

# Investigating the impacts of telecommuting on the spatial, temporal and modal distribution of travel using an agent-based transport simulation model

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**Abstract:** Technological advancements over the past few decades have facilitated telecommuting, but its adoption surged significantly when travel restrictions forced workers to work from home during the pandemic. This shift significantly reduced peak-hour traffic flow and congestion, but the impact of this travel demand management strategy on 24-hour travel is not well understood. This study aims to evaluate the impacts of telecommuting on 24-hour traffic flow using an agent-based transport simulator. Methodologically, a nested structure is implemented to generate departure time, mode, and destination choice joint decisions and accommodate inter-dependencies. Given the behavioral differences among different population groups, separate models are implemented for these different groups: commuters, telecommuters, non-workers, students attending school in-person/online. Following the generation of 24-hour activities, activity itineraries are applied within a dynamic agent-based multimodal transport network model using the open-source MATSim platform. This modeling and simulation exercise has been implemented for the entire population of the Okanagan region of British Columbia, Canada. After thorough validation, the simulation results suggest that with the increase in telecommuting population, an increase in all types of non-mandatory travel is predicted to occur near the urban centers during the off-peak hours – resulting in the spreading of the peak over the day.

**Keywords:** Agent-based model, transportation network simulation, telecommuting, departure time, mode choice, destination choice, nested model

## Article history:

Received: April 21, 2024

Received in revised form:  
September 25, 2024

Accepted: October 27, 2024

Available online:  
December 19, 2024

## 1 Introduction

Telecommuting is an effective travel demand management tool to tackle traffic congestion. It has been a subject of discussion for the last three decades (Allen et al., 2015). COVID-19 pandemic brought telecommuting into the focus as the pandemic forced many to experience telecommuting and consequently proved its effectiveness in significantly reducing peak-hour traffic (Loo & Huang, 2022; Marz & Şen, 2022). Although telecommuting reduces peak hour travel, how it impacts the 24-hour travel

needs further investigation. For example, given that many telecommuters may have flexible work hours allowing them to travel for non-mandatory purposes at different time-of-day, this may change the spatial (e.g., where to travel?), temporal (e.g., when to travel?) and modal (e.g., which travel mode to choose?) distribution of their travel, for instance, an increase in off-peak hour travel. Cities and transit agencies need to have the tools such as travel demand forecasting models to predict and simulate the impacts of telecommuting so that they can support the population with their needed transportation services and infrastructures. To this end, the majority of the municipalities maintain a four-stage trip-based travel demand forecasting model, which operates at the unit of trip—i.e., travel between two locations. These models ignore the inter-relationships among trips that individuals make over their day (Rasouli & Timmermans, 2014). Also, the four-stage model is operated at the aggregate-level in the following dimensions: temporal-aggregation (i.e., dividing the whole day into multiple disconnected temporal segments such as AM-peak and PM-peak periods), spatial-aggregation (i.e., dividing the study area into multiple zones such as traffic analysis zones and assigning traffic between and within the zones), and population-aggregation (i.e., grouping the population in a zone by the socio-economic attributes such as income and assuming the travel of all individuals within a group to be homogeneous). As a result, these models are not capable of capturing the disaggregate-level temporal, spatial, and population resolution of travel. More importantly, it is challenging to examine the impacts of temporally sensitive dynamic strategies such as telecommuting on the changes in the 24-hour travel behavior using these static demand forecasting models.

The objective of this study is to microsimulate departure time, travel mode and destination location choice decisions, and test the impacts of telecommuting on the spatial, temporal and modal distribution of travel. An agent-based microsimulation technique has been adopted, and the developed simulator has two components: 1) 24-hour demand forecasting module, and 2) transport network module. Each individual and household in the study area is an agent. The input data comes from a population synthesis procedure. The 24-hour travel demand forecasting model adopts an activity-based modeling approach which assumes that individuals travel at different time-of-day to participate in different activities which are distributed over space. These travels distributed over the day are inter-connected. Prior to this demand forecasting, the whole population is grouped into telecommuters, commuters, and non-workers, among others. Given the difference in travel behavior and schedule constraints among these groups, different behavioral models for departure time, travel mode and destination location choice are implemented for these population groups to generate their 24-hour travel itinerary. The behavior model for these three travel decisions follows a nesting structure, where departure time and mode choice use a cross-nested logit model and destination location choice adopts a mixed logit model. A logsum parameter is used to create the nesting structure between destination and departure time – mode choice. Separate models are estimated for different population groups. These 24-hour travel schedules are assigned to the traffic network using an agent-based dynamic traffic microsimulation model—i.e., MATSim to analyze the overall traffic flow. The demand forecasting and traffic network models are calibrated and validated. Finally, the validated model is used to test the impacts of the alternative percentage of workers working from home on the temporal, spatial and modal distribution of traffic.

## 2 Literature review

The recent COVID-19 pandemic event has compelled people across the globe to adjust their daily activities and travel behavior to comply with the imposed restrictions on

social gatherings and traveling (Bhaduri et al., 2020). One significant adaptation has been the widespread adoption of telecommuting among workers, which has led to a substantial reduction in traffic during the morning peak hour as work-bound trips are replaced by work-from-home arrangements (Wang et al., 2021). Consequently, there has been a notable decrease in greenhouse gas (GHG) emissions, with Canada experiencing an ~8% reduction in road transportation emissions in 2020 compared to 2019 (Environment and Climate Change Canada, 2020). The decline in traffic congestion and GHG emissions during the pandemic has renewed cities and transit agencies' interest into telecommuting as a potential travel demand management (TDM) strategy after its initial introduction five decades ago (Allen et al., 2015). Studies conducted during the pandemic, such as the work by Beck and Hensher (2020), analyzing longitudinal travel and activity data in Australia, have revealed that workers may continue to opt for telecommuting if given the option. This preference may be attributed to an improved work-life balance while telecommuting and the cost savings associated with reduced office-related expenses. Promoting telecommuting as a TDM strategy raises questions about its potential impact on traffic flow and GHG emissions when a certain percentage of workers are given the option to work from home. To address this, it becomes crucial to investigate the travel behavior of telecommuters in comparison to other population groups, as the spatio-temporal distribution of traffic on the road network depends on how different groups make their travel decisions, including trip purpose, frequency, destination, departure time, travel mode, and route choice. While several recent studies have focused on understanding the travel behavior of telecommuters, there has been a notable gap in research exploring how this behavior differs from that of other groups within the population (Asgari et al., 2016; Budnitz et al., 2020; Victoriano-Habit & El-Geneidy, 2023). For example, Asgari et al. (2016) examined activity duration for various activity types and the number of total daily trips for telecommuters in New York, U.S., using the Regional Household Travel Survey Data from 2010-2011. They utilized structural modeling equations to investigate the impact of different levels of telecommuting (part-day and full-day telecommuting) on travel attributes. Interestingly, their study revealed that telecommuting not only increased time allocation for non-mandatory activities but also resulted in an increase in the total number of daily trips. One key aspect that the study overlooked was a comparative analysis of how these travel decisions made by telecommuters differ from those of commuters. To address this limitation, Khaddar et al. (2023) employed the multiple discrete-continuous extreme value with ordered preferences (MDCEV-OP) model to understand the participation of telecommuters and commuters in various activities, along with their corresponding frequency and duration. Their findings indicated that telecommuters were more likely to engage in non-mandatory activities with higher frequency than commuters.

