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ABSTRACT

This paper presents an econometric framework of jointly modelling daily activity scheduling (activity type, time expenditure, and location choices known as the CUSTOM system) and travel mode choice considering Random Utility Maximization (RUM) behaviour. The joint model is applied to model workers' daily activity-travel demand with flexible work arrangement choices. The joint framework is flexible to capture workers' activity-travel patterns under different workplace (telecommuting, not telecommuting, or hybrid) arrangement options. The model is empirically estimated using datasets collected in the Greater Toronto Area (GTA) in 2021. The analysis explores how different workplace arrangements affect activity-travel demand. The model is calibrated to simulate scenarios where the distribution of work-from-home workers varied between the levels observed from 2016 to 2021. The scenario analysis validates the behavioural predictability of the joint CUSTOM system. This highlights the potential of the agent-based activity-based modelling system to forecast the influence of disruptive events on travel behaviours.

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Activity-based travel demand model; workers' activity-travel pattern; work-from-home; post-pandemic travel demand; CUSTOM framework

1. Introduction

Activity-based travel demand models are state-of-the-art travel demand modelling practice. All the existing activity-based modelling approaches focus on out-of-home activities; workers' weekday activity-travel patterns are specially constructed around their home-work-home commute (Bhat and Singh 2000; Frusti, Bhat, and Axhausen 2002; Habib 2018; Habib and Miller 2006; Miller and Roorda 2003). This approach was intuitive and sufficient before the covid-19 pandemic. Due to the pandemic, a significant portion of the workers shifted their usual places of work from offices to homes (Beck and Hensher 2021; Wang et al. 2021).

When the pandemic is no longer an immediate public health concern, three working patterns emerged: work-from-home, work outside home, and a hybrid mix of working at home and out-of-home. Such patterns may continue to evolve. A global management company projected that around 20–25 percent of the workforce in advanced economies could

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keep working from home (McKinsey 2021). By midyear 2023, the weekly average office occupancy in U.S. cities plateaued around 50% (Kastle Systems 2023). This indicates that half of the office space was not utilised on a typical weekday. The work-from-home trend has diminished the assumption of considering workers' commute patterns as the skeletal schedule to model daily activity-travel demands. As a result, post-pandemic travel demand datasets may exhibit a significant portion of records having zero out-of-home work activity or even immobility. So, the activity-based travel demand modelling approach needs to be systematically adjusted to accommodate such changes in workplace arrangement patterns. Wang, Hossain, and Habib (2022) proposed that an activity-based scheduling process should explicitly consider productive activities at home, namely working from home. By doing so, the home-activity-inflated dataset will then be transformed into a behaviourally meaningful distribution. The modelling framework and empirical exercises presented in this paper demonstrate the feasibility of such an approach.

To effectively address the changes in working patterns, developing a comprehensive modelling framework founded on behavioural theory and with enough flexibility to capture the evolution of various work scheduling patterns is necessary. This paper presents such a modelling system. The system is an extension of the Comprehensive Utility-based System of Activity-Travel scheduling Options Modelling (CUSTOM) framework (Habib 2018). The proposed modelling system utilises the random utility maximisation approach to jointly model activity scheduling and travel mode choices. It incorporates discrete choices for activity type, location, and mode while also considering continuous time allocation choices for activity start time and duration on a diminishing time budget as the day progresses. By integrating multiple dimensions of decision-making, the resulting modelling system is a joint econometric model capturing multidimensional behavioural tradeoffs in activity type, location, start time, duration, and travel mode choices. This framework is designed to accommodate various work arrangements, as evidenced by a travel survey conducted in the Greater Toronto Area in Fall 2021 (Wang et al. 2021). The estimated model reveals many behavioural insights, including tradeoffs 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. Using the estimated model, this study also exams different scenarios where the distribution of work-from-home workers varies between the status quo in 2021 and the pre-pandemic level observed in 2016. The analysis aims to validate the behavioural predictability of the CUSTOM model and the efficacy of its calibration process. The results also provide insights into how different work arrangements might affect activity-travel demand.

The remainder of this paper is organised in the following manners. Section 2 reviews related literature on activity-based modelling approaches. Section 3 presents the proposed joint framework. Section 4 describes the dataset used for empirical application with descriptive analysis. Section 5 presents the results of the empirical model. Section 6&7 presents a scenario analysis considering various work-from-home adaptation rates. Finally, Section 8 concludes the study by discussing the findings and future research.

2. Literature review

Current operational activity-based travel demand models adopted the following approaches: computational process models, hybrid models mixing econometric models and rules, and econometric models. The computational process models construct activity schedules using either heuristics or deterministic rules. Examples can be found in A Learning-based Transportation Oriented Simulation (ALBATROS), Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS), and Polaris frameworks (Arentze and Timmermans 2004; Auld et al. 2016; Auld and Mohammadian 2009). The mode choice in ALBATROS is modelled as decision trees, not based on any microeconomic framework. The mode choice in ADAPTS took the form of the logit model. Mobility tool availability is considered in its choice set formation. The level-of-service and cost variables were considered in the systematic utilities if the destination location is known. Otherwise, they were replaced by weighted accessibility measurements. In general, such computation process models are data-hungry and face the criticism of being vulnerable to noisy datasets (Hasnine and Habib 2021).

Travel/Activity Scheduler for Household Agents (TASHA) is an example of the hybrid rule and econometrics-based model. TASHA randomly drew on attributes of the work and other discretionary activities. Then, the randomly drawn activities were scheduled based on rules (Miller and Roorda 2003). A tour-based mode choice was developed for TASHA (Miller, Roorda, and Carrasco 2005). The mode choice model purposely separated vehicle and non-vehicle tours. Driving is the only mode available once the vehicle tour is selected. The model also considered conflicts regarding mobility tools between household members. Vehicles are allocated to the members with the highest utility if multiple members want to use them simultaneously. Activities that cannot be served by vehicles are rescheduled. At the same time, the model also considered intra-household coordination to serve auto passengers. The rules set for intra-household conflict resolution and collaboration are attractive, but collecting data to validate those rules is incredibly challenging. Typical travel diaries only provide observations on which activities are eventually scheduled and served by mobility tools. However, travel diaries can hardly offer evidence of the family members' negotiation and conflict resolution mechanisms. TASHA uses a tour-based mode choice model based on random utility maximisation (RUM) theory. However, the mode choice model, devised to handle entangled and arbitrary rules of intra-household interactions, does not have any standard and closed-form probability structure. It uses a Monte Carlo-based approach to estimate the model. Most recently, a modelling framework named Scheduler for Activities, Locations, and Travel (SALT) model hybridised machine-learning and econometric models (Hesam Hafezi et al. 2021). The SALT system used a clustering recognition algorithm, multivariate probit model, random forest model, ordered probit, Poisson regression model, and multinomial logit model. More specifically, the travel mode choice component in the SALT system is modelled using a multinomial logit model for each tour.

Conglomerates of econometric models are also a common approach. Various econometric models are used to handle different aspects of activity-travel scheduling, such as trip start time, duration location, and mode choices. Then, some rules are applied to stitch the model results together to construct complete activity-travel schedules. The Coordinated Travel – Regional Activity Modeling Platform (CT-RAMP) family of models, Comprehensive Econometric Micro-Simulator for Daily Activity/Travel Patterns (CEMDAP), Tel-Aviv model, and DaySim models followed this approach (Bhat 2001; Bowman and Ben-Akiva 2001; Davidson et al. 2010; Shiftan and Ben-akiva 2011). The CEMDAP uses the multinomial logit (MNL) model to capture tour-level mode choice. The CT-RAMP family uses a nested logit model to define tour-level mode choices. Then, the trip-level mode choice model used the same structure.

However, alternatives to the trip level choice are defined by selection at the tour level. The Tel-Aviv model considers tour and trip-based mode choices. The tour level choice determines the primary travel mode. The trip level choice is nested under a higher-level choice of using a different travel mode than the chosen primary mode on the tour level. The DaySim model uses a different approach than the frameworks stated above. It jointly considers destination and mode choices in a multinomial logit (MNL) formulation. The choice sets are a combination of destination zones and travel modes. This approach results in a large number of alternatives in the choice sets. So, candidate zones must be sampled in advance using importance sampling (Bowman and Ben-Akiva 2001). Although logsum feedback sometimes links sub-models in modelling conglomerate discussed above, they are often estimated independently, overlooking the endogeneity and implicit correlations.

All activity-based models discussed above pivot around workers' out-of-home work activities to construct activity-travel schedules (Bhat and Singh 2000; Frusti, Bhat, and Axhausen 2002; Habib 2018; Habib and Miller 2006; Miller and Roorda 2003). Most of these models assume a typical home-to-workplace work tour as the skeleton to schedule other activities of the workers. Until 2019, this was the norm in many developing cities worldwide. However, the covid-19 pandemic has changed our working patterns. Through the pandemic, workers experienced various forms of telecommuting, and few distinct work arrangement patterns emerged. These include work-from-home, work out-of-home, and a hybrid mix of work-at-home and out-of-home. This is a fundamental change in urban commuting patterns, which can be expected to last for a while. None of these modelling frameworks were designed to handle massive shifts in workplace arrangements from office to home. Miller and Roorda (2003) considered work-from-home in their model. However, they gave out-of-home work activities the highest priority and treated work-from-home as secondary activities only in the absence of usual places of work outside homes. Activity-based models that only consider out-of-home working activities can no longer accurately capture the complete picture of workers' activity-travel scheduling behaviours. Therefore, activity-based travel demand modelling applications in the post pandemic era should give work-from-home equal importance to out-of-home work activities.

The Comprehensive Utility-based System of Activity-Travel scheduling Options Modelling (CUSTOM) framework takes a robust econometric approach. It jointly schedules time allocation choices, activity-type choices, and destination location choices for individuals (Habib 2018). The framework is estimated under one closed-form likelihood function and avoids hard-coded activity scheduling rules such as pivoting work schedules to arrange the scheduling. However, the CUSTOM framework still lacks a travel mode choice component. In all previous applications, CUSTOM considered mode choice separate from activity scheduling handling after the daily schedules are formed. The proposed formulation in this paper fills this gap in CUSTOM as it proposes a joint formulation of all aspects of activity-travel scheduling, including mode choice, using one comprehensive econometric framework. It also contributes to the literature by presenting a modelling framework sensitive to different workplace arrangements. The proposed modelling framework can exclusively accommodate workers who work from/outside of the home or have hybrid workplace arrangements. The following section explains the joint modelling framework in detail.

3. Integrating mode choices within CUSTOM

The workflow of the proposed joint modelling framework is presented in Figure 1. The framework considers a 24-hour modelling time frame with a fixed home location for the activity-travel scheduling process. An individual's schedule begins with a choice of time allocated to the maintenance period before their first activity. Then, the individual will decide the types of their first activity during the day. The activity type choice includes both out-of-home and at-home activities. If an out-of-home activity is chosen, the start time of the first trip is determined by the time allocated at home before their first activity. Then, the location and travel modes for the chosen out-of-home activity will be determined. Meanwhile, the time allocation component will determine the time spent on the out-of-home activity.

On the other hand, location and travel mode choices will be skipped if an at-home activity is chosen. For subsequent scheduling episodes during the day, the individual can participate in another out-of-home activity, temporary home maintenance activity, or permanent home maintenance activity. The activity scheduling process will end once they choose a permanent home maintenance activity. This approach models home-based tour formation. Also, non-home-based tours can evolve at any stage of out-of-home activity scheduling episodes.

The model choice component is forward-looking, considering the expectation of activity-type choices in composite scheduling cycles. This is a realisation of actual behaviour that individuals take their composite activities into account while choosing their travel modes. Furthermore, the tour-based constraint is imposed in the mode choice model. The model considers the characteristics of different trip segments in tours and the formation of trip-chain-based choice sets.

