely to participate in out-of-home activities. Carrying out parental tasks typically means they are responsible for more household maintenance, caregiving, and even working for income. However, the estimated parameter for having dependent children is only statistically significant at around 93 % statistical confidence level based on the one-tail *t*-test (a positive sign is expected). Therefore, cautions should still be used when applying the behavioural explanation to the entire student population.

Table 2-1
Model summary and parameters estimation.

Number of observations	4,315
Log likelihood of full model	−103,808
Log likelihood of constant-only model	−124,471
Log likelihood of equiprobable null model	−173,856
Rho-square value against constant-only model	0.17
Rho-square value against equiprobable null model	0.40
Number of parameters	135

Table 2-2
Choice of participating in out-of-home activities.

	coefficient	*t*-statistics
constant	−0.50	−3.06
age		
age ≤ 22	−0.51	−7.25
age greater than 22	–	–
Institution types		
university students	0.89	10.53
college students	–	–
number of dependent children	0.05	1.46
logarithm of monthly travel budget	0.10	3.40

Notes: (a) The t-statistics thresholds for 85 %, 90 % and 95 % confidence interval in the two-tail test are 1.44, 1.64 and 1.96, respectively. (b) The t-statistics thresholds for 85 %, 90 % and 95 % confidence interval in the one-tail test are 1.03, 1.28 and 1.64, respectively.

Also, university students are more active than college students in participating in out-of-home activities. University students and college students may share different activity-travel patterns. The telecommuting frequency reported in the 2019 SMTO survey confirms the difference. The average telecommuting frequency is 0.46 for university students but 0.86 for college students. Lastly, students become more active with increasing monthly travel budgets.

4.2. Scale parameters

The scale parameter of the continuous activity duration choice is parameterized as the exponential of linear in parameter functions to measure heteroskedasticity. It is measured as the inverse of the variance in time expenditure choices. Thus, higher scale parameters lead to lower variation in time expenditure choices. The estimated scale parameters are reported in Tables 2-3. The scale parameters for time spent at home before leaving for the first out-of-home activity are less than one, indicating relatively higher randomness. Compared to students in Engineering, Business, Law, and Medicine programs, students enrolled in Art & Science programs revealed slightly less randomness for their time spent at home before leaving when they have similar accessibility to private vehicles. Readers should note that the estimated parameter for Art & Science students is significant at 90 % confidence level. Therefore, caution should be excised when applying the finding to general student population in the study area.

For subsequent activities during the day, the scale parameter is parameterized by the interaction between time-of-day, household size, and household incomes. Time-of-day is modelled continuously as the fraction of 24 h. Similarly, household size is also modelled continuously. Income levels are modelled as dummy variables. The interaction is then modelled by multiplying the three variables above. The scale parameter is postulated that the variance in time expenditure choice will decrease as time-of-day progress. In addition, individuals from larger households will have lower randomness in their choices, compared to their counterparts living in smaller households. This reflects the behavioural expectation that individuals from larger households are more likely to be subjected to constraints in their time expenditure choices. For example, they are more likely to bear family-related responsibilities or rules such as curfew for university-aged individuals living with parents. Moreover, different income levels also capture the heterogeneity in choice variance. The estimation results indicate that with time-of-day and household size staying the same, medium ($40,000 - $59,999) and very low (<$14,999) income groups have the lowest randomness in their time allocation choice for subsequent activities. All other income groups reveal similar degrees of heteroskedasticity in terms of their duration choice.

Table 2-3
Scale parameter function of time expenditure choice.

	Coefficient	*t*-statistics
At-home before first out-of-home activity		
Logarithm of number of vehicles interacts with faculty types		
Art & Science	−0.06	−1.62
Engineering, Business, Law & Medicine	−0.15	−3.30
Subsequent activities of the day		
Time-of-day as fraction of 24 h interacts with household size & income		
unknow/decline	0.07	8.17
>$125,000	0.05	2.69
$100000 - $124999	0.06	2.45
$60000 - $99999	0.07	4.70
$40000 - $59999	0.11	5.33
$15000 - $39999	0.05	3.12
<$14999	0.12	2.72

Notes: (a) The interaction between time-of-day, household size and income is formulated a $time\ of\ day\ (contunuous\ variable,\ fraction\ of\ 24\ hours) \times household\ size\ (contunuous\ variable) \times income\ levels\ (dummy\ variable)$

4.3. Time expenditure choices

Table 2-4 presents the parameters for student's time expenditure choices. Student's time expenditure choices are modelled separately for the duration at home before the first out-of-home activity and the duration for activities during the day. Each time expenditure choice is modelled by two parts. First, a student's marginal utility to spend a specific amount of time on activities is defined by baseline utility. Second, the rates of change in marginal utility are defined by exponential satiation parameter functions.

The duration before the first out-of-home activity at home is the maintenance period for sleep, breakfast, or leisure activities before students start to travel for their out-of-home activities. The large constant in the marginal utility function indicates students' low variances in the amount of time allocated across all observations. Younger students, having jobs and having access to private vehicles lead to more time allocated at home before the first activity. The findings regarding private vehicles fit the expectation since greater mobility could lead to more maintenance time at home due to reduced travel time. On the other hand, living in at least a 3-person household, having dependent children, and the expectation of scheduled activity will lead to less time allocated to the maintenance period before first out-of-home activity. However, readers should note that, in the baseline utility function, the estimated parameters representing accessibility to private vehicles and expectation of scheduled activity have expected signs but lower statistical significance. Based on the one-tail *t*-test, the confidence levels of estimated parameters are 88 % and 89 %, respectively. They are kept in the final specification because they correctly capture expected time allocation behaviours, as explained above. Cautions should be used when applying the findings to the general student population. The satiation parameters revealed that students are less likely to

Table 2-4
Time expenditure choices.

	coefficient	*t*-statistics
Time expenditure at-home before first out-of-home activity		
Baseline utility		
constant	35.59	26.72
age less than 23	0.30	3.66
having a job (full & part time)	0.52	3.56
living in at least 3-persons household	−0.55	−6.01
having access to private vehicle	0.10	1.18
logarithm of dependent children	−0.28	−2.99
expected maximum utility of first activity-type choice of the day	−0.02	−1.20
Exponential functions of satiation parameters		
constant	−1.91	−62.32
studying Engineering, Business, Law & Medicine	−0.0045	−2.18
living in on-campus residence	0.01	1.80
Time expenditure for activities during the day		
Baseline utility		
time-of-day as fraction of 24 h		
work	−4.82	−2.72
restaurant/coffee/bar	3.33	6.07
recreation/sports	5.27	4.34
other	3.81	3.05
staying home temporarily	4.24	4.59
activity types		
work	5.86	6.07
school	1.62	7.27
shop/market	−0.33	−1.25
restaurant/coffee/bar	−3.94	−10.69
other	−2.45	−3.17
logsum of composite activities		
work	−0.12	−5.69
recreation/sports	−0.05	−1.30
other	−0.10	−5.25
staying home temporarily	−0.07	−3.18
Exponential function of satiation parameters		
constant		
work	−0.54	−4.82
school	−0.19	−6.08
shop/market	−0.35	−7.82
restaurant/coffee/bar	–	–
recreation/sports	−0.38	−5.40
other	0.27	1.77
time-of-day as fraction of 24 h		
work	0.46	1.88
school	−0.31	−8.64
restaurant/coffee/bar	–	–
recreation/sports	−0.29	−1.89
other	−0.49	−1.82
staying home temporarily	−0.80	−8.49

spend more time at home if they study Engineering, Business, Law, and Medicine. Conversely, students will spend more time at their residences if they live on campus.

