DEVELOPMENT OF AN INTEGRATED URBAN MODELLING FRAMEWORK TO EXAMINE IMPACTS OF COVID-19 ON TRANSPORT AND LAND-USE SYSTEMS

by

Md Asif Hasan Anik

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Dedicated to

I would like to dedicate this thesis to my parents and my sister.

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Abstract

This thesis develops an integrated urban modelling framework (IUMF) to assess the short-term, medium-term and long-term impacts of COVID-19 on transport and land-use systems. It starts with analyzing public discourses in Twitter using data mining techniques to better understand the impacts of COVID-19 on transport modes and mobility behavior. Then, it advances Bayesian networks based modelling approaches to examine post-pandemic mobility choices of individuals utilizing a questionnaire survey in Halifax, Canada. To explore long-term impacts, the thesis first applies an existing integrated urban model simulating residential location and mobility tool ownership for the next 10 years (2021-2030). Finally, it develops a novel framework by coupling longer-term decisions models within the IUMF that enables to simulate individuals' residential location and mobility behavior in response to the pandemic. Developed tools can be used in case of future pandemics or any other mobility disruptive events for transport and land-use impact assessments.

List of Abbreviations and Symbols Used

LDA	Latent Dirichlet Allocation
iTLE	Integrated Transport, Land-use and Energy
BBN	Bayesian Belief Network
P (A)	Probability of event A to occur
P(B|A)	Probability of B event's occurrence when event A has already taken place
EM	Expectation Maximization
MLE	Maximum Likelihood Estimation
BS	Bayesian Search
WFH	Work from Home
ABMs	Agent-Based Models
MVVM	Model-View-Viewmodel
SUV	Sport Utility Vehicle
TAZ	Traffic Analysis Zones
DA	Dissemination Area
IUMF	Integrated Urban Framework Modelling Framework

Glossary

COVID-19	Coronavirus disease (COVID-19) is an infectious disease caused by a newly discovered coronavirus.
Loss aversion	Refers to people's tendency to prefer not to lose rather than achieving gain
Herd immunity	Herd immunity occurs when a large portion of a community (the herd) becomes immune to a disease
NVIVO 12 Pro	Qualitative data analysis software helps to discover richer insights from qualitative & mixed methods research.
TAGS	Google sheet template to collect data from Twitter.
Twitter	A popular microblogging application that is ideal for conversations and sharing small posts.
Corpus	A collection of written texts.
GeNIe	GeNIe Modeler is a graphical user interface (GUI) to SMILE Engine and allows for interactive model building and learning.
NOVATRAC	The Nova Scotia Travel Activity (NovaTRAC) Halifax survey is a research project conducted by the Dalhousie University Transportation Collaboratory (DalTRAC).
C#	C# is a modern, object-oriented, and type-safe programming language.
Residential mobility	Households' decision to relocate.
Urban sprawl	Urban sprawl is the unrestricted growth in many urban areas of housing, commercial development, and roads over large expanses of land, with little concern for urban planning.
Mode share	Percentage of people using each travel mode.

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Chapter 1

Introduction

1.1 Background and Motivation

The coronavirus disease 2019 (COVID-19) is a highly infectious respiratory disease caused by a new virus known as SARS-CoV-2 (severe acute respiratory syndrome-coronavirus-2) (*Baloch et al., 2020*). The first outbreak occurring in late 2019 in Wuhan, the capital of the Hubei Province in China, quickly spread to other countries. World Health Organization (WHO) announced this disease as a pandemic on March 11, 2020 due to its severe health risk to the global population. The trends of the daily life of all individuals have changed significantly with the emergence of this disease and more than 135 million reported cases including nearly 3 million deaths have been confirmed to date, which history is relentlessly getting updated.

Before COVID-19, there were multiple pandemics that have affected human lives across the world. The Spanish flu - a strain of influenza like COVID-19, infected approximately 500 million people from January 1918 to December 1920. The virus had a mortality rate of around 2.5% (*Taubenberger and Morens, 2006*). It killed around 675,000 people in the U.S. alone and approximately 50 million people worldwide (*CDC, 2020*). The pandemic came in two waves - with the second wave being more fatal than the first. However, the virus disappeared quite abruptly. Another more recent pandemic was the H1N1 swine flu which affected an estimated 60.8 million people between April 2009 and April 2010 (*CDC, 2019*). Some countries imposed travel restrictions during the early stage of the outbreak in an attempt to control the virus spread – which resulted in significant reduction of mobility demand (*Bajardi et al., 2011*). The overall mortality rate of swine flu was around 0.02%, which is somewhat lower than that of COVID-19 (*Baldo et al., 2016*). Other notable pandemics were HIV (1981-present), SARS (2002), among others (*Newman, 2020*). It is difficult to make direct comparisons between pandemics as they all developed within different circumstances. However, in terms of spread area, impacts on human lives, mobility, and consequences on global economy, COVID-19 pandemic has been the most challenging to deal with (*Zoppi, 2021*).