Despite these efforts to understand specific travel decisions made by commuters and telecommuters, some limitations persist. Most notably, studies often overlooked incorporating sequential decision-making in their analysis for both groups and other population segments, such as non-workers and students. On the other hand, each travel decision has an association with another decision, even some are made jointly. Individuals often make choices about departure time, destination, and travel mode simultaneously due to shared influencing factors and interdependencies between decisions (Golshani et al., 2019). Furthermore, these joint decisions are influenced by the activity type and the population group type, i.e., telecommuters, commuters, non-workers, students, etc. The scope of many studies did not encompass all these decisions, which are pivotal in understanding traffic flow patterns. Integrating differences in travel behavior among the population groups into modeling systems is crucial to capture the potential impact of widespread telecommuting adoption.

Methodologically, activity-based model such as ALBATROSS, CEMDAP, DaySim, iTLE, PCATS, TASHA etc., simulate disaggregate-level 24-hour activity schedules, providing the opportunity to accommodate travel decisions of different groups into the modeling framework. These models have also been integrated with a dynamic traffic simulation platform to test different futuristic scenarios. For example, TASHA was integrated with EMME (Roorda et al., 2008) and MATSim (Hao et al., 2010); PCATS with Dynamic Event-Based Network Simulator (DEBNetS) (Pendyala et al., 2012), CEMDAP with visual interactive system for transport algorithms (VISTA) (Lin et al., 2008), DaySim with TRANSIMS etc. PCATS (Pendyala et al., 2005), CEMDAP (Bhat et al., 2004) and DaySim (Bradley et al., 2010) incorporated travel decisions of different population groups, such as workers and others, in their modeling framework, however, these models do not incorporate the behavioral differences between telecommuters and commuters within the worker group. Shabanpour et al. (2018) addressed this limitation by developing a zero-inflated hierarchical ordered probit model to investigate workers' likelihood to adopt telecommuting. They then assessed its potential impact on travel patterns and traffic networks using the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model (Auld & Mohammadian, 2009) integrated into the POLARIS framework. In their approach, workers who adopted telecommuting, their work activity was replaced by in-home activity and their preference to participate in other activities was accommodated using rule-based approach. Although telecommuters' travel decisions differ from those of commuters, this distinction was not accommodated in the modeling framework. On the other hand, the literature suggests that travel decisions such as destination, departure time and travel mode choice are decided jointly (Elmorssy & Onur, 2020; Golshani et al., 2019; Lamondia et al., 2010). However, the existing ABM didn't incorporate three-dimensional joint decisions in the modeling framework. For example, TASHA, ADAPTS and CEMDAP simulated the destination location, departure time and travel mode choice as independent decisions. In PCATS, the destination and travel mode choice decisions are predicted using a nested logit model where the decision of travel mode is conditional upon destination choice. This limitation prevents a comprehensive understanding of the complexities involved in travel decision-making processes.

To address the gap in the literature, this study adopts a joint model that combines destination location, departure time, and travel mode choice using a nested structure. The model is estimated for three distinct population groups in Okanagan region: commuters, telecommuters, and non-workers. A mixed logit modeling technique was adopted to generate destination choice and a cross-nested logit model for departure time and travel mode choice. The models are connected through a feedback mechanism that incorporates the expected maximum log-likelihood value (logsum) from the destination choice model into the departure time-travel mode model. This feedback mechanism captures how accessibility to different destinations impacts the decisions regarding departure time and travel mode. For the traffic simulation, the study employs the Multi-Agent Transport Simulation (MATSim) model. This transport model can effectively simulate both traffic and transit on the network, including their interactions. Using this modeling framework, the study explores the effects of various Transportation Demand Management (TDM) scenarios, specifically how different percentages of workers adopting telecommuting influence the 24-hour activity patterns and traffic flow. The contributions of this study are three-fold: (1) integrating a joint model for destination location, departure time, and mode choice into an agent-based multimodal transport network microsimulation model, (2) generating a 24-hour activity schedule for different population groups while considering their distinct behavioral attributes, (3) utilizing the agent-based model to evaluate the

effects of alternative TDM strategies on the 24-hour activity patterns and traffic flow in the transportation network.

### 3 Data

The agent-based travel microsimulation model is developed and simulated for the Okanagan region, located in southern British Columbia (BC), Canada. Inputs to the modeling system include synthetic population data, activity locations, built environment characteristics, and transportation-infrastructure related variables. The synthetic population was developed using a Bayesian network and generalized raking techniques, and details can be found here (Rahman & Fatmi, 2023). The synthetic data has several household-level and individual attributes, which include dwelling type, number of rooms, household size, age distribution, marital status, education level, income level, childbirth rates and death rates based on 2016 census data. The study focuses on individuals aged 17 and above (205,681 individuals), as this is the earliest age to be an independent auto driver through obtaining a driving license and does not need a supervisor while driving. The study also utilizes 2018 OTS which reports travel diary for 8632 individuals including trip purpose, O\D location, departure time, trip duration, travel mode etc. Activity locations (i.e., destination alternatives) related information is collected from Desktop Mapping Technologies Inc. (DMTI). Each location in the dataset represents parcel-level data, providing information about the specific activities performed at that particular location. For the work activity, work locations are sub-categorized based on 10 major groups in the National Occupational Classification (NOC) system. Built environment characteristics and transportation infrastructure-related variables are collected from the open data portal of Okanagan municipalities, Statistics Canada and Abacus. Built environment characteristics include dwelling density and land-use information, specifically residential and commercial land uses. Transportation infrastructure-related variables consisted of sidewalk and bike lane lengths and length of transit route, and additional land-use information. Travel attributes include travel time of the car between each origin-destination pair, which was generated using Network Analyst toolbox in ArcMap. OpenStreetMap and General Transit Feed Specification (GTFS) have been used to build the multimodal transportation network in the traffic network module.