The joint model may capture various activity-travel patterns from each choice component's interactions. Figure 2 presents the joint framework's interrelationships and feedback

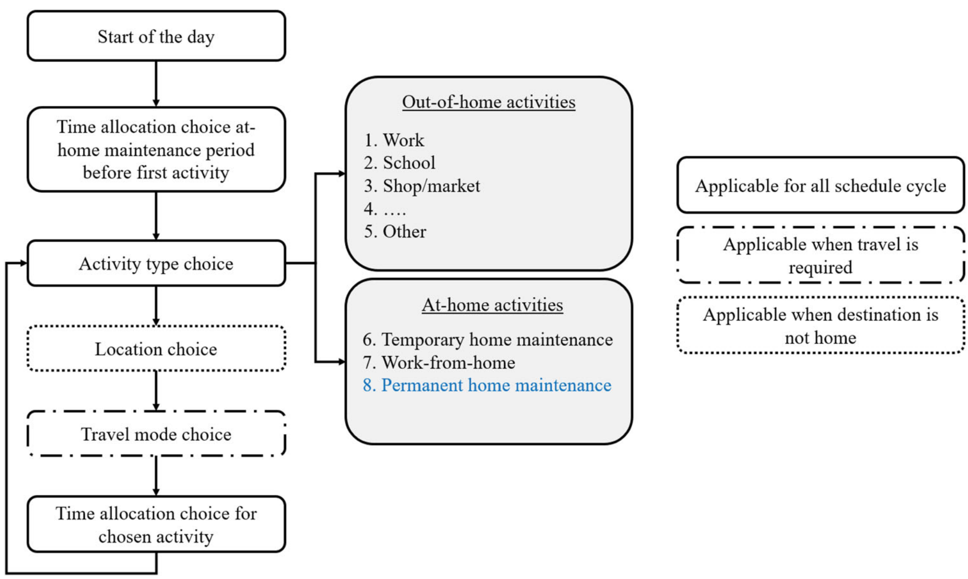

Figure 1. Flow diagram of CUSTOM & Mode choice joint modelling framework.

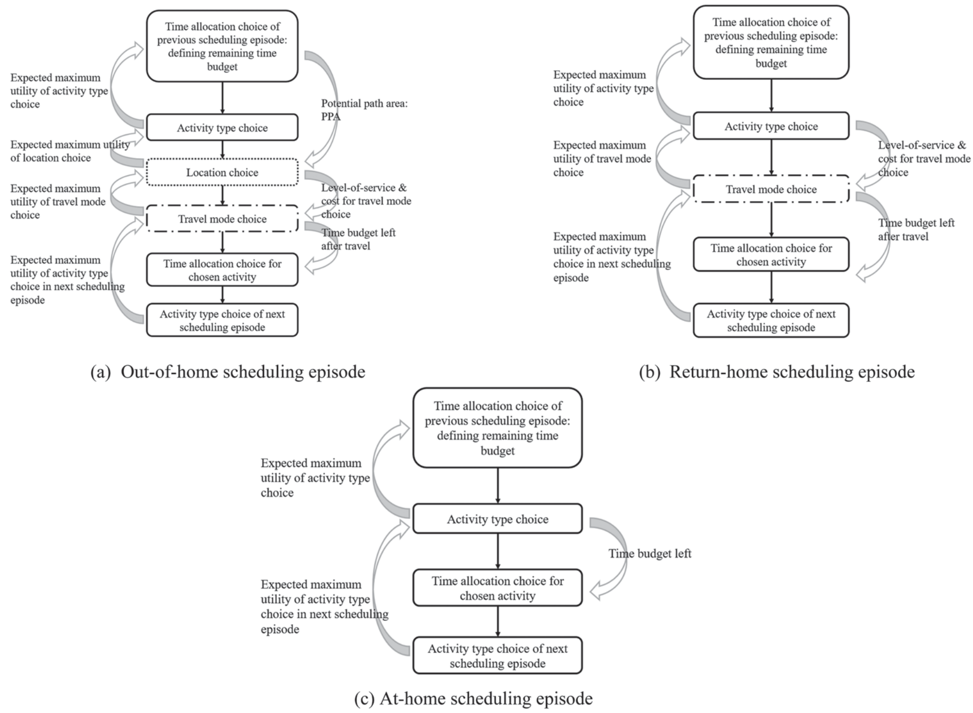

Figure 2. Feedback mechanisms in joint CUSTOM & Mode choice framework. (a) Out-of-home scheduling episode; (b) Return-home scheduling episode; (c) At-home scheduling episode.

mechanisms among choice components. Feedback mechanisms are summarised for out-of-home, return-home, and at-home scheduling episodes (see Figure 2a, b & c, respectively). The joint modelling framework contains several forward interrelationships among modelling components. For out-of-home scheduling episodes, the time budget remaining for the current cycle is defined by the time allocation choice of the previous cycle. This remaining time budget defines the Potential Path Area (PPA) of feasible locations available for the current cycle. Next, the choice of location and time-of-day specific variables define the level-of-service and cost variables for the mode choice. Finally, the mode choice determines the time budget left for the actual activity after travel.

At the same time, the joint modelling framework also contains several backward feedback mechanisms. For out-of-home scheduling episodes, the travel mode choice for the current cycle considers the expectation of activity type choice for the next scheduling cycle. The location choice considers the expectation from the mode choice, and similarly, the activity-type choice considers the expectation from the mode choice. Finally, time allocation choice takes the expectation of the activity-type choice into account. Return-home and at-home scheduling episodes have similar forward and backward feedback mechanisms. Unlike out-of-home scheduling episodes, location choice and mode choice might be omitted from the modelling process since the individual travels back home (don't need location choice) or transits between two at-home activities (doesn't need location choice & travel mode choice). Thus, they can be considered subsets of the mechanisms described for out-of-home scheduling episodes. The following section elaborates on the econometric formulation of the joint modelling framework.

3.1. Econometric formulation

The choice probability of the joint CUSTOM and mode choice framework is formulated as a three-level general extreme value (GEV) structure (Habib 2018).

For activities scheduled with J cycles in total, three alternatives are considered for each scheduling cycle j:

- Home maintenance for the rest of the day, H_j
- Temporary home maintenance activity, HUP_j
- Home productive & out-of-home activities, Act_j

Home maintenance for the rest of the day (H_j) indicates that individuals will not engage in any home-productive and out-of-home activities (Act_j) during the remainder of the 24-hour modelling timeframe. *Temporary home maintenance* (HUP) indicates that individuals will still engage in home-productive and out-of-home activities (Act_j) during the composite period of the 24-hour modelling timeframe. *Home productive activity* refers to any work-related activity individuals perform at their residence. In the literature, it is commonly referred to as working from home (WFH) or telecommuting. *Out-of-home activities* refer to activities that need to be performed outside individuals' places of residence and require travel.

Their corresponding probabilities are described as:

$$Pr(H_j) = \frac{\exp(\mu_{h_j} V_{H_j})}{\exp(\mu_{h_j} V_{H_j}) + \exp(\mu_{h_j} V_{HUP_j}) + \exp\left(\frac{\mu_{h_j}}{\mu_{Act_j}} I_{Act_j}\right)} \tag{1}$$

$$Pr(HUP_j) = \frac{\exp(\mu_{h_j} V_{HUP_j})}{\exp(\mu_{h_j} V_{H_j}) + \exp(\mu_{h_j} V_{HUP_j}) + \exp\left(\frac{\mu_{h_j}}{\mu_{Act_j}} I_{Act_j}\right)} \tag{2}$$

$$Pr(Act_j) = \frac{\exp\left(\frac{\mu_{h_j}}{\mu_{Act_j}} I_{Act_j}\right)}{\exp(\mu_{h_j} V_{H_j}) + \exp(\mu_{h_j} V_{HUP_j}) + \exp\left(\frac{\mu_{h_j}}{\mu_{Act_j}} I_{Act_j}\right)} \times \frac{\exp(\mu_{Act_j} V_{Act_j})}{\sum_{Act_j} \exp(\mu_{Act_j} V_{Act_j})} \tag{3}$$

where,
μ_{h_j} is the root scale parameter of activity-type choice.
μ_{Act_j} is the scale parameter of home productive & out-of-home activity-type choice.
V_{H_j} is the systematic utility of permanent home maintenance activity.
V_{HUP_j} is the systematic utility of temporary home maintenance activity.
V_{Act_j} is the systematic utility of home productive & out-of-home activities.
I_{Act_j} is the expected maximum utility of home working & out-of-home activity-type choice.

Also,

$$I_{Act_j} = \ln\left(\sum_{Act_j} \exp(\mu_{Act_j} V_{Act_j})\right) \tag{4}$$

The systematic utility function of out-of-home activities is:

$$V_{Act_j} = \sum (\beta x)_{Act_j} + \frac{I_{l_j}}{\mu_{l_j}} \tag{5}$$

where,
$\sum (\beta x)_{Act_j}$ is a liner-in-parameter function of variables and coefficients.
I_{l_j} is the expected maximum utility of location choice of activity j.
μ_{l_j} is the scale parameter of location choices.

The expected maximum utility of activity location choice is

$$I_{l_j} = \ln\left(w_j \sum_{l} \exp(\mu_{l_j} V_{l_j})\right) \tag{6}$$

where,
w_j is the expansion factor.
V_{l_j} is the systematic utility function of activity location choice.
μ_{l_j} is the scale parameter of location choice in cycle j.

The out-of-home location choice probability is formulated to follow GEV structure:

$$Pr(l_j) = \frac{\exp(\mu_{l_j} V_{l_j})}{\sum_{l_j} \exp(\mu_{l_j} V_{l_j})} \tag{7}$$

$$V_{l_j} = \sum (\gamma z)_{l_j} + \frac{I_{m_j}}{\mu_{m_j}} \tag{8}$$

where,
l_j is the feasible choice set of activity location on the traffic analysis zone (TAZ) level.
V_{l_j} is the systematic utility function of activity location choice.
μ_{l_j} is the scale parameter of location choice.
$\sum (\gamma z)_{l_j}$ is a liner-in-parameter function of variables and coefficients.
I_{m_j} is the expected maximum utility of travel mode choice.
μ_{m_j} is the scale parameter of travel mode choice.

The travel mode choice model considered tour-based behaviour. A tour is a journey from home to one or more out-of-home destinations and returning home again (Bowman and Ben-Akiva 2001). The mode choice model accounts for different choice behaviours in each trip segment. It includes separate sets of parameters for first, intermediate, and return-home trips of the home-based tour. Moreover, the choice sets are based on the availability of mobility tools considering trip-chaining. For the first trip of the tour, the availability of driving in the choice sets is based on automobile and driver's license ownership. For subsequent trips, driving availability in the choice set is determined by the mode choice of the previous trips. Namely, a vehicle will not be available to drive on subsequent trips if the trip-maker does not drive it on the previous trips. Additionally, walking and cycling will not be available once the trip length is excessively long.

The travel mode choice probability is formulated as GEV structure:

$$Pr(m_j) = \frac{\exp(\mu_{m_j} V_{m_j})}{\sum_{m_j} \exp(\mu_{m_j} V_{m_j})} \tag{9}$$

$$V_{m_j} = \sum (\varphi x_f + \tau x_i + \alpha x_r)_{m_j} + \frac{I_{Act_{j+1}}}{\mu_{h_{j+1}}} \tag{10}$$

where,
m_j is the feasible choice set of travel mode choice in cycle j considering mobility tool availability.
μ_{m_j} is the scale parameter of travel mode choice in cycle.
j. V_{m_j} is the systematic utility function of travel mode choice.
φx_f is a linear-in-parameter function of variables and coefficients for the first trip of tour, equals to zero for other tour segments.
τx_i is a liner-in-parameter function of variables and coefficients for intermediate trips of the tour, equals to zero for other tour segments.
αx_r is a liner-in-parameter function of variables and coefficients for the return-home trip of the tour, equals to zero for other tour segments.
$I_{Act_{j+1}}$ is the expected maximum utility of activity choice of following scheduling cycle $j + 1$.
$\mu_{h_{j+1}}$ is the root scale parameter of activity-type choice in cycle $j + 1$.

The formulation above captures travellers' dynamic, forward-looking behaviour in selecting their travel modes. The modal choice in cycle j considers expectations from activity types, locations, and mode choices in composite scheduling cycles. The mode choice model is also implicitly history-dependent through the choice set formulation. This captures the most fundamental physical constraints in mode choice since private mobility tools such as cars will become unavailable if not driven in the previous trip.