For subsequent activities, the utility for allocating a longer time duration for work will shrink as time-of-day progresses. In the utility function, time-of-day is modelled as fraction of 24 h. In terms of activity types, the positive parameters for work and school activities fit the expectation that they are the primary activities of the students. So the students tend to spend more time on work and school than other activities. The negative parameter signs for shop/market, restaurant/coffee/bar, and other activities are expected since they are not the primary activities for students. This reflects expected time allocation behaviours that students should spend less time on these activities during typical weekdays compared to work and school. However, the estimated parameter for shop/market activity is only statistically significant at 89 % confidence level. Readers should proceed with cautious, when applying the findings to the entire student body. Logsum of composite activities reflects the expectation of all unperformed activities later in the day. Parameters for work, recreation/sports, other, and staying home are all negative indicating individuals will allocate less time if they expect lots of subsequent activities on their timeline. The estimated parameters for work, other, and staying home are statistically significant at 95 % confidence level and the parameters for recreation/sports activity is significant at 90 % confidence level based on the one-tail test. However, parameters for shop/market and restaurant are having much lower statistical insignificance, so they are excluded from the final model specification. This indicates that students will not adjust their time allocation to current activities if they schedule to shop and dine next. This reflects students will not prioritize their maintenance tasks during weekdays.

4.4. *Activity-type choices*

Table 2-5 presents the parameters for students' choice of first out-of-home activity. The choice is modelled independently from all other activities. The negative alternative-specific constants (ASCs) for all non-school activities indicate that the students are most likely to schedule school as their first activity. The final specification includes two sets of parameters for students in Art & Science and Engineering, Business, Law & Medicine (EBLM) programs to account for heterogeneity among different student groups. Parameter estimation results in Table 2-5 show time-of-day effects among the student groups. Both student groups have a similar general trend in terms of time-of-day effects. As time progresses, students are more likely to schedule shop/market and other activities than work and school activities. However, the probability differs between Art & Science and EBLM students. Relative to EBLM students, Art & Science students become less likely to schedule school activities but more likely to schedule work, shop/market and other activities as time progresses.

Table 2-6 presents the parameters for students' subsequent activity-type choices during the day after the first out-of-home activity. The marginal utility for subsequent activity-type choice is a function of the number of times the same activity is scheduled, the time-of-day effect, and travel time to anchor points. The positive parameters for the number of times the same activities were scheduled earlier reflect students tend to chain similar activities in their tours. The time-of-day effects are consistent for non-school activities. The positive parameters indicate that the likelihood of scheduling non-work/school activities after the first activity increases as time progresses. Among activity types, the effects are most prominent for returning home permanently. This indicates most students tend to return home for the rest of their days after their first out-of-home activities. However, the time-of-day effects are different for the school activity. Negative time-of-day effects are found for school before 6 am, between 9 am to 3 pm, and after 7 pm. The likelihood of scheduling school as subsequent activities decreases as time progress. This is in line with the observation that students tend to schedule school as their first out-of-home activities instead of subsequent ones.

Mode-specific travel time represents spatial influences on activity-type choice. For non-school activities, the travel time between the current location to home is considered. All parameter signs are positive for auto and transit travel time. This indicates that the students are more likely to schedule another out-of-home activity if they are far away from home. This reflects trip-chaining behaviour

Table 2-5
First out-of-home activity-type choice.

	Coefficient	*t*-statistics
Alternative-specific constant (ASC)		
work	−3.86	−15.57
school	–	–
shop/market	−9.40	−17.30
restaurant/coffee/bar	−8.68	−21.57
recreation/sports	−7.81	−19.58
other	−7.99	−26.84
Time-of-day as fraction of 24 h (Art & Science Students)		
work	−1.63	−2.16
school	−3.35	−3.95
shop/market	3.02	2.51
other	2.92	3.44
Time-of-day as fraction of 24 h (Engineering, Business, Law & Medicine Students)		
work	−1.95	−2.45
school	−2.87	−3.15
shop/market	2.87	2.33
other	2.89	3.31

Table 2-6
Activity-type choice subsequent to the first out-of-home activity.

	coefficient	*t*-statistics
Alternative-specific constant (ASC)		
work	−1.67	−8.58
school	–	–
shop/market	−1.97	−12.71
restaurant/coffee/bar	−3.95	−11.06
recreation/sports	−4.46	−8.46
other	−2.94	−11.30
return home temporarily	−3.26	−14.61
Number of times same activity-type scheduled in previous cycles		
work	1.00	26.95
school	0.38	17.06
shop/market	1.18	27.46
restaurant/coffee/bar	1.47	30.82
recreation/sports	2.04	28.73
other	0.89	32.81
return home temporarily	1.43	25.26
Time-of-day as fraction of 24 h		
before 6 am		
school	−11.35	−7.96
6 am-9 am		
work	5.83	11.59
school	–	–
shop/market	–	–
restaurant/coffee/bar	6.96	7.10
recreation/sports	8.81	5.77
other	5.71	8.07
return home temporarily	5.67	8.66
return home permanently	16.03	28.31
9 am-3 pm		
work	3.79	13.67
school	−1.41	−10.24
shop/market	–	–
restaurant/coffee/bar	4.97	8.30
recreation/sports	7.00	7.79
other	4.42	10.57
return home temporarily	2.51	6.77
return home permanently	11.28	34.07
3 pm-7 pm		
work	3.91	17.51
school	–	–
shop/market	2.60	24.05
restaurant/coffee/bar	5.82	12.53
recreation/sports	7.32	10.49
other	5.17	16.01
return home temporarily	1.98	6.45
return home permanently	9.97	36.01
after 7 pm		
work	–	–
school	−1.97	−7.53
restaurant/coffee/bar	3.30	8.08
recreation/sports	3.96	5.92
other	2.14	6.35
return home permanently	7.44	30.96
Travel time		
from current location to home by auto (if using auto)		
shop/market	0.65	15.42
restaurant/coffee/bar	0.32	6.27
other	0.38	9.35
return home temporarily	0.74	13.45
from current location to home by transit (if using transit)		
shop/market	0.51	18.20
restaurant/coffee/bar	0.27	7.71
recreation/sports	0.26	5.84
other	0.36	11.62
return home temporarily	0.52	12.95
for school:		
to school by auto	0.21	6.43
to school by transit	0.31	11.88

(*continued on next page*)

Table 2-6 (*continued*)

	coefficient	*t*-statistics
for return home permanently:		
to home by auto	2.44	49.59
to home by transit	1.79	52.95
to home by non-motorized mode	1.42	40.71

in which students are trying to conduct multiple non-work/school activities once they leave their homes. Perhaps the students can manage their travel time and costs economically by doing so. The travel time between the current location and school is considered when scheduling school activities. The positive parameter indicates students tend to schedule school activities in their next cycles if they are far away from campus. The positive and relatively large travel time parameters for returning home permanently show that the students are more likely to schedule returning home permanently if they are far away from home. This reflects interesting behavioural insights that students tend to move their activities further away from home and then return home from the farthest location, rather than the other way around (travelling to conduct activities farthest away from home first, and then move to activity locations closer to home).