### 4 Methodology

The focus of this study is to microsimulate departure time, mode choice and destination location choice decisions for commuters, telecommuters, and non-workers, and test the impacts of alternative telecommuting scenarios on the spatial, temporal and modal distribution of travel. This simulation exercise is implemented within a large-scale agent-based 24-hour travel simulation tool that follows an activity-based approach. The overall modeling framework of this simulation tool is shown in Figure 1, and briefly discussed below. This transport simulation tool comprises two core modules: (1) travel demand module and (2) transport network module. Within the travel demand module, a 24-hour travel schedule is generated, accommodating the heterogeneity of individuals belonging to different population groups, including commuters, telecommuters, non-workers, students attending school in-person, and students attending school online. Subsequently, the travel decisions of each individual are simulated in the transport network module to evaluate traffic flow and assess various scenarios. The synthetic population does not include work arrangement information such as work-from-home or commuter status. To determine that, first, whether an individual is part of the labor force or not is assigned based on the dissemination area (DA) level (i.e., smallest spatial unit

for which census information is reported) distribution in the census. Subsequently, the labor force's employment status (i.e., employed or unemployed) is assigned based on DA-level distribution. Following that, rule-based techniques are used to assign the population groups, such as workers, non-workers, and students, based on age, labor force and employment status. For instance, individuals who are employed are classified as workers (60%). Among those not part of the labor force and below 26 years old, 1% of the population is considered as students, while the rest are categorized as non-workers. The assignment of worker types, such as telecommuter or commuter, is based on the DA-level distribution of workers working from home, derived from census data. In this study, 10% of workers are categorized as telecommuters for the baseline, while the remaining workers are considered commuters. Similarly, students are divided into two categories, either attending school in-person or online, based on the distribution observed in OTS data. In summary, the population has been grouped into:

1. Telecommuters
2. Commuters
3. Non-workers
4. Students attending school in-person
5. Students attending school online

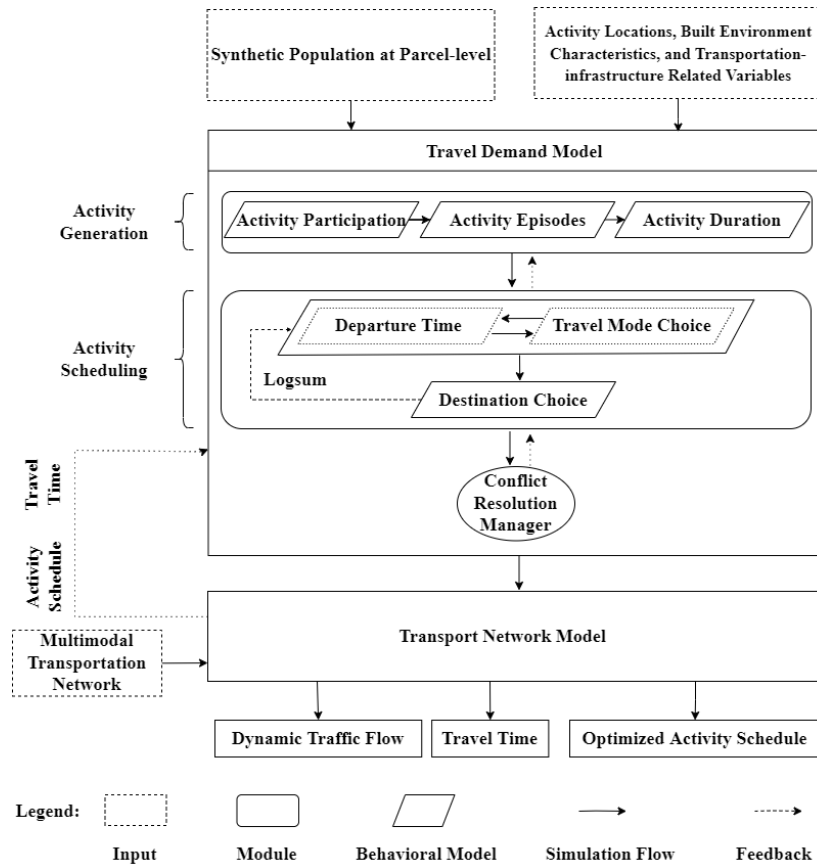


Figure 1. Agent-based modeling conceptual framework

Once the population groups are generated, the two core components, the travel demand module and transport network module are simulated accordingly to analyze travel behavior and the impacts on the transportation network.

#### 4.1 Travel demand module

In the travel demand module, agents' activities and travel decisions are simulated, and a 24-hour activity schedule on a typical weekday for the entire population is generated. The model features modular-based advanced heuristics and econometric micro-behavioral approach. The module has two sub-modules: activity generation and activity scheduling. Activities and travel decisions are generated for individuals belonging to the five groups in the population simulating these sub-modules.

##### 4.1.1 Activity generation

The activity generation sub-module operates by simulating individual-level participation in various out-of-home activities, their episodes and duration on a typical weekday, utilizing the trip distribution observed in OTS data. The out-of-home activities are categorized into eight groups, namely work, school, pick up and drop off, shopping, personal, social, recreation, and dine-in. To begin, the sub-module generates the activities performed by individuals based on the distribution of activity types. Subsequently, the episodes for each activity type are randomly drawn from the distribution of episodes, which is conditioned on the specific activity types. The activity duration for each activity type is randomly drawn from a joint activity type-duration probability density function for different population groups.

##### 4.1.2 Activity scheduling

In the activity scheduling submodule, departure time, destination, and travel mode decisions are generated for each activity performed by an individual. For the telecommuters, commuters and non-workers, these decisions have been simulated by implementing a nesting structure. Details of the model formulation and the results can be found here (Saha et al., 2024). A mixed logit (MXL) modeling technique is adopted to simulate the destination choice, where the probability of choosing a destination ( $d$ ) in an individual's ( $i$ ) choice set,  $P_d(i|\Phi)$  is expressed as:

$$P_d(i|\Phi) = \int \frac{e^{\beta_d X_{id}}}{\sum e^{\beta_d X_{id}}} f(\beta_d|\Phi) d\beta_d \quad (1)$$

Where,  $X_{id}$  is a vector of explanatory variables,  $\beta_d$  is a vector of estimable parameters which may vary across observations,  $\Phi$  is the vector of the density function parameters and  $f(\beta_d|\Phi)$  is the density function. Following that, a cross-nested modeling technique was employed to generate departure time and travel mode choice. The influence of destination choice has been incorporated into joint departure time-mode choice model through expected maximum utility (logsum) feedback. Based on the GEV theory, the probability of choosing departure time and travel mode joint decision alternative,  $j$  is as follows:

$$P(j) = \sum_n \frac{(\alpha_n e^{c + \beta_{tm} X_{itm} + \beta_d' \text{Logsum}})^{\frac{1}{\mu_n}}}{\sum_j (\alpha_n e^{c + \beta_{tm} X_{itm} + \beta_d' \text{Logsum}})^{\frac{1}{\mu_n}}} \frac{\left[ \sum_j \left( (\alpha_n e^{c + \beta_{tm} X_{itm} + \beta_d' \text{Logsum}})^{\frac{1}{\mu_n}} \right) \right]^{\mu_n}}{\sum_n \left[ \sum_j \left( (\alpha_n e^{c + \beta_{tm} X_{itm} + \beta_d' \text{Logsum}})^{\frac{1}{\mu_n}} \right) \right]^{\mu_n}} \quad (2)$$

Here,  $X_{itm}$  is a vector of attributes affecting individual,  $i$ 's departure time,  $t$  and travel mode,  $m$  joint decision and  $\beta_{tm}$  is a vector of coefficients and  $\beta_a'$  is a vector of logsum coefficients. The model estimates the probability of choosing a specific departure time-travel mode alternative based on various patterns of similarity and dissimilarity among choice alternatives defined by the dissimilarity parameter,  $\mu_n$  (Ding et al., 2015), thus allowing to capture multidimensional correlation.

