TRB Annual Meeting
Learning-based Model for Evaluating the Impact of Neighbourhood Design on Travel Behaviour
--Manuscript Draft--

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Learning-based Model for Evaluating the Impact of Neighbourhood Design on Travel Behaviour

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ABSTRACT
Auto-dependency has triggered many public health challenges for North American citizens including increases in physical inactivity rates, road collisions, and Greenhouse Gas (GHG) emissions. As a result, there has been a growing interest in addressing these challenges by promoting more sustainable and livable neighbourhood planning. This research developed an agent-based model that evaluates the impact of neighbourhood design on travel pattern by simulating agents’ daily trip activities. In addition, the results from the Capri-Landmark neighbourhood case study in Kelowna, BC are presented in this paper to demonstrate the developed model via an application to assess the impact of retrofitting the neighbourhood on travel pattern. The developed agent-based model employs a framework that integrates the traditional RUM based modelling technique with reinforcement learning concepts to account for the bounded rationality of human beings and knowledge learning process. Moreover, the model utilizes the diffusions of innovations theory to account for the impact of social interactions by simulating how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. In addition, the model accounts for the iterative feedback process between agents’ actions and the environment. The results from the case study show that providing more accessibility to non-motorized users have more impact on modal share than restricting car use. In addition, increasing activity density would cause the most significant increase in transit modal share while combing increasing activity density with retrofitting the transportation network would achieve the most significant increase in non-motorized modal share.

KEYWORDS: agent-based Modelling, Mode choice, Neighbourhood design, Sustainable community
INTRODUCTION

Historically, urban areas have been shaped by the evolution of the transportation system. For instance, the introduction of horse-drawn streetcars in 1852 enabled cities for the first time to slowly expand outward away from their walking-friendly city centers (1). Then it was followed by the innovation of the electric motor which sparked the “first urban transport revolution” that witnessed the introduction of electric street cars in 1888; elevated rapid transit lines in 1892; and subway systems in 1898 (1). These new urban transit technologies supported further expansion of cities metropolis areas as a star-shaped pattern along transit arteries (2). Meanwhile, a second urban transport evolution was in the making with the introduction of cars in American cities in the 1890s. While cars were initially used for leisure and recreational activities, their influence on urban areas was substantial by making more land available for development. This encouraged people to move away from dense “crowded” urban areas located along transit lines to newly developed low density suburban areas that feature single and multiple dwellings built on larger lots (2). By the late 1930s, people started to rely on cars on every aspect of their daily life activities which led to a significant decrease in public transport ridership and increase in congestion and road collisions (1). In response, transportation engineers focused mainly on traffic engineering in an effort to improve traffic safety and flow. In fact, transportation engineering during that era was called “traffic engineering”. This overwhelming acceptance of cars from the public as well as the widespread emphasis on them by professionals and governments further accelerated cities deconcentration and contributed to the creation of the auto-dependency culture that we are facing today.

Auto-dependency has caused many public health challenges for North American citizens including increases in physical inactivity rates, road collisions, and Greenhouse Gas (GHG) emissions. First, the increasing level of physical inactivity has become a major challenge for public health. According to the World Health Organization (WHO), physical inactivity is estimated to kill 3.2 million people annually (3). Unfortunately, only 17.5 percent of Canadian adults meet the Canadian physical activity guidelines by accumulating at least 150 minutes of moderate-to-vigorous physical activity each week (4).

Second, road collisions are one of the leading causes of death and injury worldwide, responsible for approximately 1.24 million fatalities annually (5). In Canada, almost 2000 people are killed and 165,000 are injured per year in road collisions (6). WHO research shows that 95 percent of road collisions are a result of driver errors, which has led to calls for reduced use of private automobiles and increased AT.

Finally, the Canadian Government has committed, under the Paris Agreement, to reduce GHG emissions by 30 percent below 2005 levels by 2030 (7). However, current indicators suggest that Canada will not be able to meet this target, as GHG emissions in 2030 are estimated to be only 21 percent below 2005 levels (8). Transportation is the second largest contributor to GHG emissions in Canada, accounting for 28 percent of the total emissions nationwide (9). Such high levels of transportation-related emissions highlight the critical role of the transportation sector in achieving the 2030 target.