4.5. Location choice

Table 2-7 presents the parameters for location choice models. Activity location choices are modelled with time–space constraints considering travel time for corresponding travel modes used by the students. Location choices are modelled on the level of traffic analysis zones (TAZs) with land use and level-of-service attributes. TAZ is the unit of geography commonly used in travel demand models (Miller, 2021). The urban area is divided into many mutually exclusive and exhaustive zones, so aggregated zonal land use and socio-economic attributes can feed travel demand models. The model results show that TAZs become less attractive to work, shop/market, restaurant, recreation, and other activities as their travel time to local centers (CBDs) increases. Densely populated residential zones attract less work, recreation/sports, and other activities. The estimated parameter for work is statistically significant at 93 % confidence level based on the one-tail test. It is slightly lower than the commonly considered 95 % confidence level. However, the parameter is kept in the final specification as it correctly represents the location choice behaviours of fewer work trips to residential zones. Moreover, the 93 % confidence level is still within a reasonable range to accept parameters. Parameters for auto travel time to school have positive signs indicating that students who have access to private vehicles do not mind driving far away from their campus. Zonal employment, retail stores, entertainment facilities, and restaurant density are positively associated with their related activities. Moreover, TAZs with higher retail store density attract less recreation/sports and other activities.

Table 27
Out-of-home location choice.

	coefficient	*t*-statistics
Logarithm of auto travel time to CBD		
work	−0.51	−15.57
shop/market	−0.24	−6.46
restaurant/coffee/bar	−0.15	−3.99
recreation/sports	−0.32	−6.49
other	−0.20	−5.98
Logarithm of zonal population density		
work	−0.03	−1.49
recreation/sports	−0.18	−4.41
other	−0.05	−2.28
Logarithm of travel time		
origin-school by auto	0.14	7.10
origin–destination-home by auto	−0.79	−39.08
origin–destination-home transit travel time	−0.74	−43.54
origin–destination-home non-motorized modes travel time	−0.62	−46.76
Zonal retail store density		
shop/market	0.23	9.35
restaurant/coffee/bar	0.06	1.77
recreation/sports	−0.08	−1.36
other	−0.09	−3.01
Zonal entertainment facility density		
recreation/sports	0.09	2.11
other	0.07	2.29
Zonal restaurant density		
restaurant/coffee/bar	0.13	3.17
recreation/sports	0.17	2.48
other	0.20	5.53

5. Microsimulation & scenario analyses

The empirical model estimated is used to simulate post-secondary students' activity-travel patterns. Outputs from simulations include students' activity schedule, duration, and location choices. Activities are scheduled in 5 min intervals. Students' home and school locations are treated exogenously, as reported in the survey. For non-school activities, time–space constraints with corresponding travel modes are applied to search feasible location choice sets. Students' activity schedules will continue until 'return home permanently' is chosen. Ten replications are simulated for each agent (Roorda et al., 2008). The transportation system's level of service is generated by an operational regional travel demand forecasting model for the analysis year.

Three scenarios are simulated in this study. The first scenario replicates the conditions before the pandemic, where students commute to campus for in-person courses and participate in discretionary activities freely. Using the first scenario as the base case, the

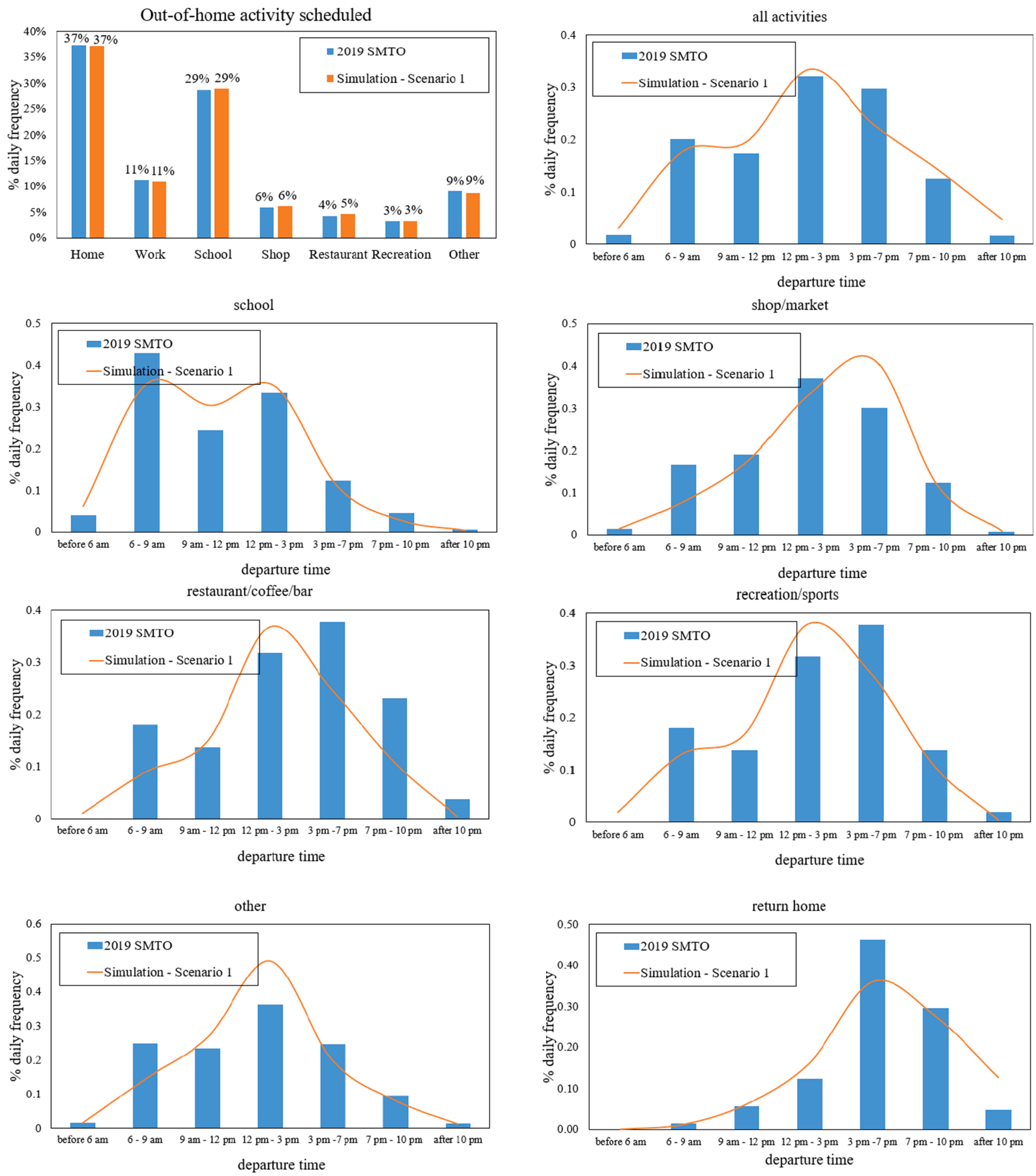

Fig. 5. Simulation outputs - before pandemic scenario.