The results for the destination location choice model suggest that travel attributes, individual and household characteristics, transportation infrastructure-related variables and built environment characteristics significantly influence the destination location choice decision (Saha et al., 2024). For example, middle-aged and elderly telecommuters and non-workers show a positive preference for destination alternatives located close to their residences, while commuters are more open to choosing destinations that may be further away from home. Furthermore, the joint model for departure time and travel mode choice suggests that logsum values derived from the destination location choice model have a positive relationship with the departure time-travel mode choice. It confirms the association of the destination location choice decision with departure time and travel mode choice decisions. The results also suggest that trip purpose, individual characteristics, household characteristics and travel attributes have a significant effect on departure time and travel mode decisions. For example, middle-aged and elderly telecommuters and non-workers exhibit a lower likelihood of using public transit during off-peak hours. Since they are traveling from home and transit services in their residential areas during those times are infrequent, they are more intended to use cars. The dissimilarity parameters for telecommuters are significantly low and closer to 0 than that of commuters, indicating telecommuters' flexibility to change their departure time and travel mode compared to commuters.

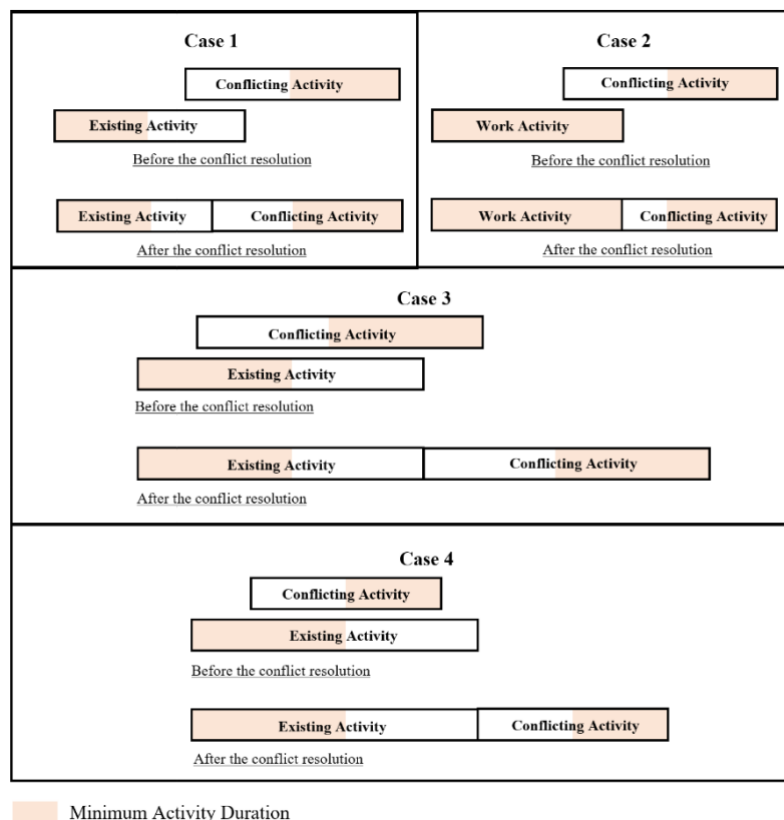
In the initial simulation process, the individual's activity sequence is initially unknown, though the travel time from the origin to potential destinations is considered as an input. Therefore, in the first simulation, the car travel time is set to 15 minutes, which represents the average car travel time of the observed trips. After the simulation process is done, the major activity points, as well as the sequence of activities, are obtained, which again gives feedback in the iterative process. The nested model for departure time, mode and destination choices was not developed for students who are attending school in-person or online. Therefore, these decisions were generated for students utilizing a Markov Chain Monte Carlo modeling approach, where their destination, departure time, and travel mode depend on the activity they are performing.

#### 4.2 Conflict resolution manager

Conflicts may occur within scheduling different activities for an individual due to overlapping, which are resolved by the activity conflict resolution manager (CRM). To resolve any conflicts arising from extended activities, CRM updates different activity attributes accordingly with the feedback mechanism. After the travel demand module is simulated, CRM implements the following temporal and institutional constraints:

1. Total time spent in a day never exceeds 1440 minutes (24 hours)
2. No school activity begins before 8 am and ends after 3 pm
3. No shopping begins before 7 am and ends after 10 pm
4. No social activity starts sooner than 7 am or later than 10 pm
5. No personal activity starts sooner than 7:30 am or later than 10 pm
6. No recreational activity starts sooner than 6 am or later than 10 pm

If any conflict occurs due to these constraints, the whole day activity schedule is modified. While forming the 24-hour activity schedule for an individual, conflict may arise, which can be categorized into two types (1) partial overlapping and (2) complete overlapping. To resolve the conflicts, activities are ranked based on the following activity priority order: (1) work/school, (2) personal, pickup/drop off, (3) recreation, shopping, social, and restaurant. If two activities have the same rank, the activity with a longer duration is given the highest priority. Work and school are the fixed mandatory activities, and other activities are considered as non-mandatory activities, which are flexible. Conflicts are resolved sequentially based on the ranking and the type of conflict. If an activity partially conflicts with a higher-ranked activity, it is resolved by first adjusting the duration and then shifting the activity (Figure 2). In the case of duration adjustment (Case 1), the duration can be reduced proportionately by up to 50% of the original duration. However, if the new activity conflicts with a mandatory activity (i.e., work or school) (Case 2), the duration of the mandatory activity remains unchanged while the duration of the new activity is truncated. If the duration needs to be truncated by more than 50% for existing activity and/or new activity, the new activity is shifted to the earliest gap, which will not create any conflict (Case 3). The same rule applies if the new activity completely overlaps with the existing activity (Case 4). If no gap is available, the activity is removed from an individuals' activity schedule. Once the conflicts are resolved, the activity schedule is conveyed into the transport network model.