In addition to its health impacts, the COVID-19 pandemic has a major influence on individuals' mobility patterns *(Vos, 2020)*. After the initial cases of the virus in countries, respective authorities adopted strict epidemic control measures such as 'restriction in international travel', 'stay at home orders', 'business closure' and 'social distancing' *(Cheng et al., 2020a).* China became the very first nation to initiate lockdown to deter the transmission of coronavirus. Following China's example, several countries which had been seriously impacted by the virus started dragging their populations under a lockdown or enforcing mass quarantines where the mobility of citizens was confined to exigent facilities only (such as food, healthcare emergencies, etc.) *(Kaplan et al., 2020).* Though these pandemic control measures are pivotal in controlling the rapid and large-scale spread of the virus, they have serious impacts on urban travel behaviour, such as, reduction in trip-making and travel mode choice change. In the areas with stay-at-home orders in the United States, the average daily travel distance declined from 8.0 to 1.6 km (5 to 1 mile) *(Glanz et al., 2020).* Because of the decline in mobility, the public transportation sector has been affected worldwide severely, with ridership dwindling significantly across several countries around the world. For instance, subway ridership was dropped by 93% in New York City *(Chung, 2021)*. Consequently, during the lockdown period, work from home (telecommuting), virtual learning, online shopping and delivery gained popularity as people welcomed the adoption of innovative technologies. Online businesses have boomed while some traditional retail stores have shifted their business online. The idea of telecommuting has allowed employers to think about giving up office spaces in downtown to curtail costs of their companies. Experts are discussing about this opportunity of reconfiguring urban centers, adopting work from home and online services as a blessing to tackle traffic congestion and climate change, at the same time focusing on active travel infrastructures.

Though the impact of the pandemic is highly negative on the society and economy, positive impacts are also observed, such as, improvement in air quality, reduction in noise pollution, increase in walking and cycling, reduction in traffic accidents and fatalities *(The Resilience Shift, 2020)*. Governments should make efforts on maintaining these positive outcomes, even after the pandemic. In addition, city mobility plans should be updated to make them more safe, efficient and affordable, that will withstand the current pandemic, and be resilient in case of any future outbreaks. For this, city authorities first need to clearly understand the complex reactions COVID-19 pandemic has had and continue to have on our transport and land-use systems. This thesis delves into developing models and tools to investigate short-term, medium-term, and possible long-term impacts of COVID-19 pandemic on transport and land-use systems, with an aim to understand the changing mobility dynamics in cities. The results are expected to assist governments and decision makers to plan on how to approach the 'new normal' or make urban policies that will be resilient in case of any future emergencies, particularly disease outbreaks.

1.2 Objectives

The specific objectives of this thesis can be summarized as follows:

1. To identify the immediate effects of the COVID-19 pandemic on transport modes and mobility behavior through public discourse analysis.

2. To develop models to explore post-pandemic mobility choices of individuals and likely changes in urban systems.

3. To develop an integrated urban system framework to predict short-term, medium-term and long-term impacts of COVID-19 pandemic on transport and land-use environment.

1.3 Significance

This thesis offers practitioners and researchers tools and models to assess impacts of sudden disruptive events (particularly pandemic) on transformation of cities. The findings of this study will provide a clearer understanding on how people are modifying their daily travel behavior and activity participation decisions due to the COVID-19 pandemic.

Overall, providing a better understanding of COVID-19's associated impacts on transportation services and land-use environment. Besides, how the pandemic may affect individuals' long-term mobility choices are also investigated in this thesis. This knowledge is particularly important for urban mobility and infrastructure planning as commuters' behavior shift as a whole dictate how transport and land-use system may shape in future. Outcomes of the developed analytic frameworks will assist the policy makers on preparing for the 'new normal', put together plans in case of any future outbreak, and configure policies to promote sustainable travel habits among individuals.

1.4 Thesis Outline

This thesis consists of eight chapters. The second chapter conducts a rigorous literature review on 'COVID-19 and transportation' and finds gaps in the literature. Chapter three explains the methodology and study area of the thesis. Chapter four presents public discourse analysis to identify initial impacts of COVID-19 on transport modes and reopening challenges, solutions as well as opportunities. Fifth chapter illustrates the development of tools to assess post-COVID mobility choices of individuals using Bayesian Belief Networks (BBNs). In the sixth chapter, pandemic scenario simulation is carried out using a long-term decision simulator (LDS) within an integrated transport, land-use and energy (iTLE) model to examine long-term changes in transport and land-use through analyzing households' future mobility decisions. The thesis culminates in the seventh chapter where BBNs and iTLE are combined to create an integrated urban modelling framework (IUMF) to perform comprehensive analysis of land-use and transport systems' transformation due to COVID-19. The final chapter, chapter eight, summarizes key findings of the thesis, lists the major contributions and draws out the overall implications of the research.