Consequently, there has been a growing interest in addressing these challenges by promoting more sustainable neighbourhood designs that reduce automobile dependency and encourage people to use more sustainable modes of transportation. Neighbourhood design influences individuals’ travel pattern in three ways: 1) it shapes potential travel routes and their characteristics, 2) determines public transit accessibility, and 3) defines available activities (e.g. 3)
shopping, work, leisure) (10). The research on modelling and evaluation of neighbourhood
design in terms of daily travel behaviour has been continuously evolving over the past decades to
provide a better understanding of the complexity of neighbourhood design. However, most of the
developed models have limited scope as they were aimed to gain further knowledge on a specific
aspect of travel behaviour. In addition, many of the proposed models in the literature either only
consider walking mode or treat walking and cycling as one mode. Besides, most of the existing
work lack the consideration for psychological factors (e.g. habits), micro-scale built environment
characteristics (i.e. current models focus on aggregated zone systems), and the feedback process
between people and the built environment. Therefore, the objectives of this paper are:

1. Propose an agent-based travel behaviour framework to provide a comprehensive
evaluation of the influence of neighbourhood design on travel behaviour
2. Demonstrate the developed framework via an application to assess the sustainability
   benefits of retrofitting a neighbourhood.

LITERATURE REVIEW
Much of the previous research on modelling transportation travel behaviour has utilized discrete
choice models based on the fundamental Random Utility Maximization Framework (RUM).
According to the RUM framework, decision makers select an alternative that maximizes their
utility among a set of discrete alternatives that are collectively exhaustive and mutually
exclusive. The framework accounts for the modeller’s incomplete information regarding decision
makers’ characteristics, trip attributes and decision making circumstances by expressing the
utility function as the summation of two components: a systematic component and a random
error term (11). The systematic component denotes the deterministic portion of the utility while
the random error term accounts for the modeller’s uncertainty and captures the unmeasured
portion of the utility (12). The assumption about the distribution of the random error term
determines the mathematical representation of the model. One of the most common assumptions
is that the distribution is Independently, Identically, and Gumbel (Extreme Value Type I)
distributed (13). These assumptions lead to the Multinomial Logit (MNL) Model formulation.
While the RUM framework accounts for the modeller’s lack of information, it fails to capture the
decision makers’ lack of information about the attributes of the trip (14). Consequently, the
modeller needs to make some assumptions about the rationality of the decision makers. The
underlying assumption of the RUM framework is that decision makers are overly rational with
unlimited knowledge of the available options and make decisions based on extremely complex
computations (13). In addition, the rationality assumption implies that decision makers are
constantly tracking the changes to the available modes and they are aware of these changes once
implemented (15).
However, it can be argued that the overly rational behaviour assumption in the RUM framework
does not appropriately describe a human decision making process and fails to capture its
limitations (16). A significant discussion on decision making was presented by Tversky and
Kahneman (17). They argued that humans tend to reduce the complexity of decision making and
use simple judgmental operations based on heuristic techniques. These findings suggest that
theories, such as bounded rationality, that do consider cognitive limitations are more suitable to
describe human behaviour. According to the bounded rationality theory, individuals have limited
capacity to access and process information and rely on simplified thought processes.
In addition, physiological factors, such as habit, play a role in influencing the mode choice
decision-making process. For example, the Theory of Repeated Behaviour proposes that habit is an important factor in determining repeated behaviour (18). This view is also supported by the Theory of Interpersonal Behaviour, which suggest that the intention to do a behaviour is mediated by both contextual situation and habit (19). For instance, a person who always drives to the convenience store would most likely keep doing so, even if the context changes and cycling/walking is as fast as driving. This repeated behaviour occurs because driving to the convenience store for that person is an unconscious, habitual behaviour and will not change without mindful intention.

All the factors discussed earlier suggest that the human decision-making process is a complex system that can not be appropriately captured using conventional mode choice modelling. Recognizing this complex nature of the transportation mode choice decision making process has led researchers to explore alternative techniques to model it without being limited by mathematical tractability. Recently, a considerable literature has developed around utilizing computational techniques in mode choice modelling. Of which Agent-based Modelling has received a lot of attention.