**Figure 2.** Conflict resolution manager

### 4.3 Transport network module

This study adopts Multi-Agent Transport Simulation (MATSim) modeling framework to simulate the large-scale transportation network. The model considers individuals as agents and uses their daily travel activity schedule as the input; thus, changes in travel behavior and traffic flow due to time-sensitive policy can be accommodated in this modeling framework. The activity schedule of an agent includes all the activities as well as the travel decisions for connecting trips that individual plans to perform. Based on the activity schedule, agents are simulated in a multimodal 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. In the execution step, the agents are assigned into the transportation network, and the activity schedules of the agents are simulated following a queue-based approach (Axhausen et al., 2016). A score is generated for the simulated activity schedule of an agent,  $i$  in the next step based on the defined utility (Ziemke et al., 2015) as shown in Equation 3:

$$U_i = \sum_{a \in i} U_a + \sum_{t \in i} U_t \quad (3)$$

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, rerouting strategy module is used to route the agent through different routes, optimizing the traffic flow (Hörl et al., 2018).

### 4.4 Calibration of the agent-based transport simulation model

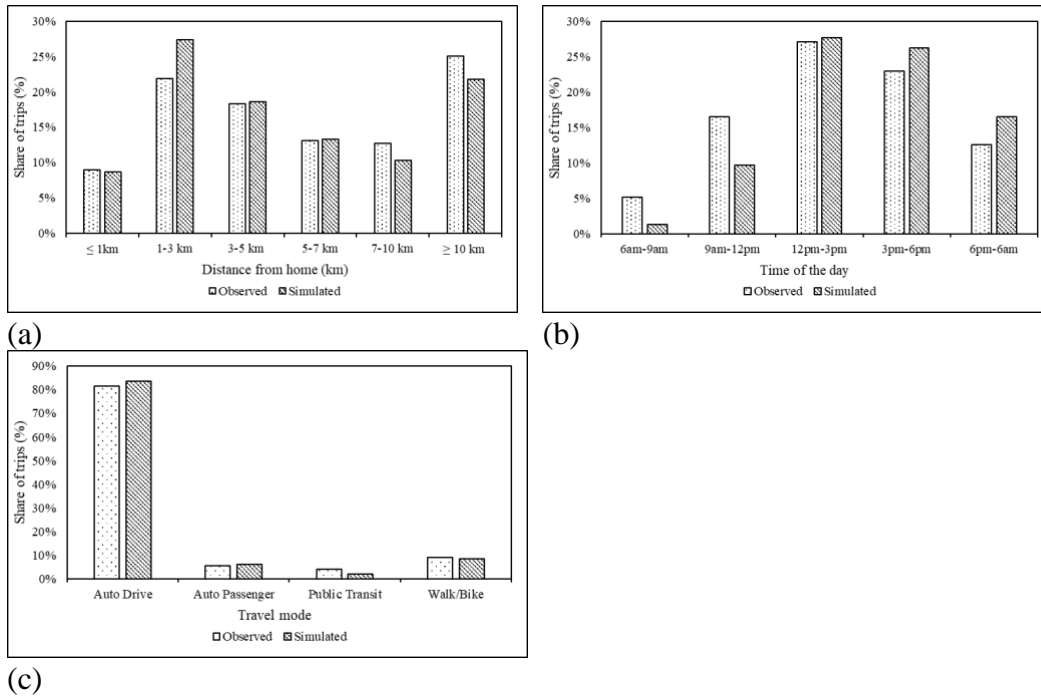
The estimated model parameters, i.e., alternative specific constants of destination choice, departure time choice, and travel mode choice joint model are adjusted for the calibration of the travel demand module. The distributions for the distance of the destination from home, departure time and travel mode for telecommuters, commuters, and non-workers are generated from the 2018 Okanagan Travel Survey data and used as a reference for calibration. In case of distance of the destination from home, trips are divided into 6 categories:  $\leq 1$ km, 1-3 km, 3-5 km, 5-7 km, 7-10 km, and  $\geq 10$  km. For all population groups, the difference between observed and simulated trips across different distance categories is 0% - 4%. For the departure time, the trip distribution is estimated for the following time segments: 6 am-9 am, 9 am-12 pm, 12 pm-3 pm, 3 pm-6 pm, and 6 pm-6 am. The difference for these time segments ranges from 0% to 7%. In the case of mode choice, the modal share of auto drive, auto passenger, public transit, walk, and bike was compared, and the difference is limited to 0%-2%. In case of traffic assignment in MATSim, flow capacity, storage capacity and free flow speed of the transportation network are usually adjusted when a sample of the total population is simulated to replicate the traffic flow (He et al., 2021). However, this study simulates the 100% population; therefore, no parameter adjustment was performed for the transportation network module.

## 5 Transport microsimulation results

This section presents the microsimulation results. At first, the microsimulation results are validated, followed by a discussion on the simulation results for alternative telecommuting scenarios.

### 5.1 Validation results

The validation of the model involves comparing the travel demand attributes such as commuting departure time, commuting travel mode and distance of workplace from home, as well as transport network attributes such as hourly traffic counts. In the case of the travel demand attributes, commute trip characteristics are validated using the 2016 journey to work data from Census Canada. For the distance of the workplace from home (Figure 3a), the observed and simulated commute trip shares show a difference of few percentage points for the majority of the case. For example, the model predicted that 8.7% of the trips are within 1 km from home, which is closely aligned with the observed (9%). The highest difference (5%) is found for trips where workplaces are located within 1-3 km from home. Regarding departure time (Figure 3b), the difference between observed and simulated commute trip shares for different times of the day ranges from 1% to 6%. The simulated commute trip shares for travel modes (Figure 3c) indicate an 83% share for auto drive and 2% for transit, whereas the observed shares for these two travel modes are 82% and 4%, respectively.



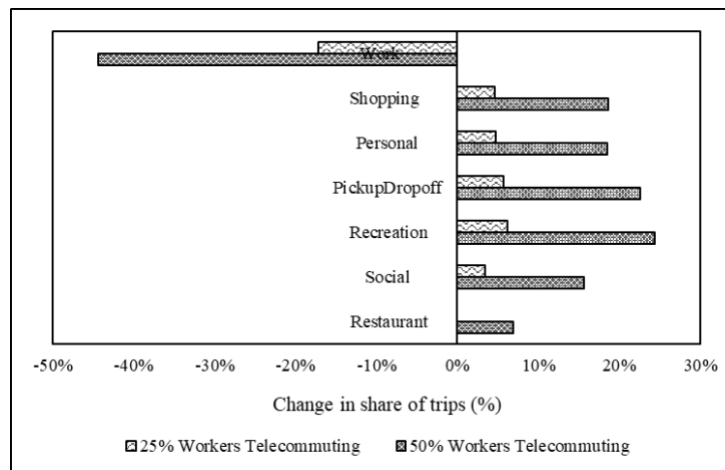
**Figure 3.** Validation results for (a) commuter's workplace distance from home, (b) commuting departure time, (c) commuting travel mode

To validate the model based on traffic counts, 2019 traffic counts are collected. Major road segments such as highways and arterials which are classified as motorway, trunk, and primary in the OpenStreetMap, have been selected for validation. Traffic volume for both peak hours and off-peak hours for 17 road segments are considered. The results suggest that the average relative difference between observed and simulated hourly counts is 30.9%, and the median difference is 26.3%. Despite a few large outliers, the error in the predicted traffic count is comparable to that of MATSim-NYC, a regional model for New York (He et al., 2021). Overall, the validation results suggest that the simulation model reasonably captures the travel behavior of the population and is well-suited for further scenario testing.

