# Assessing the Impacts of Work-from-home and E-learning Using Agent-based Transport Simulation Model

Bijoy Saha [1] and Mahmudur Rahman Fatmi [2]

[1] PhD Student, The University of British Columbia, School of Engineering, Civil Engineering, Okanagan campus, 1137 Alumni Avenue, Kelowna, BC, V1V 1V7, Canada; bijoy.saha@ubc.ca

[2] Assistant Professor, The University of British Columbia, School of Engineering, Civil Engineering, Okanagan campus, EME 3231, 1137 Alumni Avenue, Kelowna, BC, V1V 1V7, Canada; mahmudur.fatmi@ubc.ca

## Abstract

COVID-19 imposed travel restrictions have induced significant changes to our travel behaviour and daily life, such as work-from-home and online learning. The long-lasting nature of this pandemic might trigger a longer-term change in our behaviour after the pandemic, such as continued preference for work-from-home and e-learning. Such changes in work and learning arrangements do not only indicate a reduction in travel during the peak hour, it might also indicate a shift in travel to other times of day as well as changes in trip purposes and travel distances. For example, a worker telecommuting might spend the whole/part of the day at home and then go out to meet friends/family for dinner and do groceries from a store near the home while returning. Traditional four-stage travel demand models typically take the origin-destination (O\D) matrix for the peak hours as input at an aggregate-level of temporal, spatial, and population resolution and do not necessarily accommodate the trip chaining behaviour of an individual. As a result, the behavioural changes associated with time-sensitive policies such as work-from-home and e-learning are not accommodated and/or reflected by these models. This demands the development agent-based transport simulation models adopting activity-based modelling technique. This study adopts an agent-based transport network simulation technique to generate 24-hour traffic for alternative work-from-home and online learning strategies. The model is calibrated and validated for the Central Okanagan region of British Columbia, Canada. Specifically, the open source Multi-Agent Transport Simulation (MATSim) model has been adopted, which was written using the Java programming language. The 24-hour travel schedule is developed adopting an activity-based modelling technique. The findings of this study will assist the governments and transit agencies in understanding the dynamics of travel behaviour and the consequent change in traffic patterns over the 24-hour for alternative work arrangement scenarios.

**Keywords:** Work-from-home, E-learning, Agent-based transport simulation model, Activity-based model, MATSim.

# 1. Introduction

During the recent COVID-19 pandemic, people adjusted their daily activities and travel behaviour to comply with the imposed restrictions on social gatherings and travelling (Bhaduri et al., 2020). In-person activities made transitioned to virtual realm, which was reflected in the transportation network. For example, traffic dropped significantly during the morning peak hour as work- and school-bound trips were replaced by work-from-home and online learning (Wang et al., 2021). Traffic congestion and greenhouse gas (GHG) emissions reduced drastically around the world during the pandemic (Du et al., 2021), whereas these were increasing before the pandemic due to the rise in population and their travel demand. Traffic congestion may rebound and GHG emissions may take a u-turn in the post-pandemic world. To reduce traffic congestion and GHG emission in the long run, transportation researchers, practitioners and policymakers are focussing on the flexible work-place/online learning as a future transportation policy as it was one of the key factors for the traffic congestion and GHG emission reduction during the pandemic. Existing literature has explored the factors that may influence the workers and students to work/attend classes from home if they are given flexibility (Ceccato et al., 2021; Drašler and Bertoncelj, 2021). Although workers and students demonstrated continued preference for work-from-home and online learning, their travel behaviour may change due to such policy. For example, they may participate in higher discretionary activities than they usually do, to eliminate fatigue after attending work/school from home, which in turn may increase vehicle-kilometre travelled (VKT). They may also adjust their travel decisions such as departure time, mode choice, etc. which may impact the spatio-temporal distribution of traffic. It is essential to understand how flexible workplace/e-learning will affect traffic pattern for better policy-making which has been scarcely investigated in the existing literature.