A number of studies have begun to explore integrating mode choice modelling with Agent-based modelling (20–23). Mode choice models are incorporated into the decision rules component of agent-based models which provides flexibility to modellers in specifying the form and tuning the complexity of these rules. For instance, McDonnell and Zellner (20) used simple logical statements to represent mode choice behaviour in their agent-based model as a decision to switch between two transportation modes (bus and car) if the increase in travel time exceeds agents’ tolerance. In contrast, many other studies have explored incorporating more complex decision-making processes. For example, Zou et al. (21) developed an agent-based model for travel mode choice and departure time to evaluate the impact of various traffic management policies. Agents in the model decide whether to search for alternative travel modes then whether to switch to the travel mode and departure time identified earlier in the search process or make no changes based on sets of decision rules that are represented as if-then statements. Both the search rules and decision-making rules were derived using the JRip machine learning algorithm. However, this paper is limited to study the mode choice behaviour of drivers who switch to public transit only (i.e. metro or bus). Similarly, in their proposed public traffic demand forecast framework, Chen et al. (22) represented the human decision making process as logical statements based on the belief–desired–intention (BDI) model. In BDI, the belief set contains all available mode choices for different scenarios. The desired set contains all available mode choices for the current scenario, where the intention set shows the preferable mode choice for a certain agent. In contrast to Zou et al. (21), this framework does not account for human lack of information.

Although the aforementioned studies discussed how their models addressed some of the limitations of conventional mode choice modelling, most of them did not provide an evaluation on how their models performed compared to the conventional techniques. Mao et al. (23) conducted a study to compare agent-based modelling with equation based modelling by developing an agent-based model that utilizes the same framework used by Zou et al. (21) and a comparison Multinomial Logit (MNL) model using the same dataset. This study reported three main findings. First, the prediction performance of the agent-based model slightly outperformed the MNL model. However, the prediction performance for both models became similar when the dataset was categorized into two sub-groups and separate MNL models were developed for each sub-group. Second, the prediction performance for the agent-based model increased with sample
size while the MNL model revealed less dependency on sample size. Finally, the agent-based model was less influenced by noisy data compared to the MNL model.

A case could be made that all of the three characteristics discussed earlier are not inherited features of agent-based modelling. Instead, they depend on the algorithm used to generate the behavioural rules. For instance, Mao et al. (23) utilized the JRip, which implements a rule induction learner algorithm called the RIPPER, based on Cohen (24). RIPPER is known for avoiding overfitting and providing high predictive accuracy compared to other machine learning algorithms. Thus, different model behaviour is expected if the researchers were to use the same dataset with a different algorithm (e.g. neural network, random forest, etc.) to generate the decision-making rules.

A few researchers attempted to incorporate conventional mathematical mode choice models in agents’ decision rules. For instance, Jin and White (25) developed a mode choice agent-based model that represented the human decision making process as mathematical functions based on the RUM framework. While their agent-based model accounts for novel characteristics related to travel behaviour such as pedestrian-automobile interactions, it still lacks consideration for human bounded rationality as well as land use factors.

Overall, it would appear that most of the previous studies have focused primarily on using supervised learning techniques to model agents’ behavioural rules and overlooked incorporating simple traditional statistical techniques (i.e. MNL), that have been well established in mode choice modelling, in agents’ behavioural rules. In fact, it can be argued that incorporating both, agent-based modelling and traditional statistical techniques can address most of the latter limitations. Thus, maintaining the simplicity and interpretability of mode choice models for transportation planners and engineers. Further, most of the agent-based transportation mode choice models lack the consideration for psychological factors such as habit. In addition, most of the developed models treat walking and cycling as one mode, instead of studying each one individually. Accordingly, it is necessary to develop a model that appropriately characterize human behaviour and their bounded rationality, accounts for transportation networks and infrastructure, considers land use characteristics, and allows for interactions between different transportation users as well as people-to-built environment interactions.

PROPOSED FRAMEWORK
The ABM presented in this paper simulates agents’ daily travel activities for morning commuting trips. The model (see Figure 1) has been constructed using the Recursive Porous Agent Simulation Toolkit (Repast) (26). Following a typical structure of the agent-based framework, the presented model consists of three major components: environment, agents (people), and knowledge learning and interaction rules.