second scenario models students' activity-travel behaviour with telecommuting and restricted out-of-home activities during the pandemic. Finally, the third scenario assumes students telecommute but participate in out-of-home discretionary freely at the pre-pandemic level. The following section presents microsimulation results and comparisons between simulation scenarios.

5.1. Scenario 1 - student's activity-travel patterns before the pandemic

The first scenario replicates students' pre-pandemic activity-travel patterns. Fig. 5 presents simulation outputs from Scenario 1. The out-of-home activity types scheduled match well with the observation from the 2019 SMTO survey. Also, simulated trip departure times successfully replicated two peak periods observed from the 2019 SMTO survey. The morning peak period is from 6 to 9 am, and the afternoon peak period starts at noon. Moreover, trip departure times for each activity type also match the 2019 SMTO survey observations. The base scenario successfully replicates students' activity-travel behaviours captured in the 2019 SMTO survey.

5.2. Scenario 2 - enforced telecommuting with pandemic-influenced behaviour

The second scenario models student's pandemic-influenced activity-travel behaviour with enforced telecommuting. Scenario 2 modifies the following factors from Scenario 1. Firstly, Scenario 2 enforces telecommuting on students. Students' school episodes are treated as at-home productive episodes. Their home locations are considered locations for study-related activities. Travel time to school no longer be added to a student's time budget. This represents the removal of the burden to commute brought by telecommuting. Scenario 2 also considers the influence of the pandemic on students' daily activity-travel behaviour through the calibration of CUSTOM against observations from the 2020 COVHITS survey. Several discrete choice components of CUSTOM are calibrated for this. This adjustment accounts for the avoidance of non-essential out-of-home activities during the pandemic. The decision to stay at home all day or participate in out-of-home activities is calibrated. The alternative-specific-constant (ASC) is adjusted to match the market share during the pandemic (Ortúzar & Willumsen, 2009, P235). The alternative-specific-constants (ASCs) are adjusted for activity-type choice components to restrict unfavorite activity types during the pandemic, such as dining in restaurants. An iterative approach is taken until the market shared generated by simulation is matched with the market share from the 2020 COVHITS survey. Fig. 6 presents the simulation outcome after calibration. The market share matches closely with the observation from the 2020 COVHITS survey.

Besides demands, Scenario 2 also considers constrained supply for out-of-home discretionary activities during the pandemic. To ensure social distancing, grocery stores, malls, and restaurants operate at reduced capacity. The reduction in capacity might lead to queueing and, consequently, additional wait time for individuals. Theoretically, such a phenomenon fits classical queue theory; thus, the average wait time can be calculated if sufficient data are available. Unfortunately, it is not feasible for this study due to the lack of data.

On the other hand, the 2020 COVHITS survey observed that the average duration of shopping/grocery activities was increased by 21 min compared to the pre-pandemic level (Wang et al., 2021). Therefore, an ad-hoc approach is taken: an additional random wait time (out of four discrete levels: 0, 10, 20, and 30 min) is assigned to shop/market activities between rush hours (12 pm to 7 pm). Only shop/market activity is modelled with additional wait time due to its essentiality. People must complete certain purchases, especially grocery shopping, to fulfill their basic needs.

5.3. Scenario 3 - enforced telecommuting without pandemic-influenced behaviour

Scenario 3 is a hypothetical scenario that assumes enforced telecommuting but unconstrained participation in discretionary activities at the pre-pandemic level. Enforced telecommuting is modelled using the same approach discussed in **Section 5.2**. Scenario 3 is the control scenario to rule out the pandemic's influence on changes in travel patterns. Therefore, the direct effects of telecommuting can be concluded from the differences between Scenario 1 and Scenario 3. The following sections compare the differences between each simulated scenario.

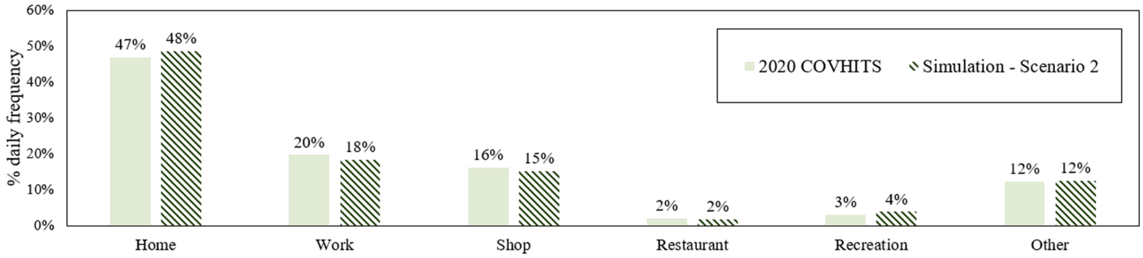

Fig. 6. Comparison of out-of-home activity scheduled after calibrating against COVHITS.

5.4. Implications on out-of-home activity types and trip rates

**Fig. 7 presents the comparison of out-of-home activity types scheduled among all three scenarios. In Scenario 1, 46 % of students' out-of-home activities are school-related, whereas telecommuting in Scenario 2 and 3 eliminates the demand for attending school-related activities outside of the home. Comparing Scenario 1 and 2 reveals the influence of enforced telecommuting and the pandemic on travel behaviours. Shop/market, work, and other activities gain significant shares from Scenario 1 to Scenario 2. Work and shopping activities accounted for 36 % and 30 % of out-of-home activities scheduled in Scenario 2. This fits the expectation that during the pandemic travelling primarily serves essential needs. As a result, work and shopping activities account for the highest relative frequencies of being scheduled by students. Other activities like visiting friends and families are among the safest activities (also recommended by governments compared to large-scale public gatherings) during the pandemic. This might increase the frequency of scheduling other activities in Scenario 2 compared to Scenario 1. On the contrary, the share of restaurant activities dropped from Scenario 1 to Scenario 2. The discouragement of dining in restaurants causes this during the pandemic.

On the other hand, a comparison reveals the influence of telecommuting on travel behaviours. When the pandemic is not a factor, work becomes the most popular purpose of out-of-home activities when telecommuting is enforced for students. Also, the shares of all discretionary activities in Scenario 3 are higher than in Scenario 1.