If the individual is out-of-home at the end of cycle j—1, choosing home activities in cycle j means the agent will travel back home. The individual will choose the travel mode for the return-home trip, but location choice should not be considered since home location is exogenously determined. In such cases, the three-level GEV structure will collapse into a two-level structure with activity type and travel mode choice. The systematic utility functions of returning home and conducting maintenance activities for the rest of the day (V_{H_j}), returning home and conducting maintenance activities temporarily (V_{HUP_j}) and returning home working (V_{Act,HW_j}) follows the following formulation:

$$V_{H_j} = \sum (\beta x)_{H_j} + \frac{I_{m_j}}{\mu_{m_j}} \tag{11}$$

$$V_{HUP_j} = \sum (\beta x)_{HUP_j} + \frac{I_{m_j}}{\mu_{m_j}} \tag{12}$$

$$V_{Act,HW_j} = \sum (\beta x)_{ACT_j} + \frac{I_{m_j}}{\mu_{m_j}} \tag{13}$$

Similarly, if the agent is at home at the end of cycle $j - 1$, choosing another home activity in cycle j means no need to consider location and travel mode choice. Therefore, their systematic utility function should directly consider the expected maximum utility of activity-type choice in the next scheduling cycle j + 1:

$$V_{H_j} = \sum (\beta x)_{H_j} + \frac{I_{Act_{j+1}}}{\mu_{h_{j+1}}} \tag{14}$$

$$V_{HUP_j} = \sum (\beta x)_{HUP_j} + \frac{I_{Act_{j+1}}}{\mu_{h_{j+1}}} \tag{15}$$

$$V_{Act,HW_j} = \sum (\beta x)_{ACT_j} + \frac{I_{Act_{j+1}}}{\mu_{h_{j+1}}} \tag{16}$$

Activity durations are random utility maximisation (RUM) based on continuous choice. The probability that each activity episode j is allocated with duration (t_j) while the total time budget of an individual is T is (Habib 2018):

$$\Pr(t_j) = \left(\frac{1-\alpha_j}{t_j} + \frac{1-\alpha_c}{T-t_j}\right)\mu_{t_j}\exp(-\mu_{t_j}(V_c - V_j))(1+\exp(-\mu_{t_j}(V_c - V_j)))^{-2} \tag{17}$$

$$V_c = (\alpha_c - 1)\ln(T - t_j) \tag{18}$$

$$V_j = (\theta y)_j + (\alpha_j - 1)\ln(t_j) \tag{19}$$

where,
$\alpha_j$and α_c are the satiation parameters for the duration of activity *j* and composite activity c.
$(\theta y)_j$ is a liner-in-parameter function of way variables and coefficients.
μ_{t_j} is scale parameter for duration of activity j.

Overall, the likelihood of observing a specific activity type, location, travel mode and durations choices for scheduling cycle *j* is:

$$L_j = (Pr(H_j)^{\delta_H} Pr(HUP_j)^{\delta_{HUP}} Pr(Act_j)^{\delta_{Act,i}} Pr(l_j)^{\delta_l} Pr(m_j)^{\delta_m}) Pr(t_{j-1}) \tag{20}$$

where,
δ_H is 1 if choose permanent home maintenance activity, 0 otherwise.
δ_{HUP} is 1 if choose temporary home maintenance activity, 0 otherwise.
$\delta_{Act,i}$ is 1 if choose a specific activity type i within the nest *Act*, 0 otherwise.
δ_l is 1 if choose a location, 0 otherwise.
δ_m is 1 if choose a travel mode, 0 otherwise.

For each worker (*k*) with *J* activity scheduling cycle per day, the likelihood of observing his/her activity type, location, travel mode, and durations choices in a typical weekday is:

$$L_k = \prod_{J=1}^{J} L_j \tag{21}$$

Finally, the joint likelihood for the sample set with a total number of *K* workers is:

$$L = \prod_{k=1}^{K} L_k \tag{22}$$

The joint likelihood function is in closed form. The joint CUSTOM & mode choice framework can be estimated altogether by the classical BFGS gradient searching algorithm in GAUSS (Aptech 2020). Thus, the modelling framework can fully capture the dynamics between each modelling component and scheduling cycle. In this study, the model is estimated using a computer with an Intel Core i7-8750H CPU and 32 GB of RAM. During empirical estimations, with 3,411 observations, each iteration will take between 2.9 and 4.7 minutes to compute. Each parameter estimation requires around 600 iterations until convergence, with stopping criteria of 5×10^{-4} applied in this study. Future applications of the proposed model could use vectorisation to improve computation times by removing loops, optimising memory access, and leveraging CPU and GPU parallelism.

4. Data for empirical investigation

Data used in this study comes from COVid-19 influenced Households' Interrupted Travel Schedules (COVHITS) survey conducted in the Greater Toronto Area (GTA) in Canada in Fall 2021 (Habib et al. 2021; Wang et al. 2021). The 2021 Fall COVHITS survey collected 9,962 trips from 9,984 individuals in 4,687 households. A subset of the 2021 Fall COVHITS survey (after cleaning for erroneous records) consisting of 3,415 workers is used for this study. Table 1 presents the summary statistics of key socioeconomic variables compared against the referenced population of workers in the study area. The 2016 Transportation Tomorrow Survey (TTS) is used as the reference dataset to evaluate the sample's representativeness. TTS is a regional household travel survey that has surveyed 5% of the population in the GTA since 1986 (Data Management Group 2018a). Table 1 shows that key socioeconomic statistics in both datasets match closely. At the person level, age, gender, driver's license ownership, employment status, and proportion of occupational types match reasonably well between the two datasets. Vehicle ownership, income, and dwelling types at the household level also match reasonably well. Thus, it is safe to conclude that the sample used in this study is representative of the population of workers in the study area, given that most key socioeconomic variables match closely with the reference dataset.

By the time the survey was conducted, all policies restricting workers' participation in out-of-home activities had been lifted. During the collection period, all businesses in the study area were allowed to open with no restrictions on capacity. However, proof of vaccination is required for most non-essential indoor activities such as dining and recreation (Government of Ontario 2021). 92.8% of the records in this study reported having fully vaccinated status as per the requirement of the Government of Ontario. Moreover, remote work and learning are no longer mandatory in the study area. Therefore, it is safe to conclude that the behaviours represented in the dataset are voluntary, with minimum government-enforced restrictions, which all lawful individuals must obey. Table 1 also shows the workplace arrangements of workers in the sample. In Fall 2021, 47.2% of the workers in the study area were working from home exclusively, 36.3% were working outside from home exclusively; 16.5% had hybrid arrangements. After the pandemic, it is anticipated that the proportion of work-from-home exclusively will gradually shift to hybrid arrangements. However, the degree of shift will be different depending on the nature of the jobs. In the long term, it is anticipated that 20–25 percent of workforces in advanced economies could work from home between three to five days a week (McKinsey 2021).

Table 1 also shows activity-travel statistics from the sample. Overall, the sample reveals a significant drop in workers' mobility compared to the pre-pandemic level of 2016. The global trip rates decrease from 2.51 to 1.32 between 2016 and 2021. The number of working trips decreases from 0.83 per worker to 0.41. Immobility is significantly higher than the pre-pandemic level. The portion of workers making no trips during a typical weekday is 44.8% in the sample, compared to only 11.2% in the reference dataset. This highlights the impact of work-from-home on workers' activity-travel behaviours.

Table 1. Summary of descriptive statistics.

	Fall 2021 COVHITS	2016 TTS
Personal attributes		
Age (mean)	43.7	41.9
Gender as male	50.2%	52.7%
Driver's license	90.6%	88.5%
Full-time workers	85.7%	81.6%
Occupation as professional/management/Technical/general office	60.2%	60.6%
Household attributes		
Household size (mean)	2.39	2.97
Number of vehicle (mean)	1.40	1.53
Household income		
below $<$ \$40,000	7.6%	12.7%
\$40,000–\$59,999	10.2%	13.8%
\$60,000–\$99,999	26.7%	24.2%
\$100,000–\$124,999	18.6%	11.7%
\$125,000 and above	30.6%	21.7%
unknow/decline	6.4%	15.8%
Dwelling types: single-detached house	45.5%	43.2%
Workplace arrangement		
Work-from-home exclusively	47.2%	
Hybrid	16.5%	
Work-outside-from-home exclusively	36.3%	
Activity-travel-related statistics		
Number of activities (at-home & out-of-home)	2.44	
Number of trips		
global trip rate	1.32	2.51
work trip rate	0.41	0.83
0	44.8%	11.2%
1	1.0%	1.5%
2	41.5%	55.3%
3	5.4%	10.0%
4	5.3%	12.7%
>4	2.0%	9.2%
Proportion of workers with specific place of work		
Work-from-home (WFH) only	54.8%	
Work-outside-from-home (WOFH) only	36.2%	
Both WFH & WOFH	2.3%	
No work activity	6.7%	
Out-of-home activity by types		
work	56.3%	33.1%
school	2.7%	1.8%
shop/market	17.2%	5.6%
other discretionary activities (e.g. restaurant, recreation, visiting, etc.)	23.8%	59.5%
Travel mode shares		
drive	66.1%	66.6%
auto passenger	6.6%	7.7%
ride-hailing & Taxi	0.8%	0.8%
other motorised mode	0.2%	0.4%
public transit	15.9%	17.6%
walk	9.1%	5.2%
bike	1.2%	1.8%

Instead of trips from out-of-home activities, the sample also collects workers' activities at home. Details on the data collection method will be discussed in Section 4.1. On average, workers participated in 2.44 daily activities in Fall 2021. It is close to 2.51 trips per day before the pandemic. It indicates a reasonable level of consistency in terms of activity participation rates between the two datasets. During a typical weekday, 54.8% of workers worked from home exclusively. 36.2% worked outside the home exclusively, and 2.3% worked at home and out-of-home locations. These statistics should be considered with the workplace arrangement reported in Table 1. It can be observed that a great portion of workers with hybrid workplace arrangements choose to work from home exclusively during a typical weekday. This highlights the preference of workers' choice of their place of work once they are given the liberty to make their own choice.

The types of out-of-home activities workers participated in changed significantly. Discretionary activities decreased from 59.5% to 23.8% between 2016 and 2021. Conversely, out-of-home mandatory (work & school) and maintenance (shopping) activities increased. Interestingly, the mode shares are similar between the sample and the reference dataset. The transit mode share decreased slightly from 17.6% to 15.9%. But the mode share of walking increased from 5.2% to 9.1%.

4.1. Collecting work-from-home schedules

Besides classical travel dairy, additional home activity information is needed to model workers' working activities at home. In the 2021 Fall COVHITS survey, workers were asked to report their detailed work-from-home schedules the same day the travel diaries were collected. The survey collected work-from-home schedules in half-an-hour time slots. This study converts the work-from-home schedules to home productive activity episodes and is integrated with travel diaries. The integrated activity schedules will feed the joint framework.

Figure 3 shows the distribution of the at-home and outside-from-home working episode duration after integrating two schedules. The two distributions have a similar shape regarding standard deviation, skewness, and kurtosis. This fits the expectation since both are working activities despite different locations. The average and median values are the only noticeable difference between the two distributions. The difference between the averages/medians of the two distributions is 43 and 50 minutes, respectively. The difference reflects travel time to work. This difference clearly shows that work-from-home alleviates the burden of commuting for workers.