Environment
The environment represents the space where agents make activities and interact with each other. In the developed agent-based model, the environment is comprised of several GIS datasets including a transportation system (e.g. roads, sidewalks), activity locations (e.g. household, facilities), and built environment (e.g. parks). The transportation system was modeled as a multi-layer network that is different transportation modes are represented by different layers. This makes it possible to simulate multi-modal trips where agents might need to use different transportation modes to reach their destinations.
Agents

Agents in this model represent autonomous and adaptive transportation users that seek to optimize their utility by learning and adapting a new behaviour based on experience. Each agent has its own characteristics (e.g. income, age, gender, occupation, residential location) and a daily trip plan that includes trips origins, destinations, purposes, and cost. Agents are grouped into households where they share some characteristics such as available number of vehicles.

In addition, the diffusions of innovations theory (27) is utilized to simulate how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. According the diffusions of innovations theory, people are classified into five categories based on their level of social influence as follows 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards. Innovators are characterised by strong social influence and are very eager to seek information about new alternatives, while laggards lack social influence and are the last to adopt new alternatives. Similar to the work of Aziz (28) and Doo (29), agents in the model are randomly assigned to one of the five categories, while keeping the number of agents in each category as per the proportions shown in Table 1. In addition, an influence probability is assigned to each group to capture how agents in different categories vary in terms of willingness to seek and propagate information.

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<thead>
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<th>Table 1 Agents Categories</th>
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<td>Category</td>
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<td>Innovator</td>
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<td>Early Adopters</td>
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<td>Early Majority</td>
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<td>Late Majority</td>
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<td>Laggards</td>
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Knowledge Learning Process

To address the bounded rationality limitation of the RUM framework, this study utilizes a novel framework developed by Idris et al. (30), which proposed an adaptive learning-based framework of mode choice that integrates the RUM framework with reinforcement learning concepts. The proposed framework employs various reinforcement learning concepts to model decision making behaviour based on bounded rationality.

Reinforcement learning is a computational approach to learning through interactions in which an agent aims to maximize its rewards by learning from experience (i.e. learn by trial and error), while having no prior information about the environment (31). At each stage, the agent observes the environment, takes an action, and then receives immediate evaluation of its action as negative or positive rewards. Reinforcement learning consists of three main sub-elements: 1) policy, 2) reward signal, 3) value function (31). First, policy refers to the way an agent selects an action at a given state of the environment (i.e. mapping from states to actions). A reward signal is a negative or positive value that an agent receives after taking an action in a given state to indicate what is good or bad now (i.e. just for the current state). Finally, the value function which, in contrast to a reward signal, determines what is good or bad in the long-term based on an agent action in the current state; an agent’s objective is to optimize the value function (i.e. maximize cumulative rewards) (31).

Similarly, Agents’ decision-making policy in the proposed ABM is to choose the transportation mode that maximizes their rewards in the long run. Rewards in this model are defined as an agent’s perceived utility for each of the available transportation modes. Agents in the model use adaptive behaviour to form their beliefs about the available transportation modes through an iterative process. In each iteration, agents choose the transportation mode that has the greatest probability based on the utility maximization framework. During the iteration, agents acquire new information (e.g. traffic conditions) by interacting with other agents and the environment, which then will be used to update agents’ perceived utility for the subsequent iteration based on the following reinforcement learning algorithm (Equation 1):

\[
V(s_{t+1}) \leftarrow V(s_t) + \alpha_i[R(s_t) - V(s_t)]
\]  

(1)

where:
- \(V(s_{t+1})\): Long term expected rewards
- \(V(s_t)\): Cumulative rewards until time step (t)
- \(R(s_t)\): Immediate reward gained at time step (t)
- \(\alpha_i\): Step size parameter \((0 \leq \alpha_i \leq 1)\), associated with agent (i)

Equation 1 includes an adaptive step size parameter \(\alpha\) to simulate habitual tendency and its influence on learning from previous experience. Idris et al. (30) hypothesized that the habitual tendency of a particular mode can be indicated by the choice probability of that mode, such that the greater the choice probability, the greater the habitual tendency. Since habitual tendency acts against learning from previous experience, the step size parameter is formulated to be inversely proportional to the previous dominating mode choice probability as shown in Equation 2. This formulation implies that the greater the habitual tendency towards a certain mode, the lower the step size parameter, and thus the less agents learn from previous experience.

\[
\alpha_i = 1 - P_{id}
\]  