This study investigates how different shares of workers and students working/learning remotely will affect travel behaviour and traffic flow by developing an agent-based dynamic transportation microsimulation to understand the impact of flexible work-place and online learning. The study area is the Central Okanagan region of Canada. The model is developed in Multi-Agent Transportation Simulation (MATSim), which adopts activity-based modelling technique. The model can accommodate individuals' behaviour and travel decisions into the modelling framework; therefore, the model can capture the travel attributes of those who will work/attend class from home as well as those who won't. Several scenarios have been developed and tested, varying the share of workers and students working/learning remotely and compared with the base scenario. The findings provide insights on how different shares of workers and students having the flexibility to work and attend classes from home change the share of daily trips for different trip purposes, departure times and travel distances.

The remainder of this paper is organized as follows. The next section presents a brief overview of the existing literature on travel behaviour during the pandemic and highlights the research gap. The third section presents the methodology of this study. In the following two sections, data and scenarios developed for this study have been discussed. Validation and simulation results have been presented in the sixth section. The final section provides a summary and conclusions of this paper.

## 2. Literature Review

The COVID-19 pandemic has reshaped the ways of interacting, working, learning and shopping (Conway et al., 2020) that individuals may continue to adopt in the post-pandemic future. Researchers have identified work-from-home and online learning as a long-term change that may evolve (Currie et al., 2020). It may also serve as a time-sensitive policy to reduce traffic on a constrained transportation network for ensuring a sustainable and resilient transportation system (Beck & Hensher, 2020). An understanding is required on how flexible work-place and e-learning will impact the traffic flow that may emerge in future. Existing literature has made a significant effort to investigate individuals' travel behaviour during the pandemic. For example, Bohman et al. (2021) analyzed the frequency of activities, modes of transport, and shift to virtual mobility for Sweden. They found a higher modal shift to car, followed by biking and walking. They also found a cluster of individuals in the lower-income areas who didn't make the transition to virtual mobility for performing any activity. Jiao and Azimian (2021) adopted two binary logit models to investigate whether individuals reduced the number of shopping trips and trips by public transit. Their study identified several socio-economic factors, i.e. age, gender, income and individual characteristics, i.e., health status and anxiousness, significantly affecting travel behaviour.

Limited studies focused on the effect of work-from-home and online learning on the travel decisions of workers and students. Among them, Drašler & Bertoncelj (2021) examined the attributes affecting the attitude and perception about work from home and online education among the students and employees of the University of Ljubljana, Slovenia. The results showed that socio-demographic factors, financial status and commute time significantly influenced the choice of work-from-home and online education. Ceccato et al. (2021) analyzed the factors influencing the decisions for travelling to work and school for the University of Padova, Italy. They used revealed- and stated-preferences mobility survey data to develop binary logistic regression models and found that younger students had a higher likelihood of attending in-person classes, whereas younger workers had a higher probability of working from home. Prasetyanto et al. (2022) identified the factors affecting the preference for e-learning in Indonesia after the pandemic using Discriminant Analysis (DA) and Multinomial Logistics Regression (MNL) model. Their results showed that students residing in well-developed neighbourhoods had a higher preference for online classes. Conway et al. (2020) assessed the effect of COVID-19 on telework, daily travel, restaurant patronage and air travel before, during, and after the pandemic using survey data from the United States. Their results showed a shift from in-person working and shopping to online alternatives and from transit to active transportation (i.e. walking and bicycling). Bari et al. (2021) investigated the traffic pattern and mode choice of the students in India, and found that parents are less interested in sending their children to school after schools/colleges reopens. Beck & Hensher (2020) analyzed longitudinal travel and activity survey data for Australia and found that a higher number of respondents would prefer to continue working from home in the future. Although preference for work-from-home and online learning has been extensively explored, there exists a literature gap in investigating how work-from-home and online learning will impact the activities that individuals may perform in a typical day, traffic patterns and travel distances. To that end, a transportation simulation model needs to be developed which will give insights into travel behaviour and traffic pattern.