5. Empirical model

The dataset described in Section 4 is used for model estimation. For the activity location choice set, 11 feasible traffic analysis zones (TAZs) are considered; this includes the chosen

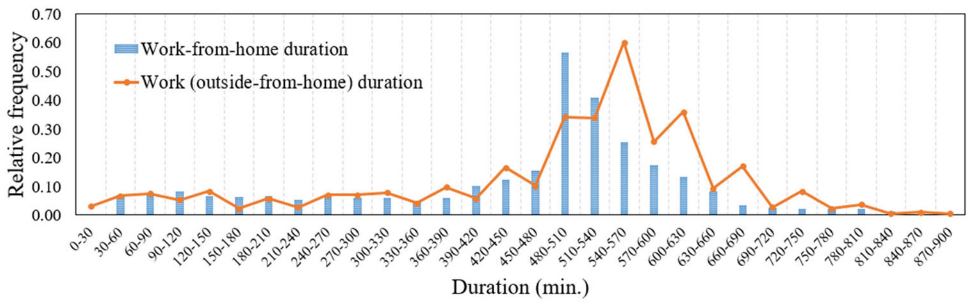

Figure 3. Comparison of work activity distributions after integrating work-from-home episodes with out-of-home activity episodes.

location and 10 randomly selected locations from the PPAs using uniform random draws. The time allocation is modelled as a continuous choice considering the 24-hour scheduling period. For any scheduling cycles, the activity-type choice considers the following alternatives:

- Work outside from home (WOFH) – primary
- Work outside from home (WOFH) – secondary
- Work from home (WFH) – primary (home productive activity)
- Work from home (WFH) – secondary (home productive activity)
- School
- Shop/market
- Restaurant/ bar/coffee
- Recreation/visiting
- Other (including personal & healthcare services, pick up/drop off, etc.)
- Home maintenance (temporary)
- Home permanently (for the rest of the day)

The activity scheduling process for an individual will end if a home permanently is chosen. Both work outside from home (WOFH) and work from home (WFH) are further classified as primary and secondary.

Primary and secondary work activities are mutually exclusive in the scheduling process. When primary work activity is scheduled, workers will not schedule any other work activities in their timeline. On the other hand, workers can schedule multiple secondary work activities in their timeline. However, once a secondary work activity is scheduled, they can no longer schedule primary activities. The classification is guided by heterogeneous time allocation behaviours observed in the dataset. The average time allocated for primary work activities is 497 minutes (8.2 hours).

Conversely, the average time allocated for secondary work activities is 194 minutes (3.2 hours). Effectively separating primary and secondary work activities ensures that the time allocation model correctly captures the average effects of corresponding activity types. Furthermore, workers eligible to work from home are permitted to do so with the entire choice set described above. Workers who must work outside the home do not have work-from-home-related activity types in their choice set. This arrangement reflects that work-from-home workers have hybrid workplace arrangements, but vice versa is not allowed.

For scheduling cycles required to travel, the mode choice considers the following alternatives:

- Drive
- Auto passenger
- Ride-hailing & taxi
- Transit
- Walk
- Bike

Table 2. Worker's activity-travel generation model estimation summary.

	Model 1	Model 2	Model 3
CUSTOM	×	×	×
Tour-based mode choice	×		
Simple mode choice		×	
Number of observations	3,411	3,411	3,411
Log-likelihood of the full model	−57,639.10	−62,794.10	−59,020
Log-likelihood of the null model[1]	−114,850.1	−114,850.1	−69,726.3
Rho-square against the null model	0.498	0.453	0.154
Number of parameters	205	182	171
Akaike information criterion (AIC)	115,688.2	125,952.2	118,382.0
Bayesian information criterion (BIC)	116,945.8	127,068.7	119,431.0

Notes: (1) The null model predicts equally likely probabilities for all discrete choice components and constant time allocation marginal utility.

The study estimates three models, and their performance results are summarised in Table 2. Model 1 represents the most sophisticated formulation, incorporating a mode choice component with tour-based considerations and choice set availability formation, as outlined in Section 3. Model 2 adopts a simpler approach, where mode choice is determined for individual trips without accounting for the full tour context. The parameters for the simple mode choice component follow the same specification described for the first trip in Table 9. Lastly, Model 3 follows a classic CUSTOM specification without mode choice considerations (Habib 2018). Model 1 demonstrates the best fit across all evaluation criteria among the three. This suggests that the CUSTOM's predictive power improves substantially when integrated with tour-based mode choice components. The superior performance of Model 1 is reflected in its log-likelihood (−57,639.10), Rho-square (0.498), AIC (115,688.2), and BIC (116,945.8), making it the most robust model. Furthermore, the comparison between Models 2 and 3 underscores the value of incorporating mode choice into the activity-travel generation process, as evidenced by the notable improvement in the Rho-square value. This enhancement in performance demonstrates that mode choice is a fundamental component that must be considered simultaneously in the modelling process.

This section focuses on Model 1, given its superior performance across all goodness-of-fit criteria. Model 1 contains 205 parameters. Most estimated parameters are statistically significant, with a 95 percent confidence limit. Still, some insignificant parameters are kept for comparison as they provide interesting insights for analysis. A detailed interpretation of Model 1 is presented in the following sections.

5.1. Scale parameters capturing variance in time allocation choice probability

The scale parameters of time allocation choice (μ_{t_j} in Equation 17) are parameterised to account for heteroskedasticity in workers' time allocation to activities. Overall, the scale (μ_{t_j}) is the inverse of variance in time allocation choice. This means that the larger the values of the scale parameters are, the lower the randomness in time allocation choices. According to Equation 17, A larger scale parameter (μ_{t_j}) means that the utility function ($V_c - V_j$) governs the time allocation probability. Conversely, a smaller μ_{t_j} makes the model less sensitive to utility ($V_c - V_j$) and the time allocation choice exhibits more randomness. Table 3 presents the estimation results. For time allocated before the first activity, the heterogeneity in variance is captured by the interaction between the number of private vehicles and household

Table 3. Scale parameters.

	coefficient	t-statistics
Scale of time allocation before the first activity of the day		
Log of number of vehicles interacts with household income		
below < $40,000	−0.36	−4.53
$40,000–$59,999	−0.24	−3.90
$60,000–$79,999	−0.20	−4.12
$80,000–$99,999	−0.09	−1.93
$100,000–$124,999	−0.08	−2.30
$125,000–$149,999	−0.13	−2.94
$150,000–$199,999	0.08	1.99
Scale of activity time allocation for activities during the day		
Time-of-day & household size interacts with household income		
below < $40,000	0.15	5.84
$40,000–$59,999	0.17	7.61
$60,000–$79,999	0.18	8.72
$80,000–$99,999	0.16	9.51
$100,000–$124,999	0.20	16.07
$125,000–$149,999	0.15	9.53
$150,000–$199,999	0.19	13.65
$200,000 and above	0.16	10.99
unknow/decline	0.20	8.56

income. It can be observed that, when considering the same number of vehicles, households with lower incomes have a higher variance in their time allocation choice before the first activity. For households earning more than $150,000 a year, the variance reduces as the number of vehicles increases.

For activities during the day, the heterogeneity in variance is captured through a function of time-of-day as a fraction of 24 hours multiplied by household size. Positive estimated scale parameters generally mean higher variance in time allocation decreases as time-of-day proceeds. This fits the expectation as the remaining time budget shrinks while time proceeds to the end of the day. Individuals are left with less freedom in their time allocation choices. Moreover, larger house sizes will lower variances in activity time allocation choices. The findings above are similar to empirical findings from workers' activity-scheduling behaviours in Canada's Nation Capital Region (NCR), another metropolitan area in Ontario, Canada (Habib 2018).

5.2. *Time allocation choices before the first activity of the day*

This time allocation choice describes the maintenance period at home (e.g. sleep, breakfast, etc.) before the workers start to travel for out-of-home activities or start working at home. The choice is modelled by baseline utility defining the marginal utility and satiation parameters defining the rate of change in marginal utility regarding the time duration allocated.

The baseline utility is a function of a worker's age, income, employment status, household size, vehicle availability, and expectation of the first activity-type choice of the day. Table 4 shows the estimation results. The large constant in the baseline utility function indicates socioeconomic variables collected in the dataset have limited contribution to the marginal utility function. All socioeconomic variables that are identified to be statistically significantly associated with the choice generally lead to less time spent before the first activity. Among them, working full-time contributes the most. The expected maximum

Table 4. Choices of time allocation before the first activity of the day.

	coefficient	t-statistics
Baseline utility		
Constant	61.62	40.26
Age		
age between 30 and 60	−0.20	−2.01
age > 60	−0.24	−1.95
Household income > $125,000	−0.10	−1.32
Full-time worker	−1.66	−16.44
Living in at least 3-persons household	−0.10	−1.29
Having access to private vehicles	−0.08	−0.75
Expected maximum utility of first activity-type choice of the day	−0.16	−23.46
Exponential functions of satiation parameters		
Constant	−2.30	−104.46
Workplace arrangement		
Hybrid & work-from-home exclusively	–	–
work-outside-from-home exclusively	0.0038	2.23

utility of the first activity-type choice of the day has a negative impact on the amount of time allocated before engaging in it.

The satiation parameter function defines the rate of change of the marginal utility. A positive satiation parameter suggests the tendency to allocate less time to the activity, while a negative satiation parameter indicates the opposite. From Table 4, workers tend to spend less time at home before their first activity if they work outside of home and have to commute. The behavioural implication revealed fits the expectation according to daily life experience.

5.3. Activity-type choices for the first activity during the day

The choice of first activity types is modelled separately from subsequent activities. As per the sample used in this study, 89 percent of workers scheduled work as their first activity (both at home and away from home). Table 5 presents the final specification of the model. The systematic utility is defined by the worker's age, household size, workplace arrangements, travel time to work, and expected maximum utilities of location choice or activity-type choice in the next scheduling cycle (if work-from-home is chosen). First, the signs for alternative-specific constants (ASCs) are all negative. This indicates that the choice of the first activity is strongly influenced by the expectation of subsequent choices represented by the logsum in the specification. The magnitude of alternative-specific constants (ASCs) also indicates that work-from-home options are the most preferred first activity of the day if workers are allowed to do so. The ASCs represent the baseline or inherent attractiveness of an alternative that is not captured by the exogenous variables in the specification. Among all the alternatives in the choice set, primary and secondary options of working from home demonstrate notably higher alternative-specific constant (ASC) values.

Furthermore, the likelihood of attending school as the first activity decreases as workers age. Contrariwise, the possibility of participating in other activities increases with workers' age. Living in larger households increases the probability of attending school as the first activity. Living in large households also decreases the likelihood of participating in recreation/visiting activities as the first activity. Longer travel time from home to work encourages workers to schedule working outside of the home as their first activity. This

Table 5. First activity-type choice.

	coefficient	t-statistics
Alternative-specific constant (ASC)		
work outside from home – primary	−16.19	−14.50
work from home – primary	−2.30	−2.22
work outside from home – secondary	−19.40	−15.47
work from home – secondary	−4.53	−4.30
shop/market	−19.32	−16.06
restaurant/bar/coffee	−22.63	−19.58
recreation/visiting	−19.53	−15.94
other	−21.64	−12.23
Logarithm of age		
school	−4.82	−14.36
other	0.76	2.00
Living in at least 3-persons household		
school	1.27	2.76
recreation/visiting	−0.57	−1.86
Workplace arrangement		
Work-outside-from-home exclusively		
work outside from home – primary	1.10	4.21
work outside from home – secondary	1.49	2.52
shop/market	0.65	1.41
recreation/visiting	1.33	2.19
Work-from-home exclusively & hybrid		
work outside from home – primary	−2.38	−6.13
work outside from home – secondary	−1.00	−1.09
shop/market	1.12	2.10
recreation/visiting	1.52	2.25
other	0.61	1.59
Home-to-work auto travel time		
work outside from home – primary	0.51	7.04
work outside from home – secondary	0.22	1.19
Logsum of subsequent choices		

reflects travel time unreliability in the region as individuals tend to schedule mandatory activities earlier than other activities (Habib 2018).

The model also captures the effect of different workplace arrangements on activity type choice. This, together with the choice set formation described in Section 5.0, enables the modelling framework to forecast activity-travel behaviour in different work-from-home scenarios. The negative coefficient indicates that workers allowed to work from home are less likely to schedule work outside. Besides that, it can be observed that work-from-home arrangements lead to a higher probability of scheduling out-of-home discretionary activities. The differences in activity scheduling behaviour might be attributed to different characteristics of workers since white-collar workers are more likely to work remotely than blue-collar workers. While searching for the final specification, several model specifications with occupation-type variables were also tested. None of the occupation-type variables were statistically significantly associated with the likelihood of scheduling dictionary activities in the first scheduling episode. Therefore, the characteristics of workers (represented by occupation types) did not influence the scheduling behaviour statistically significantly.