(2)

where:
- \(P_{id}\): Previous mode choice probability that agent (i) selects the dominating mode (d)
In addition, a soft-max selection policy based on the Boltzmann distribution to ensure an appropriate trade-off between exploitation and exploration as shown in Equation 3.

\[ P_{ia} = \frac{e^{Q_t(a)/\tau}}{\sum_{b=1}^{n} e^{Q_t(b)/\tau}} \] (3)

where:

- \( P_{ia} \): Probability of individual (i) selecting action (a)
- \( Q_t(a) \): value of action (a) at time step (t)
- \( \tau \): temperature parameter

Within this selection policy, agents choose whether to exploit, explore, and which action to explore based on three components: 1) dominating mode choice probability, 2) agents’ utility value for each available mode, and 3) the weighted average effects of social influence. First, a greater choice probability indicates a greater habitual tendency, which hinders an agent’s willingness to explore new alternatives. Thus, the temperature parameter is assumed to be inversely proportional to the choice probability of the recent dominating mode, \( (\alpha_i = 1 - P_{id}) \) (30). Second, it is hypothesized that agents choose which action to explore based on the combined effect of their formed beliefs about each available mode (i.e. utility values) and the level of social influence from an agent’s social network. Thus, the value of choosing action (a) can be estimated using a weighted average as shown in Equation 4.

\[ Q_t(a) = (1 - \omega_i) \times V_{ia} + \omega \times \lambda_{ia} \] (4)

where the \( \omega_i \) is the social influence probability assigned to agent (i) as in Table 1, and \( \lambda_{ia} \) is the social influence of all agents in agent (i) social network (J) whose their predominant mode choice is action (a), which can be estimated as follows (Equation 5):

\[ \lambda_{ia} = \frac{\sum_{j=1}^{J} (V_{ja} \times \omega_j)}{\sum_{j=1}^{J} (\omega_j)} , \forall d \in \{a\} \] (5)

In addition, agents are grouped into three categories based on their information acquisition and response behaviour. The first category conceptualizes the state of partial information provision, in which agents do not have global information (i.e. imperfect knowledge) and thus can only adapt new behaviour based on their own experience. In other words, at the end of each iteration, agents only update the utility of the selected mode while the utility of unselected modes remains intact as shown in Equation 6.

\[ V_{im}(t + 1) = V_{im}(t) + \alpha_i [R_{im}(t) - V_{im}(t)] \]

\[ V_{in}(t + 1) = V_{in}(t), \text{ for all } n \neq m \] (6)

where:

- \( V_{im}(t) \): Utility that agent (i) obtained from mode (m) until time step (t)
- \( V_{in}(t) \): Utility that agent (i) obtained from any other mode (n≠m) until time step (t)
- \( R_{im}(t) \): Immediate utility that agent (i) obtains from mode (m) at time step (t)
- \( V_{im}(t + 1) \): Updated utility that agent (i) obtains from mode (m) at time step (t+1)
- \( V_{in}(t + 1) \): Updated utility that agent (i) obtains from any mode (n≠m) at time step (t+1)
- \( \alpha_i \): Step size parameter (0 ≤ αi ≤ 1), associated with agent (i)

The model expressed in Equation 6 utilizes a temporal-difference learning method to simulate an agent’s behaviour, such as an agent updates its long-term utilities \( V_{im}(t + 1) \) based on the
difference between the immediate utility obtained at the current time step $R_{im}(t)$ and the accumulated utility until the current time step $V_{im}(t)$. Note that agents only update the utility for the selected mode, as information about the other modes would not be available.

The second category also conceptualizes the state of partial information provision; however, the updating rules are revised to incorporate how agents become unfamiliar with unselected modes. Thus, an agent’s mental and cognitive efforts to explore unselected modes declines over time as shown in Equation 7:

$$V_{im}(t+1) = V_{im}(t) + \alpha_i[R_{im}(t) - V_{im}(t)], V_{in}(t+1) = (\alpha_i + 1) V_{in}(t), \text{for all } n \neq m$$

(7)

On the other hand, the evolution of new Advanced Traveller Information Systems (ATIS) gives transportation users access to real-time information about different modes simultaneously. Thus, people are now capable of gaining knowledge and updating their preferences for each available travel mode prior to each trip (i.e. including unselected modes). Under this assumption the updating rules can be re-written as follows (Equation 8):

$$V_{im}(t+1) = V_{im}(t) + \alpha_i[R_{im}(t) - V_{im}(t)], \text{for all } m = 1 \text{ to } M$$

(8)

In the proposed framework, agents are randomly assigned to one of the three information provision categories as follows: 60% perfect information, 10% Partial information with knowledge decay, and 30% perfect information. The proportion value of each category is exogenous and is based on previous research that shows information provision has relatively small impact on travel behaviour, with an estimated impact that varies between 30-40% (32–35).