While relative proportion between activities-types is helpful to understanding the influence of telecommuting and pandemics on the activity-travel pattern, it does not necessarily provide the full picture of the influences on travel demands. Therefore, trip rates by each activity type are compared to understand the impacts on travel demands. Table 3 presents the simulation results per out-of-home activity type for each scenario. Overall, students' mobility dropped significantly due to telecommuting and the pandemic. From Scenario 1 to Scenario 2, the average trip rates, including zero-trip markers (individuals who stay at home all day) decreased by 60.1 %, dropping from 1.69 to 0.66.

Interestingly, shop/market trip rates, including zero-trip makers, remain at 0.10 between Scenario 1 and Scenario 2. This fits the expectation as shop/market is an essential activity and should be maintained at a certain level for the population regardless of exogenous conditions (enforced telecommuting and the pandemic). However, while excluding zero-trip markers, shop/market trip rates increase from 0.19 to 0.37, indicating more students are travelling for essential purposes. On the other hand, trip rates for other discretionary purposes decrease unanimously during the pandemic, reflecting students' tendency to reduce non-essential out-of-home activities. While excluding zero-trip markers, students make considerably fewer trips to restaurants. This fits the expectation that people avoid dining in restaurants during the pandemic.

Despite the significant mobility drop in Scenario 2, the modelling results in Scenario 2 might still overestimate work trip rates. There are two reasons for such overestimation. Firstly, for simplicity, this study ignored the effect of telecommuting by students as workers and employment loss due to the pandemic. Secondly, it fits the property of the modelling framework used in this study. CUSTOM is a completely RUM-based approach without any hard-coded rules. The calibration procedure discussed in **Section 5.2** reduced utility for unfavorite discretionary activity types. However, it also simultaneously increases the probability of scheduling other activity types because only differences between utilities matter in discrete choices modelling (Train, 2009). Consequently, work activity might be overestimated in Scenario 2 while other activities are suppressed.

Comparing Scenario 1 and Scenario 3 shows that enforced telecommuting still reduces students' overall travel demand after excluding the impact of the pandemic. The average trip rates, including zero-trip markers, decreased by 14.2 %, dropping from 1.69 to 1.45 from Scenario 1 and Scenario 3. This modelling result indicates that enforced telecommuting could effectively reduce travel demand. This is in line with the existing literature (Hamer et al., 1991; Mokhtarian, 1998; Mokhtarian et al., 2004; Choo et al., 2005). Interestingly, telecommuting also causes increased trip rates for all discretionary activities, except for shopping/market. This finding also confirms the literature that telecommuting induces discretionary travel (Mokhtarian et al., 2004; Zhu, 2013; Zhu & Mason, 2014; Kim, 2016). As for shopping activities, their maintenance nature discussed previously deemed their inelasticity in consumption.

To summarize, simulation results lead to very interesting dynamics between telecommuting and travel demand. Telecommuting could reduce travel demand by removing the burden to commute, but it will also induce demand for discretionary travel. In Scenario 3, the enforced telecommuting eliminates all the need to commute to school. Therefore, the overall travel demand reduction in Scenario 3 is brought by the elimination of commuting, outweighing the induced demand for discretionary activities. However, the reduction in overall travel demand will be questioned when telecommuting becomes voluntary instead of enforced. Individuals might choose to

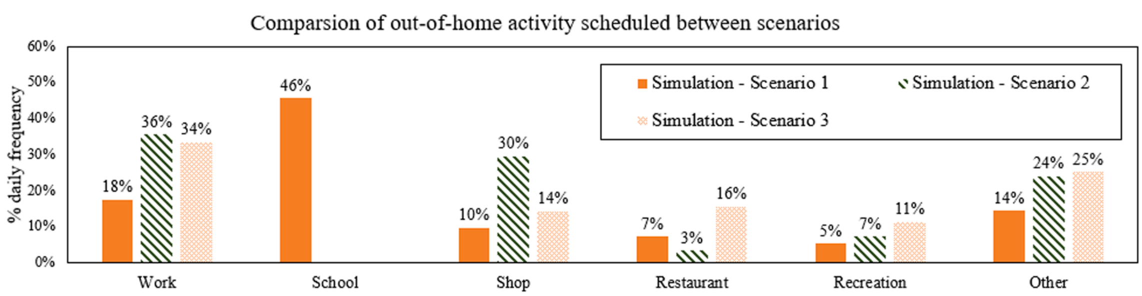

Fig. 7. Comparison of out-of-home activities scheduled between scenarios.

Table 3
Comparison of average trip rates by activity types between scenarios.

	Scenario 1	Scenario 2	Scenario 3
with zero trip markers			
Home	0.63	0.32	0.73
Work	0.19	0.12	0.22
School	0.49	0.03*	0.07*
Shop	0.10	0.10	0.09
Restaurant	0.08	0.01	0.10
Recreation	0.06	0.03	0.07
Other	0.15	0.08	0.17
Sum	1.69	0.66	1.45
without zero trip markers	Scenario 1	Scenario 2	Scenario 3
Home	1.14	1.10	1.21
Work	0.34	0.42	0.37
School	0.89	0.09*	0.11*
Shop	0.18	0.35	0.16
Restaurant	0.14	0.04	0.17
Recreation	0.10	0.09	0.12
Other	0.27	0.28	0.28
Sum	3.05	2.36	2.42

Notes: * are trips travelled back homes and activities are scheduled as school-related purposes.

commute when they are not scheduled with discretionary activities.

On the other hand, they might also telecommute when they expect to travel for discretionary purposes. Consequently, when everyone optimizes their daily activity-travel patterns in the manner described above, system optimum (overall reduction in travel demand) may not be realized. To fully realize the benefits of telecommuting, future research should investigate the dynamics between reducing the need to commute and induced demand for discretionary travel. Moreover, future studies should identify effective management approaches and policies that lead to the overall reduction in overall reduced travel demand under voluntary telecommuting.

5.5. *Implications of the trip starting time patterns*

Both Scenario 2 and Scenario 3 indicate that morning peak periods will become flattened with telecommuting. Fig. 8a demonstrates such a shift compared to the pre-pandemic pattern in Scenario 1. As opposed to a two-peaked pattern in Scenario 1, the morning peak period (6–9 am) diminishes with an enhanced afternoon peak period (3–7 pm) in Scenario 2 and 3. Students travel less during morning peak hours as most of them schedule at-home school-related activities as their first activity in the morning. Students become active in conducting the majority of their daily trips later in the day, creating an enhanced afternoon peak period. This highlights the planning attention in afternoon peak hours rather than the morning peak hours in conventional transportation planning practice.