## 5.2 Simulation results for alternative telecommuting scenarios

The microsimulation model for the base scenario includes 10% of the workers telecommuting. The alternative scenarios are developed assuming 25% and 50% of the workers telecommuting. This exercise aims to provide insights into the impacts of alternative flexible work-place strategies on daily travel activities and road network.

The baseline simulation results reveal that the highest number of predicted trips are for work (~36%), followed by shopping (~19%) and personal activities such as visiting a doctor, going to bank etc. (~14%). The changes in the number of trips for different trip purposes in different scenarios compared to the baseline scenario have been presented in Figure 4. An increase in the share of telecommuters does reduce work trips; however, trips for other purposes such as recreation, personal business, shopping, and social are predicted to increase. For example, for the 25% telecommuter scenario, work trips are predicted to reduce by ~17% and ~44% for the 25% and 50% telecommuting scenarios. On the other hand, non-mandatory activities are predicted to increase significantly with the increase in telecommuter share. For example, recreational trips are predicted to increase by ~6% and ~24% for the 25% and 50% telecommuter scenarios, respectively. The results indicate that telecommuters are predicted to attend more non-mandatory activities. Due to this, the share of non-mandatory trips is predicted to increase with the increasing share of telecommuters.



**Figure 4.** Predicted changes in trips for different trip purposes

**Figure 5** illustrates the share of different travel modes for commute trips. The results indicate that as the share of telecommuters increases, the predicted number of commute trips made by different travel modes reduces. The most substantial reduction is predicted for auto mode. On the other hand, non-mandatory trips by different travel modes increase with the increase in the share of telecommuters as shown in Figure 6. For example, the share of auto drivers is predicted to increase by 6,900 (~4%) compared to the base scenario. Auto driver trips are predicted to increase by 27,900 trips (~18%) when 50% of workers work from home. In addition to the increased auto driver trips, the number of non-mandatory trips by other travel modes also increase. Nevertheless, with a substantial decrease in commute trips by auto drivers in contrast to the modest increase in non-mandatory trips, the increase in the share of telecommuters leads to fewer cars in traffic.

The distribution of travel distances for commute and non-mandatory trips are presented in Figure 7 and Figure 8, respectively. For commute trips, trips in all distance categories are predicted to reduce in different scenarios. The highest reduction is

predicted for long-distance trips (greater than 10 km). For example, for the 25% telecommuter scenario, 6,200 long-distance trips are predicted to reduce, while the reduction is 16,000 trips for the 50% telecommuting scenario. On the other hand, short-distance non-mandatory trips are predicted to increase as the share of telecommuters increases. The increase is higher for short-distance trips, specifically for trips where the travel distance is 1-3 km, followed by 3-5 km. Non-mandatory trips with 1-3 km and 3-5 km travel distances increase by 12,500 and 8,600 trips, respectively when 50% of workers telecommute. Table 1 presents the VKT and the amount of GHG emissions for different scenarios. The results suggest that VKT in the base scenario is predicted to be  $2,259 \times 10^3$  km, resulting in 244,042 kg CO<sub>2</sub>, 7,005 g CH<sub>4</sub>, and 4,293 g NO<sub>2</sub> emissions. With a higher share of telecommuters, GHG emissions are predicted to reduce. For example, there will be a 12% reduction in GHG emissions when 25% of workers are working from home, which is predicted to reach 18% when 50% of workers are telecommuting. Although a higher reduction in VKT was expected with a higher share of workers telecommuting, due to increased non-mandatory trips, the reduction was predicted to be less than anticipated.

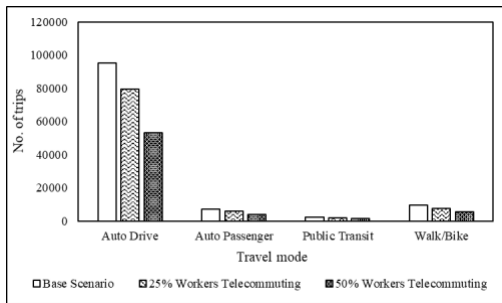


Figure 5. Predicted number of commute trips for different travel modes

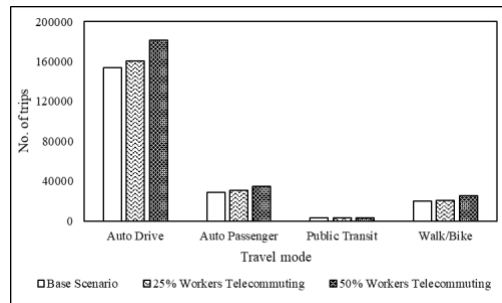


Figure 6. Predicted number of non-mandatory trips for different travel modes

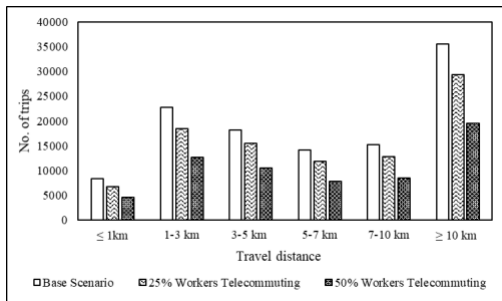


Figure 7. Predicted number of commute trips for different travel distances

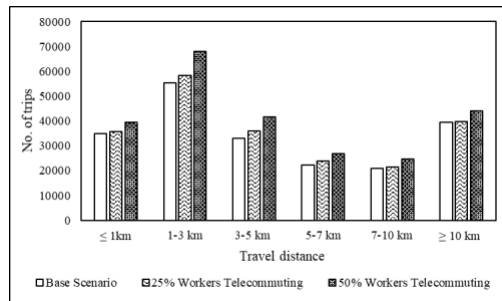


Figure 8. Predicted number of non-mandatory trips for different travel distances

**Table 1.** VKT and GHG emissions in alternative telecommuting scenarios <sup>1</sup>

Scenario	VKT	CO <sub>2</sub>	CH <sub>4</sub>	NO <sub>2</sub>	Reduction in GHG
Base scenario	2,259 × 10 <sup>3</sup> km	244,042 kg	7,005 g	4,293 g	-
25% Workers Telecommuting	1,992 × 10 <sup>3</sup> km	215,185 kg	6,177 g	3,786 g	12%
50% Workers Telecommuting	1,844 × 10 <sup>3</sup> km	199,248 kg	5,719 g	3,505 g	18%