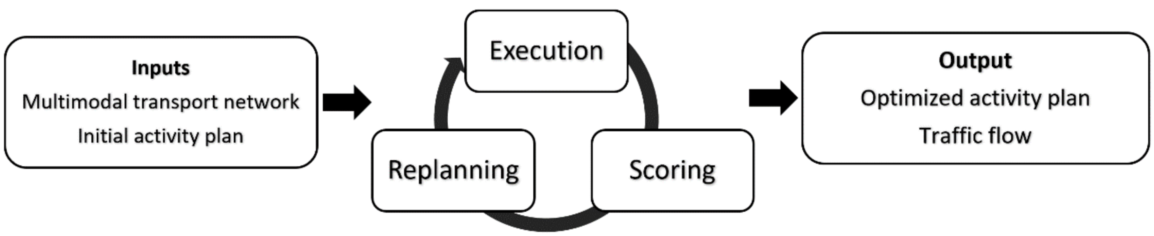
Over the years, the traditional four-stage travel demand model has been widely used, which estimates aggregate-level travel demand in four steps–trip generation, trip distribution, mode split, and route assignment. The model typically takes the origin-destination (O\D) matrix for the peak hours as an input. In this process, the dependency between an individuals' different trips (i.e., trip chain) during the day is not captured (Rasouli & Timmermans, 2014). Furthermore, this modelling framework cannot capture the temporal, spatial and population resolution at the disaggregate level. Flexible work-place and online learning options may affect travel behaviour of the individuals and result in peak hour spreading and shifting. To assess the impact of such transportation policy, a modelling framework is required which can incorporate disaggregate individual-level travel decisions and provide insights into travel demand and traffic patterns at micro-spatial and micro-temporal resolution. Therefore, this study develops an agent-based dynamic traffic simulation model following an activity-based modelling approach. Activity-based modelling assumes that trips are generated from individuals' desire to participate in different activities (Davidson et al., 2007; Zhang & Levinson, 2004). This modelling approach operates at disaggregate individual- and household-level and captures temporal and spatial interdependencies while people organize their daily activities in time and space (Liao et al., 2013). Thus, the modelling framework can accommodate individual's travel behaviour changes due to policy interventions such as flexible work-place and e-learning. This study contributes to the existing literature by investigating how flexible work-place and e-learning policy changes the trips for different trip purposes, departure times and travel distances adopting an agent-based modelling framework.

## 3. Methodology

The 24-hour agent-based traffic simulation model is developed in Multi-Agent Transport Simulation (MATSim). It adopts an activity-based multi-agent simulation framework to simulate large-scale transportation network. The model considers individuals as the agents and uses their daily travel activity plan as the input; thus, changes in travel behaviour and traffic flow due to time-sensitive policy can be accommodated in this modelling framework. The activity plan of an agent includes all the activities as well as the connecting trips that an individual plans to perform. Based on the activity plans, agents are simulated in a multi-modal transportation network consisting of links (i.e., road segments) and nodes (i.e., intersections). MATSim adopts a co-evolutionary algorithm to reach a user-equilibrium state in the iterative process. The model optimizes the initial daily plans of each agent by iteratively running the following three components: (1) execution, (2) scoring, and (3) replanning (Axhausen, 2016). In the execution step, the agents are assigned into the transportation network, and the activity plans of the agents are simulated following a queue-based approach (Hörl et al., 2018). The travel mode carrying the agent is added to the tail of the waiting queue as soon as the agent departures from a location (i.e. origin) and enters into a link to travel to a destination for performing an activity. The mode doesn't move until it can travel to head the of waiting queue with free flow speed. After reaching the head of the waiting queue, the mode travel from one link to another if the following link has space and stops where it can travel with free-flow speed. In this process. Thus, the traffic is simulated, and it slows down if the link capacity is reached. A score is generated for the simulated activity plan of agent, $i$ in the next step based on the defined utility (Ziemke et al., 2015) as shown in equation (1):

$$U_i = \sum_{a \in i} U_a + \sum_{t \in i} U_t \tag{1}$$

where, $U_a$ and $U_t$ correspond to the utility of activity and travel, respectively. This study utilizes standard MATSim scoring parameters to generate an agent's plan score. In the replanning step, activity plans are modified through innovative strategy modules that update the plan based on routing the agent through different routes, adjusting departure time, etc. (Hörl et al., 2018). The modified plan enters into the iterative process, and its' score is compared with the score of the previous one. An activity plan with a higher score is retained, and thus, optimal daily plan and




traffic flow are obtained. The model is simulated for 5% agents of the population; therefore, the flow and storage capacity is scaled down (Ziemke et al., 2015) to constrain traffic movement for the sample population. To validate the model, link capacity and free flow speed are used as calibration parameters.