While the effect of telecommuting on enhanced afternoon peak is clear, it is also interesting to observe the differences in evening

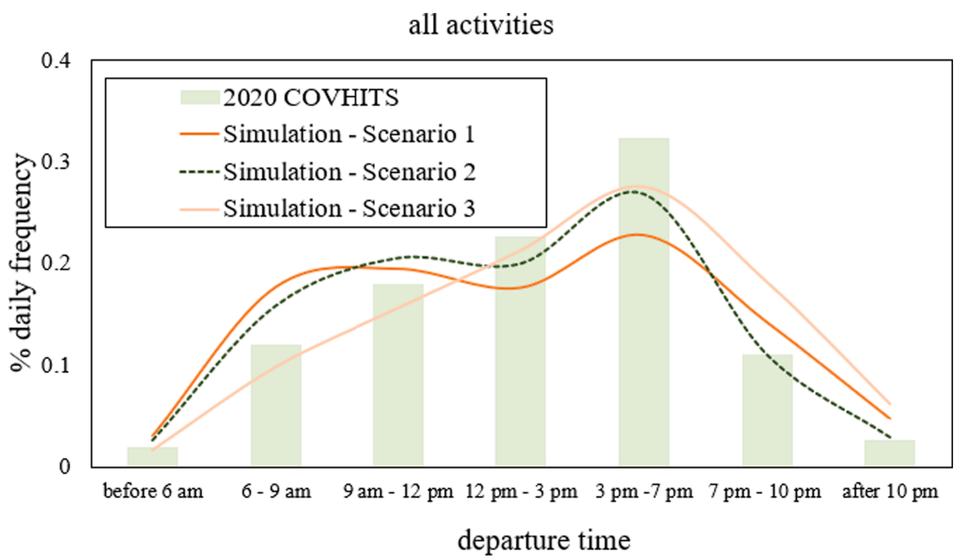

Fig. 8a. Shift of trip start time pattern – all activities.

travel patterns between Scenarios 2 and 3. Fewer trips are conducted after 7 pm in Scenario 2 compared to Scenario 1 and 3. This is driven by changes in students' behaviour in scheduling discretionary activities (see Fig. 8b). In Scenario 2, discretionary trips decreased dramatically after 7 pm. Conversely, in Scenarios 1 and 3, discretionary trips decreased gradually from 7 − 10 pm. This could be the influence of the pandemic. Due to reduced demand, most businesses operated with a reduced schedule (close in the early evening) during the pandemic. This might contribute to the sudden drop in out-of-home discretionary activities in the evening. The lack of choices for discretionary activities in the evening encourages students to schedule out-of-home discretionary activities during other day periods. This pattern might gradually recover to the patterns seen in Scenarios 1 and 3 when businesses recover from the influence of the pandemic.

5.6. Implications of discretionary activity location choices

There is a difference in choosing discretionary activity locations between Scenario 1 and Scenario 2. Fig. 9a compares Scenario 1 and 2 for TAZs in the City of Toronto, the core region in the study area. Choosing TAZs in Toronto's downtown core (TAZs less than 100) for discretionary activities is significantly higher in Scenario 1 than in Scenario 2. Conversely, Fig. 9b compares Scenario 1 and 3 for choosing TAZs in the City of Toronto. The result shows that the discretionary activity location patterns are similar when only considering telecommuting. This observation suggests that the differences observed between Scenario1 and 2 are solely caused by the reduction in travel demand (caused by the pandemic) in Scenario 2 instead of telecommuting. To confirm the causality, the relative frequencies, instead of absolute frequencies, of choosing each TAZ in each scenario are plotted against each other in Fig. 10. The results suggest no significant differences between the patterns of relative frequencies across all simulated scenarios. The simulated relative frequencies in each scenario are strong predictors for frequencies in other scenarios. To examine the influence of telecommuting, the relative frequencies for choosing a particular TAZ in Scenario 1 are 0.897 times the frequencies in Scenario 3 (telecommuting is the only difference between Scenario 1 and 3). Therefore, the simulations do not provide strong evidence of the shifting of locations due to telecommuting.

5.7. Modelling post-pandemic era with telecommuting

This study sets the initial effort to model enforced telecommuting on post-secondary students during the pandemic. The modelling framework proposed in this study successfully captures pandemic-influenced travel behaviours and telecommuting. Telecommuting by students and workers is expected to retain its popularity in the post-pandemic era. Anecdotally, companies have started to consider permanent telecommuting after the pandemic (McLean, 2020). Some hybrid work/study arrangements can be expected in the post-pandemic future. Both students and workers are expected to perform their productive activities at homes and schools/offices based on the availability of telecommuting options and their preferences. Such flexible arrangements in work/study places might challenge the current activity-based travel demand modelling approach. Therefore, activity-based travel demand modelling and their data requirements must be rethought to model the post-pandemic time when voluntary telecommuting will become prevalent.

Currently, activity-based travel demand modelling primarily focuses on out-of-home activities. One basic assumption is that most students and workers will have to commute and perform their productive activities at usual places outside of their homes. Productive activities refer to study-related and work-related episodes for students and workers, respectively. Unlike the CUSTOM framework, which is entirely econometric-based, some operational activity-based models schedule work and school episodes with the highest priority and insert discretionary activities into the remaining time slots (National Academies of Sciences, Engineering, and Medicine,

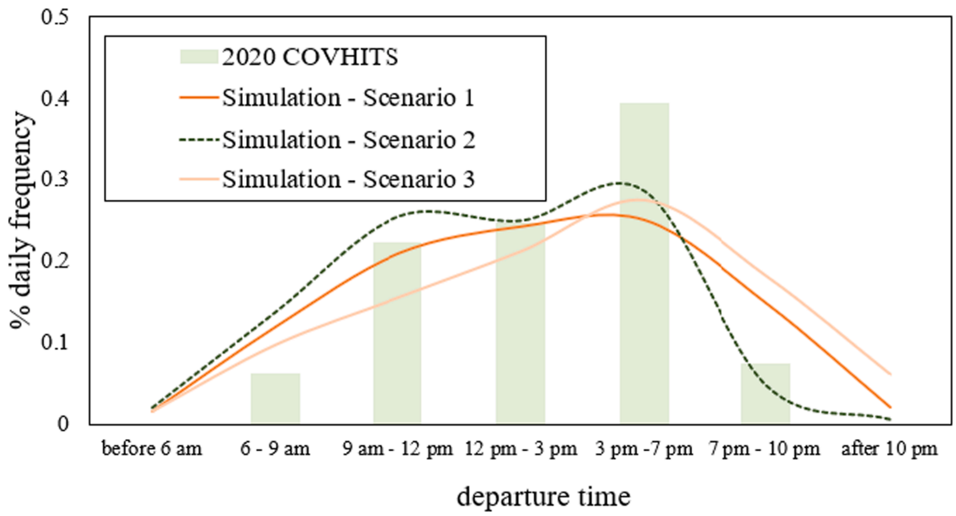

Fig. 8b. Shift of trip start time pattern –discretionary activities.