**Simulation Setup**

In period 0, the initialization process, the model reads the shapefiles that contain information about the transportation system, as well as agents’ information and locations. The next step in the model initialization process is to compute base utility and the corresponding probability of choosing available modes for each agent using an MNL model. In the first iteration, agents choose the travel mode with the highest probability and travel on the map according to the calculated shortest path. During the iteration, agents acquire new information (e.g. traffic conditions, volume of pedestrians and automobiles encountered) by interacting with other agents and the environment, which then will be used to update agents’ perceived utility for the subsequent iteration. In the following iterations, agents choose whether to explore or exploit using a generated random number; if the number is less than the exploration rate, then agents will choose to explore new alternatives using the soft-max selection process described in the previous section. On the other hand, if the generated random number is greater than the exploration rate, agents will exploit the action with the highest Q-value, as shown in Figure 2.
CASE STUDY
To demonstrate the proposed ABM framework, it was implemented for the Capri-Landmark neighbourhood, a major employment hub in Kelowna, British Columbia, Canada. In addition, different scenarios were analyzed to examine the influence of neighbourhood design on mode and route choice behaviours in the case study.

Study Area
The Capri-Landmark neighbourhood is one of the five official urban centres in Kelowna as shown in Figure 3. The neighbourhood area is approximately 94 hectares with a total population of approximately 2400 residents and 5200 jobs. Of the five official urban centres, Capri-Landmark has been identified as top priority for a new comprehensive urban centre plan due to the lack of previous comprehensive planning, increasing development pressure, and built environment challenges including limited green spaces and discontinuous Active Transportation (AT) infrastructure (36).
The study area was then hypothetically retrofitted using SMARTer Growth design principles, similar to Masoud et al. (37). The neighbourhood retrofit includes a series of local road closures to prevent shortcutting through local roads. The areas that resulted from road closures were preserved to provide green spaces and active transportation corridors in order to maintain high connectivity for pedestrian and cyclists, as shown in Figure 4. It is important to note that there are few actual trips reported in the provided dataset where both trip ends are located in the neighbourhood. This means that for the majority of the trips, only a small portion of the trip would happen inside the neighbourhood. Thus, trips were not expected to be significantly influenced by the retrofitted design. For this reason, the authors decided to randomly generate 5,000 trips within the neighbourhood.
Three type of data were used for the development of the mode choice models: travel diary, transportation networks, and land use data. First, travel diaries were obtained from the Okanagan Household Travel (OTS) survey. The last survey was conducted during the weekday in the fall 2013 with a response rate of 3.3 percent, a total response of 3050 households, and 22,500 trip records. The OTS data includes both socioeconomic and demographic characteristics as well as information on mode choice. The data was filtered to only include work trips during morning peak (6 am- 9 pm) for which both trips ends are in Kelowna (2047 trips). In addition, travel time and distance for all reported trips were estimated for car, transit, walk, and cycle using the Google Directions API.

Second, Transportation networks GIS data was obtained from City of Kelowna’s open data portal. The data includes road centerlines, road intersections, sidewalks, bike lanes, cycle tracks, multi-use paths, and walkways. In addition, transit routes and stop locations were created using the General Transit Feed Specification (GTFS) dataset.