Chapter 2

Literature Review

2.1 Short-Term Changes in Travel Behavior due to COVID-19

There has been a substantial amount of research works published in the form of scholarly papers, reports and reviews to examine the COVID-19 pandemic's impacts on mobility behaviour in cities. Table 2-1 illustrate some of those papers' study area, author names, objectives, methods adopted, and key findings.

Table 2-1 Literatures on COVID-19 and Travel Behaviour (Short-Term Impacts)

Country (City)	**Author**	**Objectives**	**Methods (Time of Study)**	**Major Findings**
Hungary (Budapest)	*Bucsky, 2020*	Understanding urban modal share developments due to COVID-19	Descriptive statistics (March, 2020)	Mobility was severely reduced, at least by 51% and maximally by 64%. The number of daily trips dropped from 10.1 to 4.3 million in the most likely scenario.
Italy (Whole Country)	*Beria and Lunkar, 2020*	In-depth analysis of Mobility during COVID-19 first outbreak and lockdown using the data provided by Facebook Data for Good programme.	Temporal and spatial analysis of Mobility (February-April, 2020)	Due to stay-at-home orders, mobility was reduced significantly. Population in cities also got reduced which is interpreted as the result of migration of tourists and foreigners from Italy.
Japan (Sapporo)	*Arimura et al., 2020*	To interpret the change in the population density of	Mobile spatial statistics	Residents have been more likely to stay home and less likely to travel to the center area. It led to a

		Sapporo city in the emergency period declaration using big data	(January-May, 2020)	decrease of up to 90% of the population density in crowded areas. Result indicates 70%–80% reduction of contact between people in line with the purpose of the emergency declaration.
Colombia (Bogota)	*Duenas et al., 2020*	To analyze mobility changes following the implementation of containment measures. To assess the effect of socioeconomic conditions on mobility flows.	Gravity model (January-July, 2020)	Overall reduction in mobility trends, but the overall connectivity between different areas of the city remains after the lockdown, reflecting the mobility network's resilience. Responses to lockdown policies depend on socioeconomic conditions.
Canada (British Columbia)	*Fatmi, 2020*	To analyze individuals' adjustment in daily out-of-home travel activities, in-home activities, and long-distance travel during the COVID – 19 travel restrictions.	Descriptive statistics (March-May, 2020)	Out-of-home activities were reduced by more than 50%. Higher income households were found to be predominant in tele-working for a longer duration, whereas lower and middle income groups were more involved in leisure and discretionary activities. Majority of the completed long-distance travel was made regionally using private car.
Spain (Santander)	*Aloi et al., 2020*	To analyze the impact that the confinement measures imposed in Spain on 15 March 2020 had on urban mobility in the northern city of Santander.	Origin-destination trip matrix analysis (March, 2020)	Public transport use has fallen the most with 93% fewer users. Mobility during the morning and midday has dropped less than in the afternoon, when the fall is much more drastic with the disappearance of afternoon peak traffic periods.

Italy (Sicily)	*Campisi et al., 2020*	To investigate the influence of the COVID-19 pandemic on road users' perceptions, needs, and use of sustainable travel modes (i.e., public transport, walking, and cycling).	Correlation matrix and ordinal logistic regression (March to May, 2020)	Women were less likely to walk during the pandemic than men. Participants were more likely to resume remote work even after the second phase in order to reduce their daily travel needs and keep their isolation. Participants have expressed a positive opinion on the use of micromobility during pandemic situations.
China (Chongqing)	*Nian, 2020*	To analyze the impacts of COVID-19 on taxi usage behaviors	Spatial error model (SEM) and spatial lag model (SLM) (January-June, 2020)	The number of taxi trips dropped sharply, and the travel speed, travel time, and spatial distribution of taxi trips had been significantly influenced during the epidemic period.
Singapore (Whole Country)	*Jiang et al., 2020*	To analyse the spatial-temporal potential exposure risk of residents by capturing human behaviours based on spatial-temporal car park availability data	Spatial and temporal analysis (May, 2020)	The reduction rate of mobility reaches 36.4% in the first week during the stay at home order (only essential travel allowed). The maximal reduction rate of potential exposure risk reaches 37.6% by comparing with its peak value. Fluctuations and uncertainties along the time horizon have been observed for the heat and potential exposure risks, implying the spatial-temporal interactions among different regions.
India (Whole Country)	*Thombre and Agarwal, 2020*	To capture travel choices in different stages (before, during and after) of the pandemic.	Descriptive statistics (March-June, 2020)	Increase in the car-dependency level. The captive users of public transport and non-motorized transport mode (walk) are also willing to