5.4. Activity-type choices subsequent to the first activity

The activity-type choice after the first activity is a function of activity sequence, characteristics of trip chain, time-of-day, travel time, and expected maximum utilities of subsequent

Table 6. Subsequent activity type choice.

	coefficient	t-statistics
Alternative-specific constant (ASC)		
Second activity during the day		
work outside from home – primary	−4.76	−11.10
work from home – primary	−1.98	−4.22
work outside from home – secondary	−11.28	−18.54
work from home – secondary	–	–
school	−21.06	−8.66
shop/market	−13.70	−28.39
restaurant/bar/coffee	−11.99	−26.49
recreation/visiting	−12.41	−24.25
other	−12.72	−22.26
home maintenance	−6.50	−11.20
Third activity during the day		
work outside from home – primary	−5.90	−11.85
work from home – primary	–	–
work outside from home – secondary	−11.54	−15.00
work from home – secondary	1.55	2.97
school	−16.74	−10.12
shop/market	−13.36	−31.05
restaurant/bar/coffee	−9.41	−21.41
recreation/visiting	−13.14	−24.14
other	−12.37	−23.34
home maintenance	−10.83	−18.02
Fourth & later activity during the day		
work outside from home – primary	−9.35	−7.01
work from home – primary	–	–
work outside from home – secondary	−18.42	−15.94
work from home – secondary	−5.15	−9.32
school	−17.53	−5.62
shop/market	−15.74	−35.80
restaurant/bar/coffee	−7.64	−24.87
recreation/visiting	−14.75	−25.82
other	−13.99	−22.67
home maintenance	−16.67	−23.66
Number of times same activity-type scheduled in previous cycles		
work outside from home – secondary	2.94	12.00
work from home – secondary	2.69	12.13
school	3.67	2.73
shop/market	2.38	20.49
restaurant/bar/coffee	1.59	8.41
recreation/visiting	4.30	15.20
other	2.80	11.55
home maintenance	7.62	26.67
Time-of-day as fraction of 24 hrs		
before 6 am		
work outside from home – primary	7.65	2.52
home maintenance	43.00	8.86
home permanently	35.61	17.57
6 am-9 am		
work outside from home – primary	–	–
work from home – primary	20.83	16.49
work outside from home – secondary	–	–
work from home – secondary	–	–
school	17.74	4.59
shop/market	14.33	13.44
other	8.23	6.77
home maintenance	18.24	12.03
home permanently	12.25	15.92

(*continued*).

Table 6. Continued.

	coefficient	t-statistics
9 am-12 pm		
work outside from home – primary	−10.38	−8.46
work from home – primary	–	–
work outside from home – secondary	–	–
work from home – secondary	−7.41	−7.21
school	9.32	1.93
shop/market	3.30	4.46
restaurant/bar/coffee	−10.76	−13.06
home maintenance	5.98	5.39
12 pm – 3 pm		
work outside from home – primary	−10.37	−8.89
work from home – primary	−6.89	−3.96
work outside from home – secondary	–	–
work from home – secondary	−6.59	−7.53
school	–	–
shop/market	–	–
restaurant/bar/coffee	−13.92	−8.89
other	−2.52	−18.45
home maintenance	1.70	1.91
home permanently	−3.25	−6.41
3 pm-7 pm		
work outside from home – primary	−9.74	−7.82
work from home – primary	−7.28	−4.37
work outside from home – secondary	−6.92	−10.33
work from home – secondary	−6.52	−3.80
restaurant/bar/coffee	−11.10	−24.13
recreation/visiting	−1.67	−3.24
other	−2.94	−4.89
home permanently	−2.78	−7.55
after 7 pm		
shop/market	−0.84	−1.19
restaurant/bar/coffee	−10.07	−9.98
recreation/visiting	−1.72	−1.65
For work outside from home		
origin-to-work auto travel time	0.57	4.79
For home permanently if travel is needed		
origin-to-home auto travel time	0.18	2.28
Logsum of subsequent choices		

choices. Table 6 shows the final specification and estimated parameters. Three sets of ASCs are estimated to account for the activity sequence effect. Different ASCs are specified for activities located as second, third, fourth, or later episodes during the day. Each group of ASCs has different estimated coefficients and is highly statistically significant. The specification accounts for significant market share variations attributed to different episode sequences on the timeline. As shown in Figure 4, resting at home permanently dominates the second and fourth or later episodes on the timeline. In contrast, the market share of activity types appears to be more evenly distributed during the third episode of the timeline.

The positive coefficients for the times the same activity is scheduled in previous cycles reflect the worker's tendency to chain similar activities in their schedules. This finding implies that individuals cluster and repeat similar activities consecutively, potentially driven by convenience, efficiency, or habit formation. The time-of-day effect indicates that trips started before 6 am will likely be work and homebound. Choices of making school, shop/market, and home maintenance activities are most likely between 9 and 12 pm, compared to other activities. The preference for resting at home temporarily between 3 and

7 pm is the highest. Lastly, like the discussion in the first activity-type choice, a positive parameter for travel time to an out-of-home workplace indicates that longer travel time encourages workers to schedule work earlier. Similarly, longer travel to home also increases the choice of returning home permanently.

5.5. Time allocation choice for activities during the day

The time allocation choice for activities during the day is also modelled by baseline utility and satiation parameter functions. The baseline utility is a function of activity types, time-of-day, and expected maximum utilities of the activity-type choices in the next cycle. Table 7 shows the estimation results. A larger marginal utility corresponds to a higher time allocation to a particular activity. Thus, positive and relatively large coefficients associated with all primary work activities indicate that workers dedicate much time to their productive tasks. However, primary and secondary work activities conducted outside the home and primary work-from-home activities have negative parameters for time-of-day variables. It means less time will be allocated to them as the day proceeds.

Conversely, more time will be allocated to secondary work-from-home activities that start later in the day. This reflects the flexibility of remote working. Meanwhile, the marginal utility of restaurant/bar/coffee increases as the day proceeds. This indicates that workers spend more time in restaurants and bars for dinner than lunch. The parameters for expectations of the activity in the next cycle are negative. This indicates that workers allocate less time to current activities if they expect to schedule other activities later. The most significant reduction comes from primary work activities, which are less flexible.

The satiation parameter function defines the rate of change of marginal utility. A negative satiation effect means the tendency to allocate more time and vice versa. The main effects for primary work activities have the lowest constant in the satiation function. The constant remains the same across all workers. It accounts for unobserved factors influencing the satiation parameter. Possible factors include company policies, job characteristics, personal habits, etc. Besides the main effect, workers tend to allocate more time to their primary work activities if scheduled as the first activity during the day. However, they tend to spend less time if primary working activities are scheduled as subsequent activities during the day. It is interesting to find an opposite time-of-day effect on two primary work activities with different locations. Positive satiation effects are found for primary work outside of home activity for increased time of day. However, the opposite is found in primary work-from-home activity. This indicates that workers are willing to work longer even if they start working remotely later. This observation suggests that flexible working schedules compounded with work-from-policy might stimulate productivity.

5.6. Activity location choice

The location choice is generic for all scheduling episodes. The choice sets for each episode are defined by the time budget remaining. Table 8 presents the model estimation results. Travel time from the central business district (CBD) to alternative traffic analysis zones (TAZs) is found to have significant effects on work, shop/market, and dining-related activities. Proximity to CBD will increase the likelihood of TAZs being chosen for work,

Table 7. Time allocation choice of activities during the day.

	coefficient	t-statistics
Baseline utility		
Constant		
work outside from home – primary		
as first activity of the day	45.75	33.87
as second or later activity of the day	47.81	26.67
work from home – primary		
as first activity of the day	37.35	20.08
as second or later activity of the day	15.16	2.70
work outside from home – secondary	2.05	1.90
work from home – secondary	–	–
home maintenance	0.22	0.58
school	−3.18	−4.10
shop/market	−0.93	−2.75
restaurant/bar/coffee	−3.63	−3.21
recreation/visiting	0.15	0.75
other	−1.99	−11.54
Time-of-day as fraction of 24 hrs		
work outside from home – primary	−43.62	−32.15
work from home – primary	−11.50	−2.62
work outside from home – secondary	−3.70	−2.72
work from home – secondary	1.75	4.24
restaurant/bar/coffee	3.80	3.13
Logsum of subsequent activities		
work outside from home – primary	−0.22	−21.80
work from home – primary	−0.21	−21.83
work outside from home – secondary	−0.06	−3.22
work from home – secondary	–	–
shop/market	−0.01	−1.22
restaurant/bar/coffee	−0.02	−0.98
recreation/visiting	−0.06	−5.55
other	−0.04	−4.16
home maintenance	−0.03	−2.95
Exponential function of satiation parameters		
work outside from home – primary		
main effect	−1.94	−69.62
as first activity of the day	−0.09	−2.00
as second or later activity of the day	0.95	2.26
work from home – primary		
main effect	−1.60	−28.39
as first activity of the day	−0.11	−2.33
as second or later activity of the day	0.50	1.58
school	0.50	1.90
shop/market	−0.32	−4.27
home maintenance	−0.15	−2.74
Time-of-day as fraction of 24 hrs		
work outside from home – primary	1.02	26.46
work from home – primary	−0.23	−1.60
shop/market	0.11	0.92

shop/market activities. However, TAZs further away from CBD are more likely to be chosen for dining. Travel impedance is measured by mode-specific origin–destination-home travel time. Modelling results indicate that zones are more likely to be selected if they have less travel impedance in auto and transit travel time. This finding suggests that individuals prefer zones that offer shorter travel times between their current location and homes and are more accessible by both private vehicles and public transit. In terms of land-use characteristics, population density attracts recreation/visiting activities. The density of zonal employment, retail establishments, entertainment facilities, and restaurants are positively

Table 8. Out-of-home location choice.

	coefficient	t-statistics
Logarithm of auto travel time to CBD		
work outside from home – primary	−0.13	−2.01
shop/market	−0.97	−3.76
restaurant/bar/coffee	1.55	16.85
Logarithm of travel time		
origin-destination-home by auto	−1.64	−40.95
origin-destination-home by transit	−1.28	−23.55
Logarithm of zonal population density		
school	−0.17	−0.94
recreation/visiting	0.14	1.25
Zonal employment density		
work outside from home – primary	1.25	12.40
work outside from home – secondary	1.06	3.75
Zonal retail point of interest (POI)		
shop/market	0.51	6.77
other	0.21	1.57
Zonal entertainment facility POI		
recreation/visiting	0.54	4.70
Zonal accommodation and food service POI		
other	0.36	2.23
Zone from same municipality	0.81	14.47
Logsum of subsequent choices		

related to their corresponding activities. Lastly, the dummy variable indicating the destination zone is from the same municipality as the origin zone has a positive coefficient. This may be due to factors such as higher levels of familiarity, convenience, and habitual behaviour.

5.7. Travel mode choices

The mode choice model considers different types of trips within home-based tours. It models first, intermediate, and return-home trips as separate components. The mode choice model can capture the specific characteristics and factors influencing mode selection at each stage of the tour. Factors such as trip purpose, availability of mobility tools, and level-of-service of each alternative may vary for different trip segments within the home-based tour. The mode choice model is forward-looking. The systematic utility contains the expected maximum utilities of activity-type choices in the next cycle. The model is also history-dependent. The choice set of each trip segment in the trip chain is formed based on the availability of mobility tools determined by mode choice in previous trips. Moreover, the dummy variable indicating the inertia effect is included in the systematic utility of intermediate and return-home trips.

Table 9 presents the estimation results. Overall, all level-of-service and cost parameters retained in the final specification have expected negative signs. The estimation results suggest that trip markers thoroughly evaluate the level-of-service and travel costs for their first and returning home trips. Both motorised and non-motorised travel time, transit fare, and parking costs are evaluated for trips that leave and return home. Conversely, fewer level-of-service and cost variables can explain systematic utilities for intermediate trips. Only walking time and parking costs are retained in the final specification. Cost variables reveal drivers and auto passengers are sensitive to parking expenses incurred throughout their tours. Contrariwise to parking costs, drivers and auto passengers are indifferent to automobile operational costs, such as fuel and maintenance costs. Parameter estimation shows coefficients with operational costs are statistically insignificant. This highlights the importance of parking cost in travellers' mode choice. Effective parking management strategies are critical in densely populated cities with limited parking capacity and intense congestion (Nourinejad and Roorda 2017).