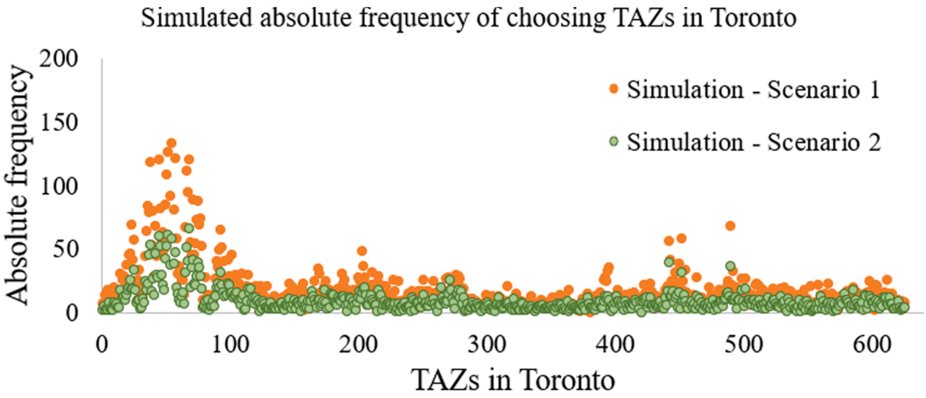

Fig. 9a. Simulated absolute frequency of choosing TAZs in Toronto for discretionary activities.

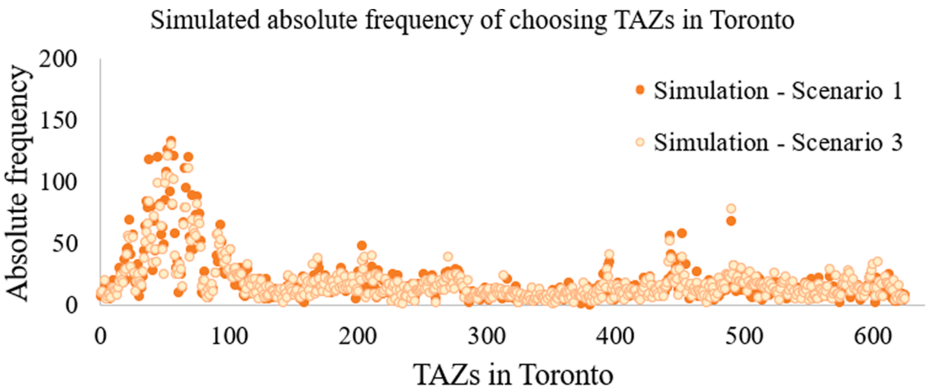

Fig. 9b. Simulated absolute frequency of choosing TAZs in Toronto for discretionary activities.

2014). However, with the liberty to telecommute, students and workers can perform productive activities at home.

Moreover, by removing the burden of commuting, their mobility might drop, and a large number of them might become zero-trip makers, staying at home all day, as per observation from this study. Currently, most activity-based modelling approaches treat home episodes qualitatively the same. It is crucial to recognize home productive and maintenance episodes to model telecommuting scenarios. Fig. 11 illustrates the importance of doing so. The example contains four activity scheduling cases. In case 1, the individual starts his/her day with a maintenance episode at home. Then he/she starts studying/working at home (telecommuting). Finally, he/she starts another maintenance episode at home until midnight. In case 2, the individual spends all day at home unproductively. In case 3, the individual telecommutes after a maintenance episode in the morning. Next, he/she travels for shopping and then travels back home and spends the rest of the day unproductively. In case 4, the individual stays unproductive from the beginning of the day. Then, he/she travels to shop and then travels back home and spends the rest of the day unproductively again.

Without proper recognition of home productive and maintenance episodes, cases 1 and 2 will be treated the same; similarly, cases 3 and 4 will be treated the same by current activity-based models. However, they are, in fact, qualitatively different, and failure to recognize these cases will jeopardize modelling accuracy significantly. For example, in this study, case 2 is appropriately captured by the decision of staying at home all day or participating in out-of-home activities. The activity-based modelling framework handles cases 1, 3 and 4. On the other hand, failure to recognize home productive and maintenance episodes will force the decision to stay at home all day or participate in out-of-home activities to handle cases 1 and 2. Therefore, the activity-based modelling framework can only handle cases 3 and 4. Moreover, the activity-type choices and time expenditure will inappropriately blend home maintenance and productive episode in case 3 because home productive episodes are invisible to the activity-based modelling framework.

From the above discussion, additional information on home activities is required to model voluntary telecommuting. The critical assumption in this study is the enforced telecommuting where all students must switch their study place from school to home. Based on this assumption, this study directly converts school episodes into home productive episodes. But the assumption will lose validity if telecommuting is not mandatory. Supplementary data are needed to distinguish individuals' at-home productive and maintenance episodes. Thus, future household travel surveys should consider collecting relevant information to feed activity-based models.

6. Conclusion & future research

This study uses agent-based simulations on post-secondary students in the Greater Toronto Area (GTA) to identify changes in their