**Figure 1:** Multi-Agent Transport Simulation (MATSim) modelling framework

## 4. Data

For developing the dynamic agent-based traffic simulation model, a 24-hour activity plan and multimodal transportation network are required as input. In this regard, the study utilizes 2018 Okanagan travel survey (OTS) data to generate the 24-hour activity plan. In addition, OpenStreetMap and General Transit Feed Specification (GTFS) have been used to build the multimodal transportation network. The 2018 OTS reports travel diary for 8632 individuals, which includes trip purpose, O\D location, departure time, trip duration, travel mode etc. The survey also includes personal information, i.e., age, occupation class and status, home location, work location, school location etc. In the survey, occupation status has 11 types which are further aggregated into the following four types for this study: (1) full-time worker, (2) part-time worker, (3) student, (4) non-worker. This study considers only those individuals who are aged 18 years or above since individuals below 18 years mostly travel with their parents. It is also considered that an individual can participate upto five episodes for any activity type. After removing the responses which don't meet the requirements, a total of 8192 respondents are considered for the analysis which is 5% of the total population.

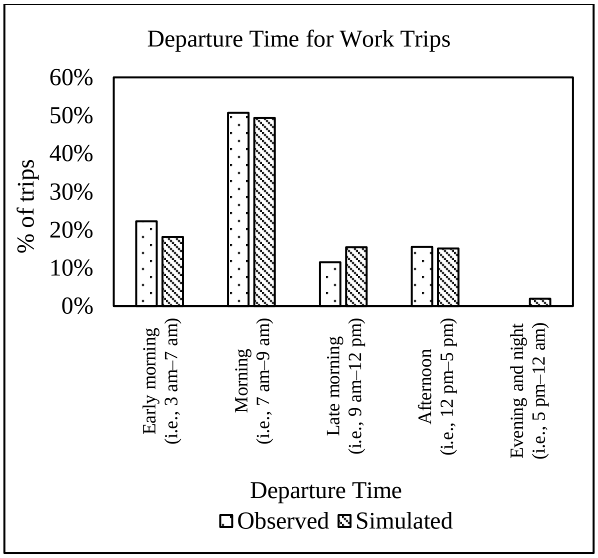
## 5. Scenario Development

The study has developed five scenarios to assess the impact of flexible work-place/online learning on the number of trips for different trip purposes, departure times and travel distances in the post-pandemic future. These scenarios include a certain percentage of full-time workers and students (10%-50% at 10% increment) who will have the flexibility to work-from-home and attend online classes, respectively. To generate the activity plans for these scenarios, workers and students who didn't travel to work/school have been identified. According to the survey, 459 full-time workers and 100 students didn't make work/educational trips. The study assumes that these workers and students had the flexibility to work/study from home and have used their travel schedule to generate the 24-hour activity plan of the workers and students who will work and attend school remotely.

## 6. Results

### *6.1. Validation Results*

The model is adjusted to match the departure times, travel times, travel distances and travel modes for work trips with Census Canada's statistics for journey to work in 2016. Figures 2-4 present the validation results for the share of trips for different departure times, travel times, travel distances, and modes, respectively. The Y-axis corresponds to the percentage of trips for different attributes. Figure 2 shows that the difference between observed and simulation results varies from 1% (for afternoon work trips) to 4% (for early morning work trips) for different departure times. On the other hand, the model predicts a higher percentage of commuting trips with travel time less than 15 minutes, however, commuting trips with travel time more than 15 minutes are less compared to observation (Figure 3). The highest difference (10%) was for commuting trips with travel time between 15-29 minutes. Prediction for work trips varied from 1% to 3% over different categories based on distances (Figure 4). In contrast, the model predicted a higher modal share for auto drivers and a lower modal share for other travel modes. The comparisons indicate that the model prediction is close to observation for work trips.