The inertia effect represents the momentum of using the same mode for the entire tour. To capture the inertia effect, dummy variables are included in the mode choice model to indicate whether the same mode was chosen in the previous trip segments of the tour. The positive and statistically significant values of dummy variables for all alternatives indicate that the previous mode choice significantly influences the subsequent mode choice. This means that individuals are more likely to continue using the same mode they chose in earlier segments of the tour, potentially due to factors such as convenience, habit, or the need to return home with the mobility tool.

To sum up, the formulation of the mode choice component is fully based on the RUM-based econometric approach. The choice set formation is only governed by the availability of mobility tools considering trip-chaining, as described in Section 3.1. The formulation avoids the choice set explosions for tour-based discrete mode choice models that use main tour modes and are conditioned on trip-level mode choices (Bradley, Bowman, and Griesenbeck 2010; Davidson et al. 2010; Zhou et al. 2023). Moreover, the formulation did not enforce the organising principle such as the tour-based model implemented in TASHA that '*if a car is to be used on a tour, it must be used for the entire chain, since the car must be returned home at the end of the tour*' (Miller, Roorda, and Carrasco 2005). However, the study also checks the consistency of driving modes within each home-based tour. Based on the simulation results (details are presented in Sections 6&7), 15,030 trips are simulated to depart home with cars, and 14,810 returned home with cars. Only 1.46% left home with cars but did not return home with their cars. This indicates that more than 98% of the simulated home-based tours followed the organising principles proposed by Miller, Roorda, and Carrasco (2005). However, the results are achieved through a behavioural-based arrangement, such as choice set formation and inertia effects instead of rules. The margin of irregularity (1.46%) can be tolerated in demand modelling. It is certainly possible that individuals park their vehicles at the worksite overnight and pick them up on the following day. However, behaviour beyond a single day is out of the current study's scope and needs to be addressed with multi-day models and multi-day datasets.

6. Model calibration & validation

The estimated CUSTOM model requires calibration before scenario analysis. Activity type choice and travel mode choice are calibrated to match the market share observed in the COVHITS dataset. The ASCs in both modelling components are tuned using the simultaneous perturbation stochastic approximation (SPSA) algorithm (de Dios Ortúzar and Willumsen 1994; Spall 1998). The SPSA algorithm calculates multi-dimensional gradients by introducing random perturbations at a given point. It has been widely used to calibrate microscope traffic simulation models (Jingtao, Dong, and Zhang 2007; Yu and Fan 2017). Wang et al. (2021b) recently applied the SPSA algorithm to calibrate a large-scale agent-based travel demand forecasting modelling system. The goal of the calibration

Table 9. Travel mode choice.

	coefficient	t-statistics
First trip of tour		
Alternative-specific constant (ASC)		
drive	14.51	58.85
auto passenger	11.74	46.42
ride-hailing & Taxi	–	–
public transit	13.57	46.45
walk	15.16	50.22
bike	10.61	22.67
Level-of-service & cost		
auto in-vehicle travel time	−0.03	−4.30
transit out-of-vehicle travel time	−0.02	−1.99
walk time	−0.10	−11.98
bike time	−0.03	−1.43
travel cost (transit fare)	−0.27	−6.49
parking cost	−0.04	−5.04
Trip purpose as work (drive & passenger)	−0.13	−0.92
Logsum of subsequent choices		
Intermediate trip of tour		
Alternative-specific constant (ASC)		
drive	13.18	37.42
auto passenger	9.08	20.62
ride-hailing & Taxi	–	–
public transit	9.33	22.17
walk	11.68	23.02
bike	4.96	2.50
Level-of-service & cost		
walk time	−0.09	−3.58
parking cost	−0.04	−5.04
Inertia		
drive	0.38	1.59
auto passenger	2.72	10.29
ride-hailing & Taxi	3.71	7.64
public transit	2.20	7.88
walk	1.83	4.88
bike	7.52	7.11
Logsum of subsequent choices		
Return home trip of tour		
Alternative-specific constant (ASC)		
drive	4.75	13.90
auto passenger	0.002	0.01
ride-hailing & Taxi	–	–
public transit	−0.09	−0.17
walk	1.31	2.55
bike	−4.00	−1.47
Level-of-service & cost		
auto in-vehicle travel time	−0.18	−11.03
transit in-&out-of-vehicle travel time	−0.06	−5.49
walk time	−0.06	−4.98
bike time	−0.11	−1.08
travel cost (transit fare)	−0.06	−0.48
Inertia		
drive	0.38	1.59
auto passenger	2.72	10.29
ride-hailing & Taxi	3.71	7.64
public transit	2.20	7.88
walk	1.83	4.88
bike	7.52	7.11
Logsum of subsequent choices		

Figure 4. Comparison of simulated (a) activity type choice (b) travel mode choice (c) activity/trip start time, and (d) trip distance distributions vs. observed distributions in the COVHTIS dataset.

process is to minimise the loss function so that the simulated travel demand matches the observation.

Figure 4 presents calibrated CUSTOM outputs against the observation. Overall, the model successfully reproduces the sequence effect in activity-type choice. The activity types scheduled for first, second, third, fourth, and later episodes match well with the observation from the COVHITS survey. The travel mode share for trips that were leaving, returning home and intermediate in home-based tours also closely matched their corresponding market share. Moreover, the model accurately replicates morning and afternoon peak periods through the simulated activity and trip start time. It reflects that the time allocation components exhibited satisfactory performance. The activity and trip start time distribution is a product of activity-type choices and their corresponding time allocation choice.

Additionally, the simulated trip distance distribution closely resembled the observed distribution, with only minor discrepancies noted for trips shorter than 3 km. This slight divergence could be attributed to the calculation of distances for same-zone trips. The observed trip distance is directly calculated using reported origin and destination coordinates and the Google Maps API. In contrast, the CUSTOM outputs selected Traffic Analysis Zones (TAZs), and distances are computed based on the travel distance matrix between TAZs.

The validation above demonstrates that the CUSTOM model can construct a representative portrait of behaviours that aligns well with observation at the aggregate level. Individual-level validation is also performed to examine the number of individuals whose activity-travel behaviours are accurately reproduced by CUSTOM. The individual-level validation is based on the following criteria:

- total number of trips/activities
- number of trips/activities for each activity type
- total durations of activities per day ($\pm$ 60 minutes)
- total durations of activities by activity type per day ($\pm$ 60 minutes)

The individual-level validation follows the approach outlined by Yasmin, Morency, and Roorda (2016), which includes macro-, meso-, and micro-level validations of the TASHA model. The validation of the TASHA model is used as the reference in this validation exercise. TASHA is a pioneering activity-based travel demand model developed for the Greater Toronto Area (GTA), Canada, which employed a rule-based approach (Miller and Roorda 2003). Direct comparisons between the CUSTOM and TASHA models provide valuable insights into the differences between these two modelling approaches. According to Yasmin, Morency, and Roorda (2016), individual-level validation identifies the percentage of correctly simulated samples based on the sequential and cumulative application of each criterion. The results of the individual-level validation are summarised in Table 10. First, the CUSTOM model achieves a 66.4% match for the total number of activities, outperforming the 43.4% match reported for TASHA by Yasmin, Morency, and Roorda (2016). A detailed confusion matrix for the number of activities scheduled by type is also provided in Table 10. The total error rate for the CUSTOM model ranges from 4.4% to 17.9%, which is within an acceptable range. Moreover, CUSTOM correctly replicates approximately 15.3% of sample behaviours when jointly considering the total number of activities and their total duration. The success rates for each activity duration are also reported.

In addition to activity schedules, distances travelled by various travel modes are also compared at the individual level. The results are presented in Figure 5. Generally, the percentage of samples with larger variation follows a diminishing trend as the discrepancies between observation and simulation increase. This suggests that the mode and location choice components perform as expected at the individual level. For automobile and transit modes, half of the observed variations are within 20 km, while half are within 2 km for active modes. Exact matches are not expected, as individuals' schedules are randomly simulated. However, the results indicate that most samples do not show excessive travel distance for a particular mode. In summary, activity-based travel demand models are not designed to precisely replicate activity-travel behaviours at the individual level (Yasmin, Morency, and Roorda 2016). Instead, activity-based models aim to construct a representative portrait of behaviours that aligns with aggregate-level observed patterns with reasonable confidence.

Table 10. Individual-level comparison of simulated & observed activity schedules.

	Matched percentage		
Criteria	CUSTOM	TASHA (Yasmin, Morency, and Roorda 2016)	
Total number of activities	66.4%	*Total number of trips*	43.40%
Duration of activities per day	15.3%	*Duration of activities per day*	8.70%
Duration by activity type		*Duration by activity type*	
WOFH (primary & secondary)	25.6%	Work	8.60%
WFH (primary & secondary)	25.5%		
Shopping/market	54.7%	Shopping	8.60%
Other discretionary[1]	35.2%	Other discretionary	8.60%

Number of activities by type	CUSTOM					
	True positive	True negative	Accuracy	False positive	False negative	Total error
WOFH primary	28.7%	57.4%	86.2%	7.5%	6.3%	13.8%
school	0.4%	97.0%	97.4%	1.3%	1.3%	2.6%
shopping/market	1.5%	80.7%	82.1%	8.0%	9.8%	17.9%
restaurant	0.3%	92.0%	92.2%	3.4%	4.3%	7.8%
recreation	0.3%	90.7%	91.1%	4.3%	4.6%	8.9%
other	0.7%	88.2%	88.9%	5.8%	5.2%	11.1%
WFH primary	43.0%	46.3%	89.3%	4.9%	5.8%	10.7%
WOFH secondary	0.01%	95.5%	95.6%	2.0%	2.5%	4.4%
WFH secondary	0.1%	89.6%	89.7%	4.7%	5.6%	10.3%

Notes: (1) Other discretionary activities include restaurant, recreation and other activities described in Section 5.0.

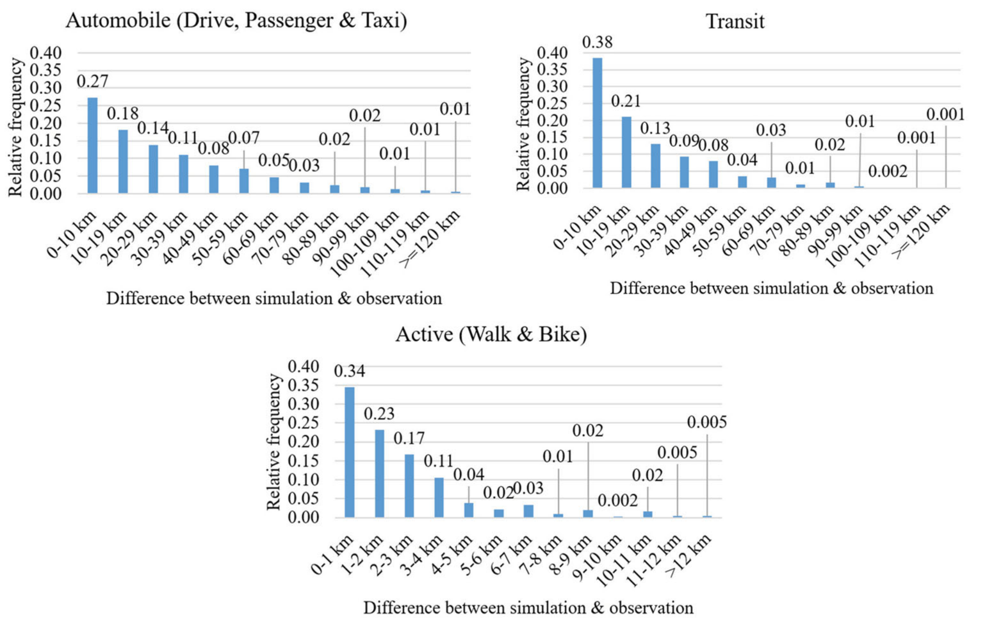

Figure 5. Individual-based comparison of simulated & observed distance travelled by different modes.

7. Work-from-home scenario analysis

The calibrated CUSTOM model is then used to simulate travel demand with different work-from-home adaption rates. The scenario analysis assumes that workers working outside of home (WOFH) would continue to do so. On the other hand, the analysis considered the possibility of workers who were originally working from home (WFH) being required to transition and work outside of home. By examining different scenarios where the distribution of WFH and WOFH workers varied, the analysis aimed to provide insights into how different work arrangements might affect activity-travel demand.