The trip distribution over a 24-hour period in alternative telecommuting scenarios is shown in Figure 9. The results suggest that in the base scenario, the AM peak hour was observed from 7 am to 9 am, while the PM peak hour occurred from 3 pm to 5 pm. As the share of telecommuters increases in the population, a noticeable decline in the AM peak period is observed, and traffic gradually increases during off-peak hours. Particularly, when the share of telecommuters reaches 25%, the morning peak starts to shift towards the off-peak hours. The peak-hour spreads further during mid-day when 50% of workers choose to work remotely. This shift in peak hours can be attributed to telecommuters having work flexibility, allowing them to engage in non-mandatory activities.

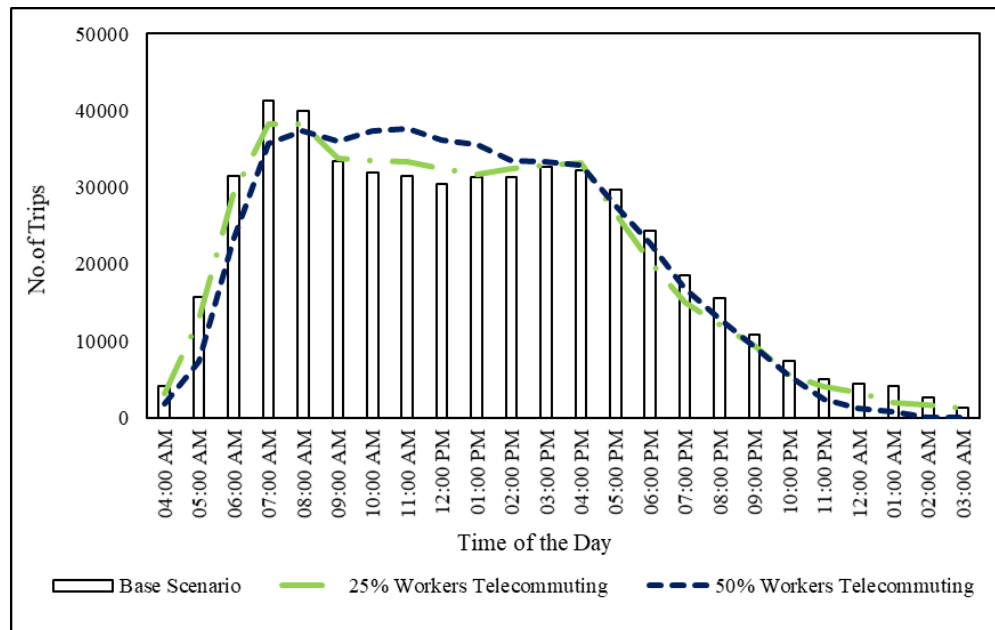
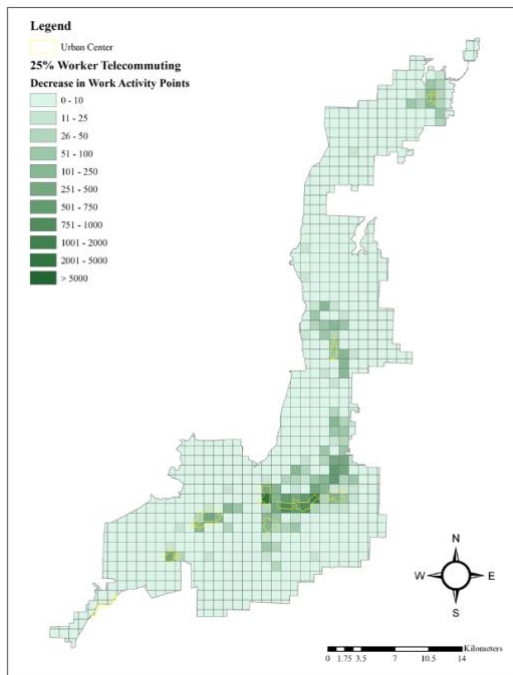
**Figure 9.** Trip distribution over a 24-hr period

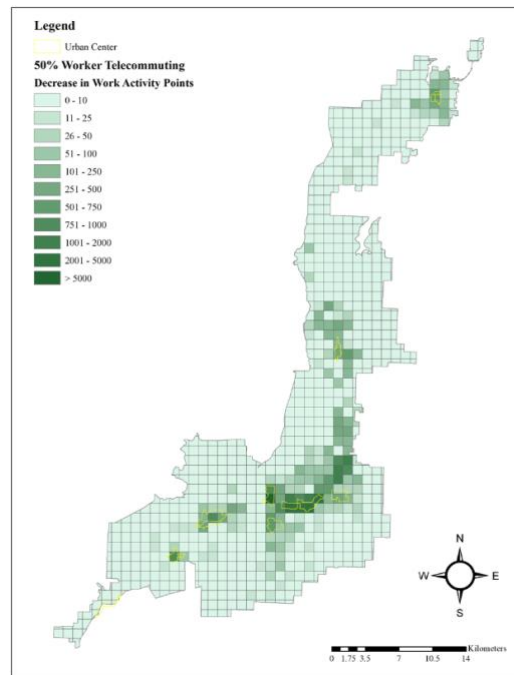
Figure 10 and Figure 11 show the spatial distribution of reduced work activity points for the 25% and 50% telecommuting scenarios, respectively. The results suggest a

<sup>1</sup> Emissions from cars have been calculated by multiplying vehicle kilometers traveled (VKT) with emission factors provided by the US Environmental Protection Agency (EPA, 2024). According to the US EPA, emission factors for CO<sub>2</sub>, CH<sub>4</sub>, and NO<sub>2</sub> are 0.108 kg/vehicle-kilometer, 0.0031 g/vehicle-kilometer, and 0.0019 g/vehicle-kilometer, respectively.