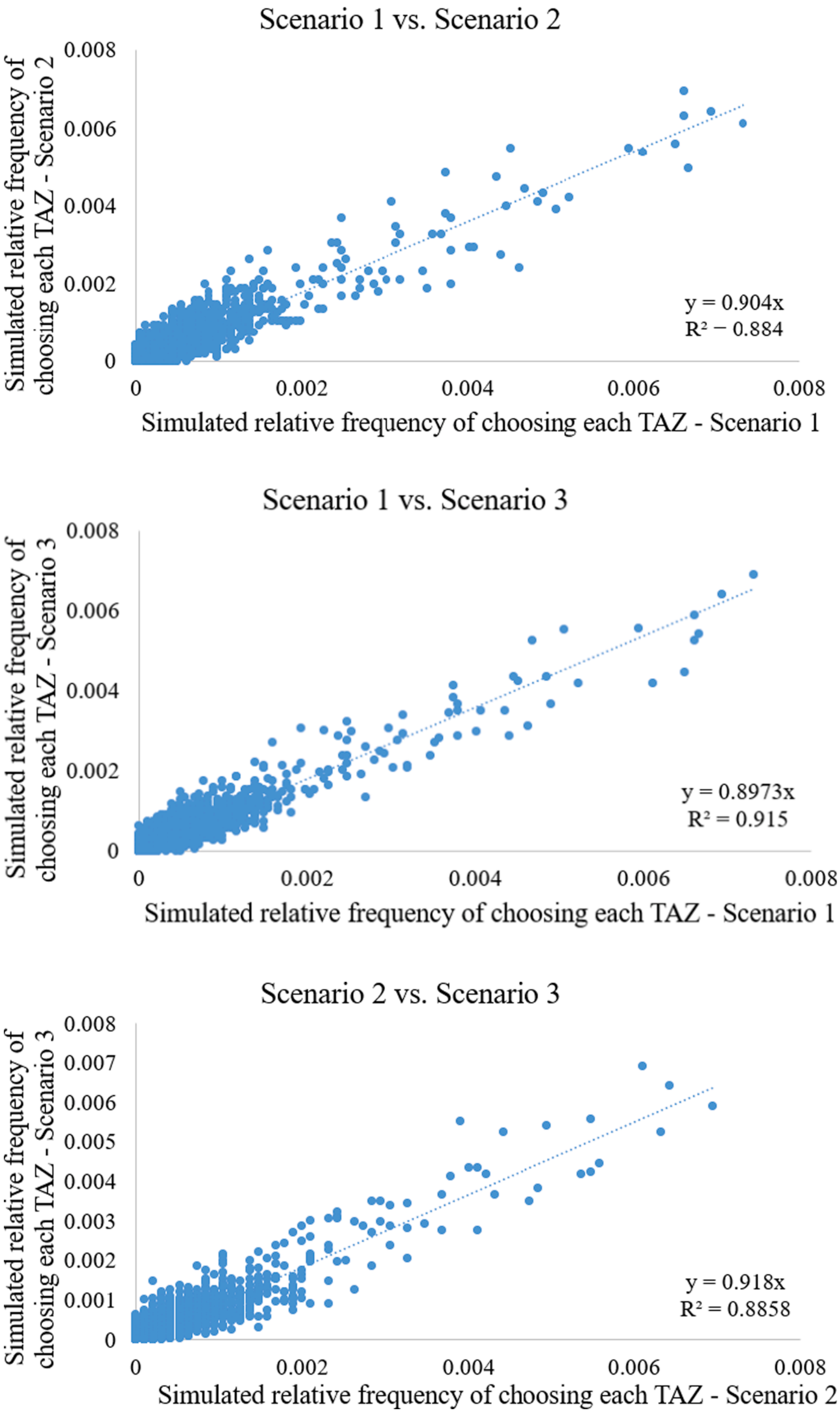

Fig. 10. Simulated relative frequency of choosing each TAZ for discretionary activities.

activity-travel behaviour followed by enforced telecommuting during the pandemic. The simulation result shows that students' mobility dropped due to telecommuting and the pandemic. The overall trip rate dropped from 1.69 to 0.66. In the control scenario ruling out the influence of the pandemic, the overtrip rate still drops 14.2 %, from 1.69 to 1.45, highlighting the effect of telecommuting on travel demand. Interestingly, complementary effects of telecommuting are also found in this study. Enforced telecommuting also increases trip rates for all discretionary activities, except for shopping/market. This suggests that telecommuting may

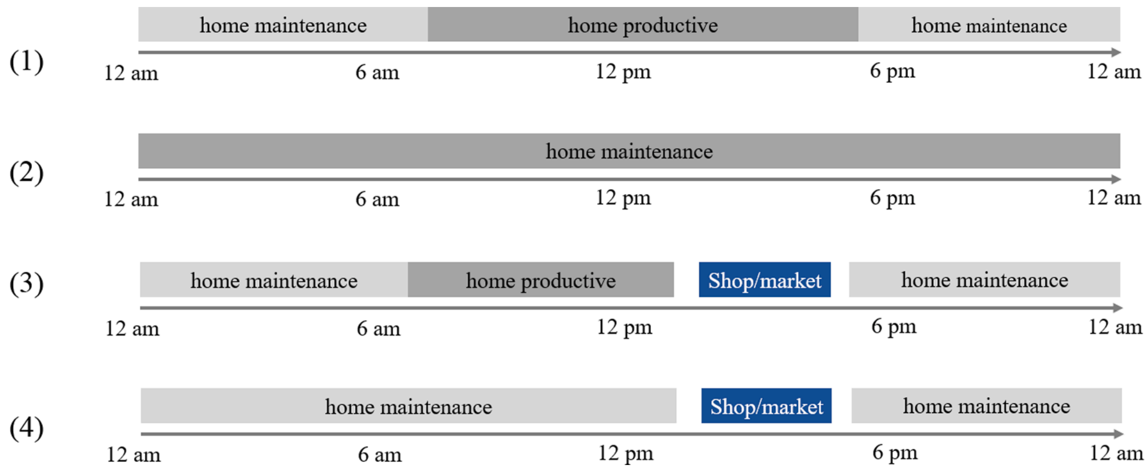

Fig. 11. Example of activity scheduling with/without considering home production episode.

still reduce travel demand even if it induces some discretionary travel.

This reveals the potential feasibility of using telecommuting as a formidable travel demand management strategy to reduce overall travel demand, building toward sustainable urban transport systems. However, the reduction might become marginal when telecommuting becomes voluntary instead of enforced. To fully realize the benefits of telecommuting, future research should further investigate the dynamics between the flexibility of scheduling telecommuting and induced discretionary travel demand. Moreover, future studies should examine and identify feasible management strategies that reduce total travel demand under voluntary telecommuting. This study also identifies the diminishing morning peak hours caused by telecommuting. When telecommuting, students will become active in the afternoon, creating an enhanced afternoon peak period between 3 and 7 pm. Simulation results show Toronto's downtown core zones are chosen less frequently as destinations due to the pandemic. However, simulation results suggest no evidence of changes in location choices caused by telecommuting.

Besides behavioural insights, the modelling framework proposed in this study could be used to forecast various telecommuting scenarios post the pandemic. In application studying post-pandemic travel demand, the enforced telecommuting assumption in this study could be relaxed considering voluntary options to telecommute by students and workers. The enforced telecommuting episodes simulated in this study could be probabilistically assigned as commuting and telecommuting episodes. Moreover, future activity-based travel demand modelling practices need to recognize productive and maintenance episodes at home for telecommuters. Otherwise, the current activity-based modelling approach might produce less accurate results. Additional data is also needed for this purpose. Future household travel surveys should collect relevant home episodes information (distinguishing between home productive and maintenance episodes) to facilitate accurate modelling of telecommuting scenarios using activity-based travel demand models.

As with any research, there are several limitations in the study. First, the modelling frameworks used in this study lack a travel mode choice component. Observation from the 2020 COVHITS survey indicates that transit ridership suffered during the pandemic in the study area (Wang et al., 2020). Urban residences preferred private cars and active modes such as walking and biking rather than transit during the pandemic. Such a shift in travel modes might also lead to changes in activity-travel patterns. Second, this study primarily considers pandemic-influenced on activity type choices and the decision to stay at home all day while leaving the location choice model unchanged. During the pandemic, location choices for discretionary activities might also change as people might strategize their destination choices to keep themselves safe. However, calibrating location choice components is challenging because they lack alternative-specific constants (ASCs). Therefore, it is practically infeasible to calibrate location choice components. Moreover, the location choice components cannot consider heterogeneity in travellers' choices. In reality, individuals might have several go-to-places for out-of-home activities. Future studies should explore the feasibility of considering probabilistic location choice set formation with individual heterogeneity. Future studies can try to overcome the limitations mentioned above. Nonetheless, Batty (2020) concluded that unpredictability is the norm for modelling, especially in complicated urban systems. However, with careful investigation and reasonable assumptions, this modelling exercise can provide a useful generalization of students' activity-travel patterns during the pandemic and facilitate more accurate modelling for the post-pandemic era.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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