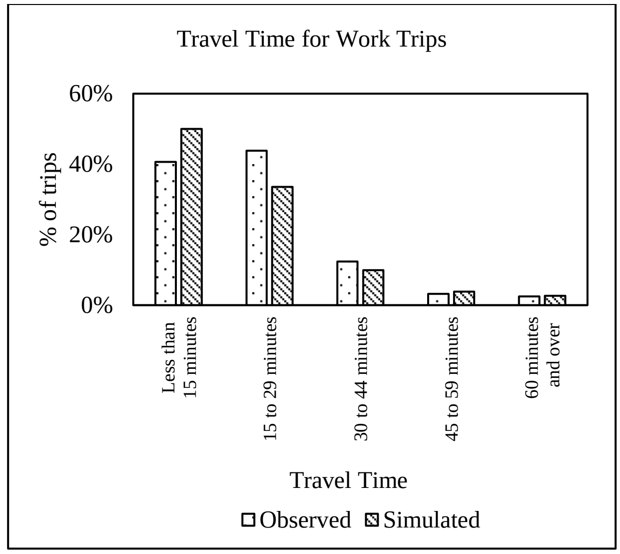
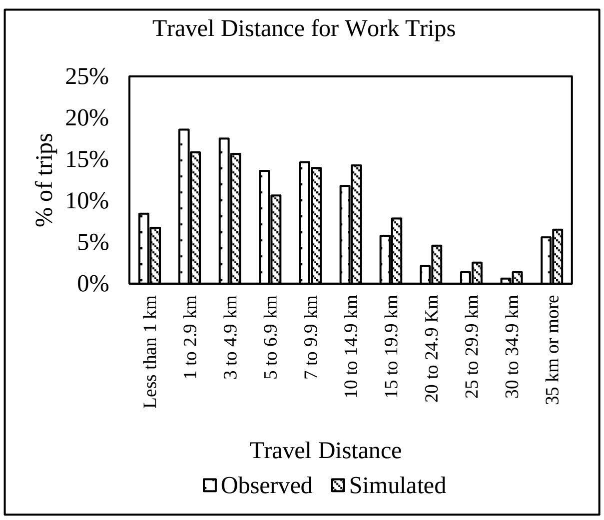




**Figure 2:** Validation results for departure time (work trips)

**Figure 3:** Validation results for travel time (work trips)



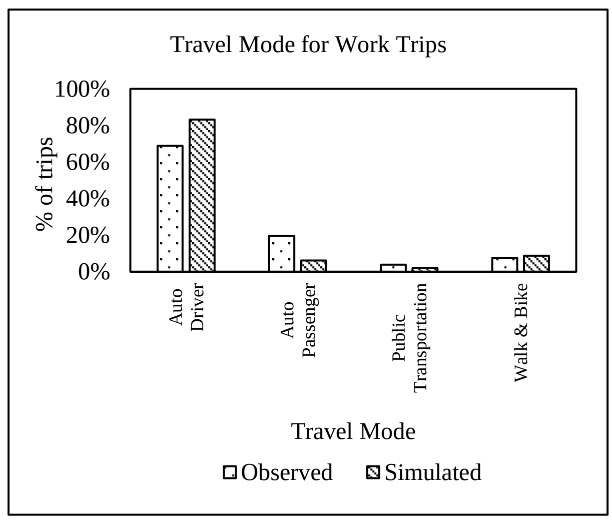




**Figure 4:** Validation results for travel distance (work trips)

**Figure 5:** Validation results for travel mode (work trips)

### *6.2. Simulation Results*

This study simulates 24-hour traffic for base scenario and different shares of workers and students remotely working/learning. The results show that individuals make the highest number of trips for work and school (~18%), followed by shopping (~13%) and social/restaurant (~9%) in base scenario. Table 1 presents the changes in the number of trips for different trip purposes if work-from-home/e-learning is introduced as a policy. Work and educational trips significantly reduce in alternative work-from-home and e-learning scenario; however, other trips with different trip purposes increase. For example, work/educational trips reduce by ~9% if 10% of workers and students are given the flexibility to work/study from home, which can reach up to ~46% if the 50% of workers and students work/attend school from home. On the other hand, personal, recreation and shopping trips increase by ~4% if 10% of workers and students have the flexibility and ~22% if the share of workers and students working/attending school from home is increased to 50%. The results indicate that workers and students who have the flexibility may travel more for different trip purposes.