Finally, land use data were obtained from the city of Kelowna and it was compiled using various sources. Employment data were quantified at the traffic analysis zone level by combining information from the census, BC Assessment, Canada Business Points, and enrollment counts from the Central Okanagan School District.
Mode choice model

An MNL model for home-to-work mode choice decisions was developed for the city of Kelowna. The model accounts for socioeconomic characteristics, level of service attributes, and built environment measures. Numerous built environment measures were quantified at various buffer distances (100, 200, ..., 1000m) for all trips’ origins and destinations, including population density, employment density, land use diversity, proximity to bus stops, and length of each AT infrastructure type. Land use diversity was computed using population/employment entropy as shown in Equation 9:

\[ \text{Entropy} = \frac{\sum_{j} [P_j \times P_j]}{\ln J} \]  

(9)

where:

- \( P_j \): Proportion of land use development for type \( (j) \)
- \( J \): Number of land use types

Four utility functions were estimated for each mode as follows: 1) automobile, 2) transit, 3) walk, and 4) bike. The stepwise method was used for variable selection and the models parameters were estimated using Biogeme (38), with the model specification shown in Table 2. The developed MNL models show that those in the range from 15 to 24 are less likely to use the auto mode, which could be explained by youth having access to discounted monthly public transit passes (including a mandatory U-PASS program for UBCO students) and having limited regular access to a vehicle. The number of vehicles and bikes per person in the household are positively associated with auto use and bike use, respectively. Moreover, the results indicate that higher population density near trip origins increases the likely of using the transit while higher employment density near trip destinations decreases the likelihood of using the auto mode. In addition, land use diversity, measured by entropy, was found to be positively associated with using transit.

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<th>Variable</th>
<th>Auto</th>
<th>Transit</th>
<th>Non-motorized</th>
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<tr>
<td>Alternative Specific Constant</td>
<td>—</td>
<td>-5.49</td>
<td>-0.346</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 3 (15-24)</td>
<td>-0.639 (-2.87)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Bikes/person in the household</td>
<td>-0.433 (-1.86)</td>
<td>—</td>
<td>0.505 (2.06)</td>
</tr>
<tr>
<td>Vehicles/person in the household</td>
<td>1.24 (5.30)</td>
<td>-1.06 (-2.34)</td>
<td>—</td>
</tr>
<tr>
<td>Female</td>
<td>—</td>
<td>—</td>
<td>-0.281 (-1.63)</td>
</tr>
<tr>
<td>Driver's license</td>
<td>—</td>
<td>-1.02 (-2.48)</td>
<td>—</td>
</tr>
<tr>
<td>Monthly transit pass</td>
<td>-1.44 (-3.86)</td>
<td>3.11 (8.26)</td>
<td>—</td>
</tr>
<tr>
<td>Bike Lanes Length 400m Origin</td>
<td>—</td>
<td>0.406 (2.94)</td>
<td>—</td>
</tr>
<tr>
<td>Population Density 800m Origin</td>
<td>—</td>
<td>0.016 (2.10)</td>
<td>—</td>
</tr>
<tr>
<td>Employment Density 600m</td>
<td>0.0088 (-4.91)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Destination</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Land use entropy 600m

<table>
<thead>
<tr>
<th>Destination</th>
<th>—</th>
<th>1.21 (1.68)</th>
<th>—</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel distance</td>
<td>—</td>
<td>—</td>
<td>-0.838 (-11.02)</td>
</tr>
<tr>
<td>Trip time</td>
<td>-0.159 (-3.83)</td>
<td>-0.012 (-1.09)</td>
<td>—</td>
</tr>
</tbody>
</table>

Values within parenthesis () show t-stat value, —- = variable is not statistically significant

Results and Discussion

This case study presents several policy scenarios that examines the influence of increasing AT to vehicle route directness ratio and activity density. First, three scenarios were tested to examine the influence of the transportation network connectivity on travel behaviour: retrofitting the road network only, retrofitting the non-motorized network only, and Retrofitting both the road and non-motorized networks. The road network retrofit includes a series of local road closures to prevent shortcutting through local roads. For the non-motorized network, a continuous grid network of off-road paths, local parks, and local roads is provided to achieve high walk/bike connectivity. To comprehend the magnitude of change in both networks, the percentage change in travel time and distance between the existing scenario and the proposed retrofit are estimated as follows: 19.3% increase in driving travel time and 9.2% decrease in non-motorized travel distance.

The second set of scenarios examines the influence of increasing population and employment densities on travel behaviour. The three scenarios considered in this set correspond to 10%, 20%, and 30% increase in activity density (i.e. population and employment densities combined). The last scenario examines the combined effect of retrofitting the transportation network and 30% increase in activity density on travel behaviour.