In total, 6 scenarios are simulated in this study. Each scenario represents a different distribution of workplace arrangement choices between work-from-home (WFH) and work-outside-from-home (WOFH). The first scenario involved 60% WFH and 40% WOFH, which was set to reflect the status observed in the 2021 COVHITS. The subsequent scenarios explored a gradual shift from WFH to WOFH. Scenario 2 has an equal distribution of 50% WFH and 50% WOFH, followed by 40% WFH and 60% WOFH, 30% WFH and 70% WOFH, and 20% WFH and 80% WOFH in Scenario 3, 4 and 5, respectively. Finally, Scenario 6 has 10% WFH and 90% WOFH, representing the pre-pandemic work dynamics observed in the 2016 Transportation Tomorrow Survey (TTS). It is the workplace arrangement equilibrium in the pre-pandemic world. Logically, the post-pandemic work arrangement equilibrium between Scenarios 2, 3, 4, and 5 will exist.

Bootstrapping is used to report the simulated demands. One thousand bootstrapped sub-samples are created to calculate average sample statistics. WFH workers required to become WOFH are randomly selected in each bootstrapped sample. Figure 6 presents a visual comparison of key sample statistics. Three types of sample statistics are reported. They are the number of activity episodes per day by type, average daily trips, and vehicle kilometres travelled (VKT) by driving and transit. Appendix A reports the detailed statistics of each simulated scenario to provide sufficient information for readers.

Overall, the results show that the total number of activities scheduled is similar between simulated scenarios. The total number of daily activities decreased by 2.8% from 2.47 to 2.40 from Scenario 1 to Scenario 6, compared to 2.51 observed in the 2016 TTS. However, the scheduling of activities by purpose varied, highlighting the trade-offs between activity types. From Scenario 1–6, the average WOFH daily activities gradually recovered to the pre-pandemic level observed in 2016. Interestingly, the number of scheduled shopping episodes gradually decreased as the proportion of WFH workers decreased.

Conversely, Figure 6-e shows that other discretionary activities remained steady across the simulated scenarios but consistently fell below pre-pandemic levels. The magnitude of this difference reflects the structural changes in discretionary activity participation caused by the pandemic and the growing influence of information and communication technology (ICT) between 2016 and 2021 (Gössling 2017; Lee and Eom 2023). The scenario simulations did not account for direct treatment for out-of-home discretionary activity participation from pandemic recovery or the impact of ICT adoption. As a result, the participation in other discretionary activities remains stable across Scenarios 1–6 but differs from the 2016 TTS. However, the total number of trips, namely the travel demand, recovered from 1.47 to 2.21 per day from Scenario 1 to Scenario 6. The number of daily driving trips by travel modes recovered from 1.06 to 1.43 per day.

Meanwhile, daily transit trips recovered from 0.26 to 0.40 per day from Scenario 1 to Scenario 6. Looking at the VKT across simulated scenarios, driving VKT rebounded from 15.5 km per worker per day to 22.7 per worker per day to 85.6% of the pre-pandemic level. Transit VKT recovered to 92.1% of the pre-pandemic level from 4.02 km per worker per day to 6.3 per worker per day.

7.1. Validating activity-based model through behavioural predictability test

The scenario analysis results provide an example of validating the activity-based travel demand modelling system using the behavioural predictability test. The covid-19 pandemic dramatically changed workers' workplace arrangements and corresponding commuting patterns. However, the CUSTOM model and the scenario analysis utilise the behavioural insight that workers' engagement in productive activities remained irrespective of workplace arrangements to reconstruct pre-pandemic travel behaviours. Figure 6-b shows that the average daily WOFH activities in Scenario 6 (90% of workers WOFH) is 0.82. It closely matches the sample statistics obtained directly from the 2016 TTS (90.7% of workers WOFH), which is 0.83. This indicates the behavioural realism of the modelling approach presented in this paper.

The scenario analysis validates behavioural predictability of the CUSTOM modelling system. As mentioned above, as the percentage of workers recovered to the pre-pandemic level, the CUSTOM model predicts similar WOFH activities in Scenario 6 as observed in the 2016 TTS. Meanwhile, statistics such as the average number of activities per day by each

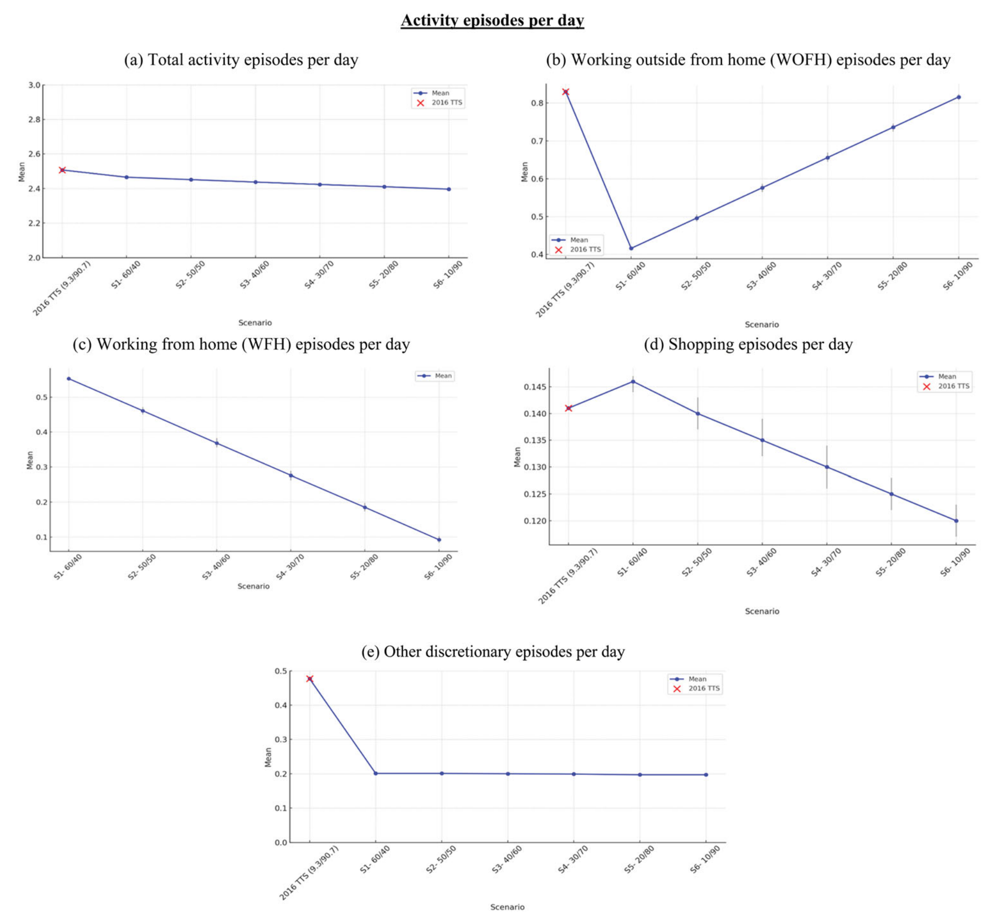

Figure 6. Comparison of activity episodes per day by types, total trips, driving & transit trips per day, and vehicle kilometres travelled (VKT) by driving and transit modes between scenarios.

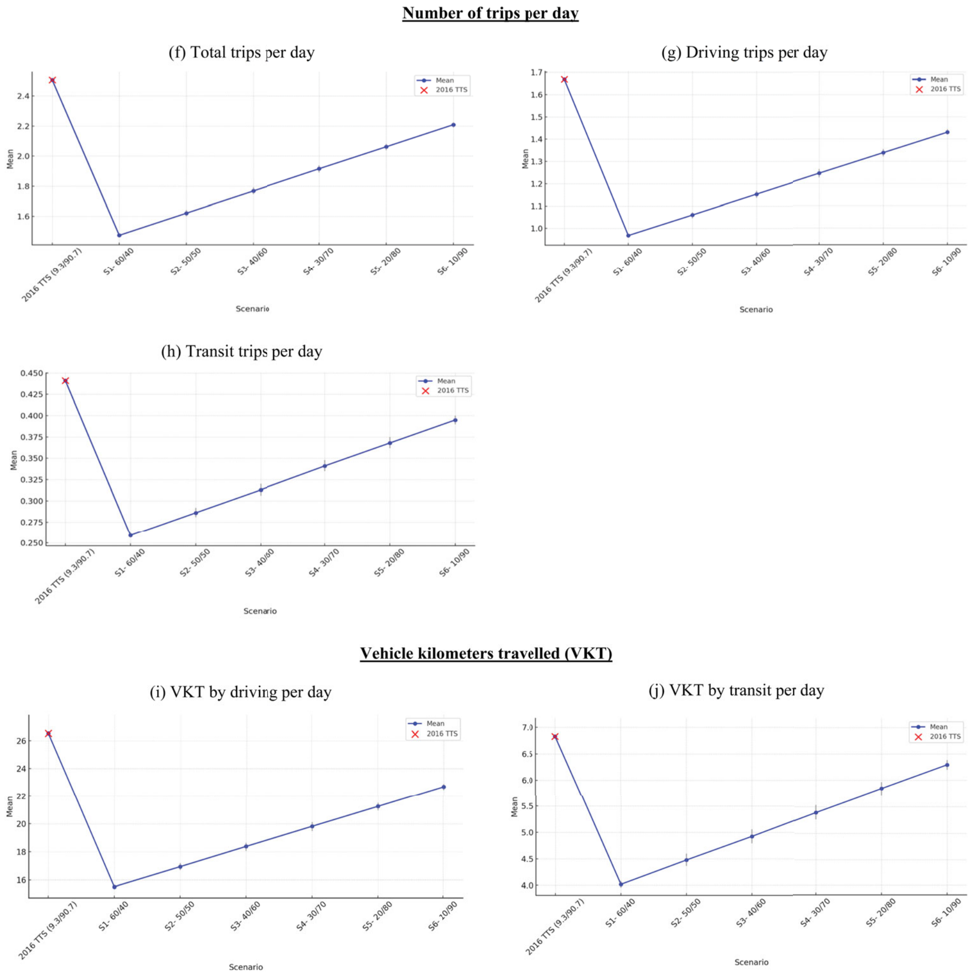

Figure 6. Continued..

type, average trips per day, and average VKT by each mode all recovered to the direction observed in the 2016 TTS. The CUSTOM model estimated based on data from 2021 can reasonably reproduce the observed workers' travel demand from the 2016 TTS data by carefully removing the disruptive change in workplace arrangements introduced by the pandemic. This validation indicates that the model can capture the dynamic nature of travel demand, particularly in response to disruptive events. It shows the potential of the agent-based activity-based modelling system. Modelling frameworks like the CUSTOM system have reliability and credibility in forecasting travel behaviours to inform strategic decisions.

Travel demand modellers validate the performance of activity-based models to ensure their models' practical applicability and credibility in real-world contexts (Deng, Miller, and Vaughan 2014; Khan, Shahrier, and Habib 2021; Roorda, Miller, and Habib 2008; Yasmin, Morency, and Roorda 2016). Typical model validation approaches include testing the temporal forecastability or spatial transferability of the modelling system. The model is first calibrated in the temporal forecastability test to match travel demand from a base year. Then, it is used to forecast travel demand for future years, and the model's predictions are compared against actual observations from those years. Roorda, Miller, and Habib (2008) and Khan, Shahrier, and Habib (2021) provide examples of the temporal forecastability approach. The spatial transferability approach involves applying the modelling system developed for a specific study area to another region (Deng, Miller, and Vaughan 2014; Yasmin, Morency, and Roorda 2016). The simulated travel demand in the transferred region is validated against actual observations. This test assumes the same activity-travel behaviour mechanism between the two regions. This is a convenient assumption, especially for rule-based and hybrid-based activity-based models. For example, Roorda, Morency, and Woo (2008b) compared the factors influencing trip rates between Toronto and Montreal, Canada's two largest urban regions. Despite similar trends such as population aging, increased motorisation, and decreased household size, sufficient geographic and cultural differences concerning travel demand were found between the populations.