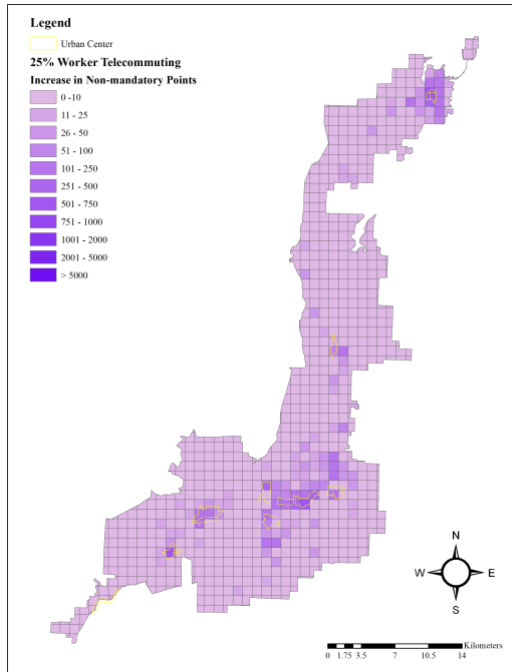
predicted reduction in activities in areas close to the urban centers. For example, a higher reduction is predicted in the Midtown, Rutland and Downtown areas of Kelowna. On the other hand, Figure 12 and Figure 13 present the spatial distribution of increased non-mandatory activity points for 25% and 50% telecommuting scenarios, respectively. The results indicate that increased non-mandatory activity points are predicted in the Midtown and Downtown areas of Kelowna. Due to mixed land use in the urban center, the increased share of telecommuting results in a decrease in work activity points and an increase in non-mandatory activity points. Since telecommuters are predicted to opt to travel during off-peak hours for non-mandatory trips, there will be increased traffic near the urban center during those times, while traffic during peak hours is predicted to decrease due to reductions in work-related travel activities.



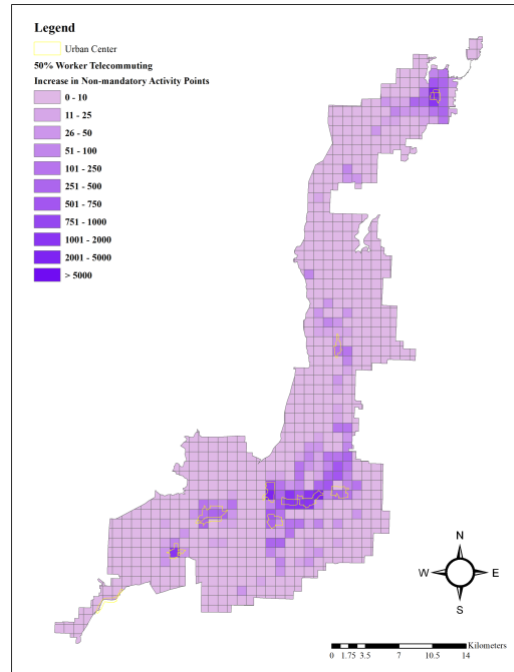
**Figure 10.** Spatial distribution of reduced work activity points for 25% workers telecommuting



**Figure 11.** Spatial distribution of reduced work activity points for 50% workers telecommuting



**Figure 12.** Spatial distribution of increased non-mandatory activity points for 25% workers telecommuting



**Figure 13.** Spatial distribution of increased non-mandatory activity points for 50% workers telecommuting

## 6 Conclusions

The testing of alternative telecommuting scenarios using the travel demand and network microsimulation model presented in this paper has significant policy implications. Cities and different government agencies need to prepare for a substantial amount of the population working-from-home as we come out of this pandemic. The simulation results for the alternative shares of the telecommuting population indicate a reduction in commuter travel with an increase in the share of telecommuters. However, the model predicts an increase in travel for all types of non-mandatory purposes such as shopping and personal business, with the increase in telecommuting share of the population. This indicates a new demand for travel could be attributed by the flexible working hours associated with many telecommuting work arrangements. The distribution for the departure time indicates a shift in travel from peak-period to off-peak period of the day. The 24-hour departure time distribution further illustrates the predicted peak spreading possibility. This indicates a need to review the transport service options which are typically planned to serve commuters during the peak hours. Given the increase in travel during the off-peak periods, cities and transit agencies need to investigate ways to offer accessible, affordable, and sustainable travel modes during the off-peak periods of the day. Given that many people will be traveling from home, in addition to adjusting the temporal distribution of transportation services, spatial distribution of these services also needs to be assessed. An increase in telecommuting may lead to higher traffic for non-mandatory activities in urban centers due to mixed land use. Therefore, new establishments serving non-mandatory activities should be located away from the urban center to alleviate traffic congestion in these areas.

This study has several limitations. For example, this study utilizes cross-sectional travel diary data to develop the behavioral models. One of the limitations of this cross-sectional data is that it provides travel itineraries for a sample population only on a typical weekday for a particular time point, which does not capture the variations in travel decisions throughout the week, as well as the changes in travel behavior over time after starting to telework. For example, depending on the work arrangement, workers may work remotely on certain days of the week and commute to work the rest of the days, which has not been accommodated in the existing model due to data limitations. To address this, week-long and longitudinal data should be collected to account for these variations in travel decisions over the week and in the long term. In the future, research should evaluate whether, and by how much, the magnitude of changes in travel behavior captured in this study could differ if the model is developed using week-long and longitudinal data. Another limitation of the study is the use of heuristics to adjust departure times and activity durations to fit conflicting activities into an individual's 24-hour schedule, which may affect the resulting distributions of activity frequency, travel length, and mode choice. Future research should investigate alternative methodologies, such as behavior-based models and data-driven techniques, to better capture individuals' rescheduling behaviors. On the other hand, occupation type is the only considered factor affecting the choice of telecommuting, as it dictates the nature of the job and whether employees are allowed to work remotely. However, in addition to occupation type, many other factors may influence the choice of telecommuting, such as the location of home and work. This has been identified as another limitation of this study. As immediate future work, behavioral models will be developed to investigate the choice of telecommuting and its interdependency on the location of home and work, as well as how these choices vary in one-worker vs. two-worker households. Overall, this study demonstrates the benefits of agent-based transport simulation models adopting an activity-based modeling technique to test dynamic plans, policies and strategies such as work-from-home. The findings of this study will assist transportation planners and policymakers in understanding the impacts of transportation demand management strategies such as telecommuting on 24-hour travel and help in making informed decisions to offer economic and environmentally friendly transport options to different population groups in an equitable way.

### **Acknowledgments**

The authors would like to acknowledge the Natural Sciences and Engineering Research Council (NSERC)–Discovery Grant, and Environment and Climate Change Canada (ECCC –Climate Action and Awareness Fund for their financial support. The authors would also like to thank Canada Foundation for Innovation–John R. Evans Leaders Fund for funding the lab infrastructure for this research. The authors extend their thanks to the City of Kelowna for providing the data. Lastly, the authors would also like to thank Nathan Nichol for proofreading the manuscript.

### **Author contribution**

The authors confirm contribution to the paper as follows: B. Saha, N. A. Khan, M. R. Fatmi: study conception and design. M. R. Fatmi, B. Saha: data collection. B. Saha, M. R. Fatmi, and N. A. Khan: analysis and interpretation of results. B. Saha, M. R. Fatmi, and N. A. Khan: draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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