All scenarios were run twice in this case study, once assuming that all agents are assigned to the third information provision category, perfect information, while the other run assumes that agents are randomly assigned to an information provision category. The perfect information category was chosen since it reflects conventional mode choice modelling in which decision makers are overly rational with unlimited knowledge. The percentage change in modal split in each scenario compared to the existing for both runs are shown in Figure 5 and Figure 6, respectively.
One unanticipated finding is the slight increase in auto modal share in the road scenario. A possible explanation would be that the reduction in auto utility due to retrofitting the road network was relatively small compared to the decline of unselected modes’ utilities over time for agents with learning approach 2. This hypothesis can be validated by looking at the results of perfect information run which show that the auto modal share decreases as expected.

Another interesting finding is that the modal shift in the non-motorized scenario was greater than the road network scenario despite the fact that the change in travel time in the former scenario was less than the latter scenario. This result indicates that providing more accessibility to non-motorized users have more impact on modal share than restricting car use. Nevertheless, the combined effect of retrofitting both networks has more substantial impact on mode choice than the individual effect of retrofitting each network.
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Figure 6 Modal Shift for each scenario in percentage

Moving to increasing the activity density scenarios, 10%, 20%, and 30% increase in activity density resulted in 5.4%, 9%, and 13.8% modal shift towards transit and reduced auto modal share by 0.28%, 2.53%, and 4.68%, respectively. Finally, the combined scenario shows the highest modal shift from auto towards transit non-motorized modes. Note that the shift towards transit in this scenario is slightly less than the scenario of increasing activity density by 30%, which illustrates how transit competes with non-motorized modes.

RESEARCH CONCLUSIONS AND LIMITATIONS

Conclusions
The performance of a neighbourhood design and the emerged travel behaviour are results of a complex interaction between many factors including transportation network layout, personal preferences, socio-economic status, behavioural aspects, operating conditions and social interactions. As a result, evaluating a neighbourhood design in terms of each one of these performance measures individually, without accounting for their cumulative interactions, does not draw the full picture of its performance.

This research developed an agent-based travel behaviour framework, using repast as the simulation platform, to provide a comprehensive evaluation of the influence of neighbourhood design at a fine spatial resolution (i.e. parcel level) on travel behaviour. The developed model employs a framework that integrates the traditional RUM based modelling technique with reinforcement learning concepts to account for the bounded rationality of human beings and
knowledge learning process. Moreover, the developed agent-based model utilizes the diffusions of innovations theory to account for the impact of social interactions by simulating how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. In addition, the developed model accounts for the iterative feedback process between agents’ actions and the environment.

In addition, demonstrate the proposed ABM framework via an application to assess the change in travel behaviour due to retrofitting the Capri-Landmark neighbourhood in Kelowna, BC, Canada, using SMARTer Growth design principles. Several scenarios were tested including individual effect or combination of retrofitting the road network, retrofitting the non-motorized network, and increasing population and employment densities. For the transportation network related scenarios, the results show that providing more accessibility to non-motorized users have more impact on modal share than restricting car use. In addition, increasing activity density by 30% caused the most significant increase in transit modal share while the combined scenario caused the most significant shift towards non-motorized modes.

The results reported above are specific to the presented case study and cannot be generalized. However, the case study demonstrates how the proposed ABM can be used to help planners and stakeholders to envision the impact of future policies on modal and route choices by running scenarios and modifying various components of the system based on the proposed policies.

Limitations and future research

More variables can be added to the mode choice model including built environment design indicators (e.g. availability of public spaces and AT facilities), and transit service indicators (e.g. transit accessibility, local index of transit availability), and indirect measures of safety (e.g. intersection density, availability of sidewalk/bike lane, and proportion of pedestrian actuated traffic signal). Including such variables would improve the model sensitivity to a wide spectrum of transportation and land-use policies; however, this was not possible in the presented case study due to data availability.

In addition, agents are currently randomly assigned to a social influence group and an information provision category. Future research would benefit from developing a systematic procedure to assign agents to each of these groups based on empirical data.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: A. Masoud, A. Idris, G. Lovegrove; methodology: A. Masoud, A. Idris; analysis and interpretation of results: A. Masoud; draft manuscript preparation: A. Masoud, A. Idris. All authors reviewed the results and approved the final version of the manuscript.
REFERENCES


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