**Table 1:** Changes in trip shares for different trip purposes

| Trip purpose | 10% of workers and students working/ learning remotely | 20% of workers and students working/ learning remotely | 30% of workers and students working/ learning remotely | 40% of workers and students working/ learning remotely | 50% of workers and students working/ learning remotely |
|---|---|---|---|---|---|
| Work / school | -9% | -18% | -27% | -36% | -46% |
| Personal[1] | 5% | 9% | 14% | 18% | 23% |
| Recreation[2] | 4% | 8% | 13% | 18% | 22% |
| Shopping | 4% | 8% | 13% | 17% | 20% |
| Social / Restaurant | 2% | 5% | 8% | 9% | 12% |

[1] Personal trip includes trips to bank, doctor, errands, etc.

[2] Recreation trip includes trips to gym, swimming, etc.

The changes in share of trips for different departure times are shown in table 2. Model results show that morning (i.e., 7 am–9 am) trips will reduce by 3%, compared to the base scenario when 10% of workers and students have the flexibility to work/attend classes from home. The reduction in trips is increased to 29% and 19%, respectively if the share of workers and students is increased to 50%. Flexible work-place and online learning will reduce trips to work and school, which usually take place in the morning. In contrast, the share of trips in late morning and afternoon increases with the increase in the share of workers and students remotely working/learning. It suggests that traffic will be higher in the late morning and afternoon as individuals may travel to various destinations for recreation, shopping, shopping and dining-in. Trips during the evening reduce due to the work-from-home and e-learning policy. Since workers and students do not travel to work and school, their returning trips to home may not occur, which eventually results in trip reduction during the evening. The traffic pattern during different time periods suggests that the morning peak-hour may shift to late morning or the afternoon peak-hour may be extended due to flexible work-place and e-learning.

**Table 2:** Changes in trip shares for different trip departure times

| Departure Time | 10% of workers and students working/ learning remotely | 20% of workers and students working/ learning remotely | 30% of workers and students working/ learning remotely | 40% of workers and students working/ learning remotely | 50% of workers and students working/ learning remotely |
|---|---|---|---|---|---|
| Morning (i.e., 7 am–9 am) | -3% | -7% | -11% | -15% | -19% |
| Late morning (i.e., 9 am–12 pm) | 3% | 6% | 10% | 13% | 16% |
| Afternoon (i.e., 12 pm–4 pm) | 2% | 4% | 6% | 8% | 10% |
| Evening (i.e., 4 pm–7 pm) | -1% | -2% | -2% | -4% | -4% |

**Table 3:** Changes in trip shares for different travel distances

| Travel Distance | 10% of workers and students working/ learning remotely | 20% of workers and students working/ learning remotely | 30% of workers and students working/ learning remotely | 40% of workers and students working/ learning remotely | 50% of workers and students working/ learning remotely |
|---|---|---|---|---|---|
| Less than 1 km | 6% | 7% | 9% | 10% | 12% |
| 1 to 2.9 km | 1% | 2% | 4% | 4% | 5% |
| 3 to 4.9 km | 0% | 1% | 1% | 2% | 0% |
| 5 to 6.9 km | 1% | 0% | 2% | 2% | 3% |
| 7 to 9.9 km | -2% | -2% | -1% | -1% | 0% |
| 10 to 14.9 km | -3% | -2% | -5% | -5% | -7% |
| 15 to 19.9 km | 0% | 1% | 0% | 3% | 3% |
| 20 to 24.9 Km | -2% | -4% | -5% | -7% | -7% |
| 25 to 29.9 km | 3% | 0% | 2% | 4% | 2% |
| 30 to 34.9 km | -3% | -4% | -9% | -2% | -6% |
| 35 km or more | -3% | -2% | -4% | -8% | -6% |

Flexible work-place/online learning also impacts the number of trips for different travel distances, and that is evident from the simulation results. Changes in the number of trips for different travel distances are presented in table 3. The results show that short distance trips (i.e. less than 5 km) increase if flexible work-place/online learning is adopted. For example, trips within 1 km increase by 6% if 10% of workers/students work/attend school remotely, which further increase to 12% if 50% of workers/students adopt work-from-home/online learning. Since individuals participate more in personal, recreational and discretionary activities due to flexible work-place and online learning policy, individuals may travel to the nearest locations for these trip purposes. However, long-distance trips drop with the increase of the share of workers and students remotely working and learning. The results indicate that GHG emissions may significantly drop as the long-distance trips drop with the flexible work-place/online learning policy.