On the other hand, the behavioural predictability test assesses the predicting power of activity-based models. The behavioural predictability test demonstrates the predicting power of activity-based models facing emerging behavioural changes. For an activity-based model to be a truly useful tool for policy analysis, it must be capable of generating emergent behaviour that reflects such real-world changes (Miller 2018). The temporal forecastability and spatial transferability tests assume that the underlying travel behaviours remain the same between the model's development and forecasted instances. However, urban travel demands can be significantly influenced by disruptive innovations or events, such as the introduction of ride-hailing, advancements in information and communication technology (ICT), and crises like the covid-19 pandemic (Clewlow 2017; Le, Carrel, and Shah 2021; Shabanpour et al. 2018; Wang et al. 2021; Wang, Hossain, and Habib 2022). Thus, validating behavioural predictability becomes crucial in advancing activity-based models, particularly for long-range planning where disruptive changes are highly likely to occur.

8. Limitation & future research

The proposed approach has several limitations that need to be addressed by further model developments. Firstly, the current model formulation gives mandatory and discretionary activity the same scheduling priority. Individuals might have less flexibility in terms of scheduling their mandatory activities. Therefore, the model can be further developed to consider skeleton schedules on individuals' timelines (Dianat, Habib, and Miller 2020). Skeleton activities refer to out-of-home work and school activities that are mandatory for people based on their socio-economic status. Individuals' skeletons can be generated first, then discretionary activities can be filled out as a secondary step. Secondly, the mode choice component in this study only considers tour-based choice set formulation but is estimated separately for each trip leg. Alternatively, individuals might choose their modes while considering all trips in their trip chain at once. Thus, future studies should examine the approach that mode choice is evaluated based on cost and level-of-service attributes of all trips in the trip chain.

Thirdly, this study presents an individual-based model. Household interaction is only implicitly captured with household-level socioeconomic variables (e.g. household size variable, etc.). However, accounting for household-level decisions and intra-household interactions is crucial, especially as the CUSTOM model includes in-home activities and automobile passengers as a travel mode. These interactions can significantly influence the household's allocation of time and resources. Therefore, future developments of the CUSTOM model should adopt a household-based approach, incorporating intra-household interactions. Intra-household consideration can be applied at both the model estimation and simulation stages. During the estimation stage, factors such as vehicle and household members' availability should be explicitly considered for intra-household resource allocation.

Similarly, these availability constraints should be factored into the simulation process to ensure a more accurate representation of household dynamics. A fully household-based approach would also allow for a more detailed analysis of auto-passenger trips. In this study, the auto passenger mode is categorised into two cases: in the first case, the traveller is driven by a household member, and in the second case, the traveller is driven by a non-household member. The dataset used in this study is relatively small, containing only 299 auto-passenger trips, with 75% driven by household members and 25% by non-household members. Future research should utilise larger-scale data sources to treat these two auto-passenger trips separately. The first case could focus on household interactions, while the second could be available to all travellers.

Fourthly, the dataset used in this study was collected during the covid-19 pandemic. The overall telecommuting rate was high, and participation in discretionary activities was still recovering. Exogenous factors such as fear of infection are unaccounted for in the current modelling exercise. Therefore, this dataset is only used to demonstrate the application of the proposed model. The CUSTOM model need be estimated and examined thoroughly again with a dataset collected in the post-pandemic era for its practical application. Lastly, activity-travel behaviours are influenced by latent factors such as habitual behaviour and exogenous factors such as the popularity of online shopping and other tele-activities (Bamberg, Ajzen, and Schmidt 2003; Mokhtarian 2004). The current model formulation lacks consideration of the above factors and should be further developed.

Moreover, the choice set formations of alternative locations are purely random with time–space constraints. However, individuals might develop habits in their location choices in real life, such as several go-to-places for out-of-home activities. Therefore, future development should investigate the feasibility of probabilistic location choice formation considering individual heterogeneity. The CUSTOM framework should be estimated using multi-day travel diaries containing information about habitual travel behaviour. Moreover, the model should be integrated with e-commerce demand models, such as the cooked meal delivery demand generation model developed by Chen, Wang, and Habib (2024).

9. Conclusion

The paper introduces a prototype of a joint CUSTOM and mode choice framework and demonstrates its application. The joint framework is consistent with time–space constraints and random utility maximisation (RUM) theory. The modelling framework considers activities at home. The framework strictly follows the organising principle in activity-based travel demand modelling, which states that travel is derived demand from the needs for activities (Bowman and Ben-Akiva 2001). Capturing workers' at-home activity patterns is critical for travel demand forecasting when workplace arrangements become flexible. Under the joint modelling framework, one scheduling cycle at an out-of-home location generates one trip, either to home or to another out-of-home location. Transiting between productive and maintenance activities at home will not require travel. This study estimates the modelling framework using the COVHITS survey collected in 2021. Through simulation exercises, the study demonstrates that this modelling framework successfully replicates the activity-travel behaviours of workers, as captured in the regional household travel survey conducted in 2016.

The empirical model reveals many behavioural features of a worker's activity-travel behaviour. The heterogeneity in time allocation choices is captured by income and time-of-day effects. In general, variance in the time expenditure choice reduces as the level of income increases. Also, the time expenditure choice variance reduces with time to the end of the day. From marginal utility functions of time allocation choices, workers allocate most of their time to work-related activities regardless of workplace arrangements. Also, workers will spend less time on current activities if they expect to schedule other activities later. The model also captures the influence of workplace arrangements on workers' choices of the first activity of the day. Work-from-home leads to a higher probability of scheduling out-of-home discretionary activities as first activities. For subsequent activities, the systematic utility is a function of activity sequence, characteristics of trip chain, time-of-day, travel time, and expected maximum utilities of following choices. The activity location choice component shows that land-use traits of specific types (e.g. population density, employment, retail, restaurants, entertainment, etc.) attract individuals to related activities, such as recreation/visiting, work, shopping, etc. The mode choice component shows that trip markers thoroughly evaluate the level-of-service and travel costs for each alternative for their first and returning home trips.

In contrast, only walking time and parking costs are sufficient to explain systematic utilities when it comes to intermediate trips. The mode choice component also includes the inertia effect. Results show that individuals are more likely to continue using the same mode they chose in earlier segments of the tour. The behavioural predictability of the CUSTOM system presented in this paper is validated by scenario analysis considering different proportions of work-from-home workers. Six scenarios are simulated. The first scenario involved the status quo observed in the 2021 COVHITS. The subsequent scenarios explored a gradual shift from WFH to WOFH. The last scenario has the same proportion of WFH workers as observed in 2016. As the percentage of workers recovered to the pre-pandemic level, the CUSTOM model predicts similar WOFH activities as observed in the 2016 TTS. All other statistics also recover towards the direction observed in 2016. This validation indicates that the model can capture the dynamic nature of travel demand, particularly in response to disruptive influential factors.

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Appendix A. Sample statistics of simulated workplace arrangement scenarios.

Activity per day					
	Scenario	Mean	95% CI		% diff
Total activities	S1- 60/40	2.465	2.461	2.469	−1.7%
	S2- 50/50	2.451	2.443	2.459	−2.2%
	S3- 40/60	2.437	2.428	2.446	−2.8%
	S4- 30/70	2.423	2.414	2.433	−3.4%
	S5- 20/80	2.410	2.401	2.418	−3.9%
	S6- 10/90	2.396	2.388	2.404	−4.4%
	2016 TTS (9.3/90.7)	2.507			reference
	Scenario	Mean	95% CI		% diff
WOFH episodes	S1- 60/40	0.416	0.410	0.421	−49.9%
	S2- 50/50	0.496	0.487	0.505	−40.2%
	S3- 40/60	0.576	0.565	0.586	−30.6%
	S4- 30/70	0.656	0.645	0.669	−21.0%
	S5- 20/80	0.736	0.725	0.746	−11.3%
	S6- 10/90	0.816	0.808	0.824	−1.7%
	2016 TTS (9.3/90.7)	0.830			reference
	Scenario	Mean	95% CI		% diff
WFH episodes	S1- 60/40	0.553	0.547	0.559	reference
	S2- 50/50	0.461	0.450	0.471	−16.6%
	S3- 40/60	0.368	0.356	0.382	−33.5%
	S4- 30/70	0.276	0.262	0.289	−50.1%
	S5- 20/80	0.185	0.173	0.197	−66.5%
	S6- 10/90	0.092	0.083	0.102	−83.4%
	2016 TTS (9.3/90.7)	–			
	Scenario	Mean	95% CI		% diff
Shopping episodes	S1- 60/40	0.146	0.144	0.147	3.5%
	S2- 50/50	0.140	0.137	0.143	−0.7%
	S3- 40/60	0.135	0.132	0.139	−4.3%
	S4- 30/70	0.130	0.126	0.134	−7.8%
	S5- 20/80	0.125	0.122	0.128	−11.3%
	S6- 10/90	0.120	0.117	0.123	−14.9%
	2016 TTS (9.3/90.7)	0.141			reference
	Scenario	Mean	95% CI		% diff
Other episodes	S1- 60/40	0.201	0.199	0.204	−57.9%
	S2- 50/50	0.201	0.195	0.205	−57.9%
	S3- 40/60	0.200	0.194	0.205	−58.1%
	S4- 30/70	0.199	0.193	0.205	−58.3%
	S5- 20/80	0.197	0.192	0.203	−58.7%
	S6- 10/90	0.197	0.193	0.201	−58.7%
	2016 TTS (9.3/90.7)	0.477			reference
Trips per day					
	Scenario	Mean	95% CI		
Total trips	S1- 60/40	1.474	1.464	1.486	−41.2%
	S2- 50/50	1.621	1.602	1.641	−35.3%
	S3- 40/60	1.768	1.746	1.790	−29.5%
	S4- 30/70	1.916	1.891	1.939	−23.6%
	S5- 20/80	2.062	2.039	2.081	−17.8%
	S6- 10/90	2.209	2.191	2.225	−11.9%
	2016 TTS (9.3/90.7)	2.507			reference
	Scenario	Mean	95% CI		
Driving trips	S1- 60/40	0.968	0.961	0.976	−42.0%

(*continued*).

Trips per day

	Scenario	Mean	95% CI		% diff
Total activities	S1- 60/40	2.465	2.461	2.469	−1.7%
	S2- 50/50	1.060	1.045	1.073	−36.5%
	S3- 40/60	1.153	1.137	1.168	−30.9%
	S4- 30/70	1.246	1.227	1.264	−25.3%
	S5- 20/80	1.338	1.321	1.354	−19.8%
	S6- 10/90	1.430	1.419	1.443	−14.3%
	2016 TTS (9.3/90.7)	1.669			reference
	Scenario	Mean	95% CI		
Transit trips	S1- 60/40	0.259	0.256	0.262	−41.3%
	S2- 50/50	0.286	0.281	0.292	−35.1%
	S3- 40/60	0.313	0.306	0.320	−29.0%
	S4- 30/70	0.341	0.335	0.348	−22.7%
	S5- 20/80	0.368	0.362	0.375	−16.6%
	S6- 10/90	0.395	0.390	0.400	−10.4%
	2016 TTS (9.3/90.7)	0.441			reference

Distance (km) travelled by modes

	Scenario	Mean	95% CI		
Driving	S1- 60/40	15.515	15.376	15.656	−41.5%
	S2- 50/50	16.942	16.697	17.197	−36.1%
	S3- 40/60	18.385	18.063	18.659	−30.7%
	S4- 30/70	19.821	19.491	20.133	−25.2%
	S5- 20/80	21.250	20.953	21.509	−19.8%
	S6- 10/90	22.684	22.454	22.894	−14.4%
	2016 TTS (9.3/90.7)	26.511			reference
	Scenario	Mean	95% CI		
Transit	S1- 60/40	4.019	3.959	4.083	−41.2%
	S2- 50/50	4.477	4.365	4.599	−34.5%
	S3- 40/60	4.923	4.791	5.058	−28.0%
	S4- 30/70	5.389	5.258	5.530	−21.1%
	S5- 20/80	5.841	5.713	5.965	−14.5%
	S6- 10/90	6.293	6.196	6.382	−7.9%
	2016 TTS (9.3/90.7)	6.834			reference

Note: (1) 60/40 means 60% WFH and 40%. Readers could interpret accordingly.