## 7. Conclusions

During the COVID-19 pandemic, workers and students made adjustment in their activity plan and travel decisions as they worked and attended school remotely to stop the spread of virus. Recent studies found that individuals may prefer to work/attend school from home if they are given option to work/attend school in-person or remotely. However, there exists a gap in investigating the impact of flexible work-place and online learning on daily traffic if they are implemented as a time-sensitive policy to reduce traffic. The study develops an agent-based dynamic traffic simulation model to investigate how share of trips changes for different trip purposes, departure times and travel distances if a certain share of workers and students are given flexibility to work/study from home. Canada's Central Okanagan region has been chosen as the study area. The model is simulated in MATSim for 5% agents of the total population. A total of 5 scenarios has been developed with varying share of workers and students working/learning remotely and compared with the base scenario to estimate the changes in share of trips for different attributes. The results suggest that the share of work and school trips reduces with the adoption of flexible work-place/online learning; however, the share of trips for other purposes such as personal, shopping, social and recreation increases. It indicates that such time-sensitive policy will be effective in reducing work and school trips, however, workers and students will utilize their available time to make more trips for other trip purposes. Such changes in the share of trips for different purposes also influence the share of trips at different departure times. Trips during morning peak-hour reduce with the adoption of remote working and learning policy. In contrast, the share of trips in the late morning and afternoon increases which may be attributed to the increased number of trips to shopping mall, restaurants and places for social gatherings and personal activities. The study also founds that the share of short-distance trips increases with the increase in share of workers and students working/learning remotely. It suggests that individuals may travel more to nearby places for shopping, social and recreation etc. to get rid of fatigue after working and studying from home. However, longer-distance trips reduce gradually if the share of workers and students working/learning remotely is increased.

The study has some limitations, for example, the study generates the activity plan using data from pre-COVID period i.e., 2018 OTS data. However, the activity participation and travel decisions of this group may have changed during the pandemic which has not been explored in this study. The model has been simulated for 5% population, which has been identified as another limitation. The flow and storage capacity of road segments has been adjusted to constrain traffic movement for the sample population, so it can replicate the traffic flow if 100% population is simulated. However, the total population should be simulated by generating their activity plan of the synthetic population. The model is validated based on departure times, travel times, travel distances and mode choices for work trips only due to limited data availability. Further validation should be carried out for other trip purposes in future research. Spatial transferrability of the model hasn't been tested in this study which is identified as another of the limitations of this study. The following approach can be undertaken to deploy this model to another area. Firstly, the direct transferability of the full model can be tested. To that end, the multimodal transportation network data of the region of interest is required. For validation purposes, travel activity survey data and/or Census Canada's (if the region is from Canada) journey to work data could be useful. Traffic count data could also be useful for validating the traffic flow component of the model. Note that the model has not been validated based on traffic count in this study, which is one of the immediate future works. The predictive accuracy of the transferred model can be assessed based on goodness-of-fit measures such as root mean square error (RMSE) (Tang et al., 2015) and/or transfer index (TI) (Koppelman & Wilmot, 1982). If the results derived from this approach do not adequately represent the behaviour of the population of interest, some of the components of the model may need to be recalibrated and/or re-estimated. This recalibration/reestimation procedure will require 24-hour travel diary data from the region of interest. The study will assist the transportation researchers, planners and policymakers by giving insight into how flexible work-place and online learning will influence the individuals' traffic patterns and travel distances if it is implemented in future as a transportation demand management (TDM) strategy.

## Acknowledgements

The authors would like to thank Rogers Communications and Mitacs Accelerate for their financial support (Grant number: GR019822).

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