				make a shift towards private vehicles. Demand as well as the willingness to pay extra for a safer, faster, cleaner, comfortable, and most importantly, resilient public transport exists.
Poland (Whole Country)	*Wielechowski et al., 2020*	To assess changes in mobility in public transport	One factor variance analysis (ANOVA) and the Tukey's honest significance test (Tukey's HSD test) (March-July, 2020)	Significant differences observed regarding the changes in mobility in public transport depending on the level of stringency of anti-COVID-19 regulation policy. Forced lockdown to contain the development of the COVID-19 pandemic has effectively contributed to social distancing in public transport and reduced ridership.
Greece (Chania and Rethymno)	*Tarasi et al., 2020*	To capture the impact of the COVID-19 outbreak and the subsequent restrictive measures on citizens' commuting habits and travel mode choice.	Descriptive statistics (April-July, 2020)	A significant share (almost 30%) of citizens have already decreased car usage and opt for alternative and sustainable transport modes (walking, cycling, public transport). It is critical that measures are taken to rebuild people's confidence in public transport and discourage car use.
USA (Boston)	*Basu and Ferreira, 2021*	To investigate the challenges and opportunities for sustainable mobility in the post-COVID time	Descriptive statistics and spatial analysis (December, 2020)	Within a week after the onset of the pandemic, mass transit ridership dropped to 85% below expected levels. Although transit ridership has picked up since then, it currently stands at 75%

				lower than expected, implying a long and slow recovery to pre-COVID levels.
Australia (Whole Country)	*Beck and Hensher, 2020*	To identify the changing patterns in travel activity of Australian residents as a result of the stage 2 restrictions imposed by the Australian government	Descriptive statistics and ordered logit model (March, 2020)	78% of respondent households had already made many changes to their weekly household travel. Some employers encouraging working from home and others requiring it, in addition to job losses, and many children attending school online from home, the implications on travel activity is extreme.

Table 2-1 indicates that, in countries such as, United States, Canada, Australia, Japan, China, India, Greece, Italy, Spain, due to combination of stay at home orders, fear of contracting the virus, out of home activities were reduced significantly. In most of these countries, public transport ridership had seen an all time low. People were working from home and their daily household travel decisions were heavily affected. In some countries, for example, in India and Greece, people were shifting from public transport to sustainable transport options (e.g., walking, bicycling). People were feeling safe travelling in cars rather than in closed spaced public transits, which led to increased car use during the lockdown period. Schools and businesses got closed, unemployment rate increased, and due to reduction in mobility - traffic congestion, air pollution, and noise pollution dropped significantly. However, most of studies discussed above used survey data, perception studies to analyze initial abrupt changes in travel behavior among individuals. Very few studies used social media data mining, which can be an excellent platform to assess people's real-time experience, concerns, opinions and views on their daily travel. Such information can be synergised with analytical frameworks to gather insights on how COVID-19 has affected transport services and transformed peoples' travel behavior in cities.

Nevertheless, it is also necessary to determine whether travel behavior during COVID-19 outbreak may leave a permanent mark and become long-lasting. Researchers have been prompt to investigate possible medium and long-term impacts of the pandemic on urban transport and land-use dynamics. Some of those studies are discussed in the next section.

2.2 Possible Medium and Long-term Changes in Travel Behaviour

Apart from examining short-term effects, some of the studies explored possible medium-term and long-term travel behavior shifts of commuters due to COVID-19 in cities across the world. Some of those studies are summarized in Table 2-2.

Table 2-2 Literatures on COVID-19 and Travel Behaviour (Long-Term Impacts)

Country (City)	Author	Objectives	Methods (Time of Study)	Major Findings
USA (Boston)	*Basu and Ferreira, 2021*	To investigate the challenges and opportunities for sustainable mobility in the post-COVID time	Descriptive statistics and spatial analysis (December, 2020)	One in five currently car-less households intend to purchase a car because of COVID-19. Long-term urban choices have been affected by the pandemic and these effects are acute for low-income households.
Greece (Thessaloniki)	*Nikiforiadi et al., 2020*	To investigate whether the pandemic could result in a greater or lesser share of trips that are being conducted through shared bikes	Descriptive statistics (June-July, 2020)	Bike-sharing is more likely to become a more preferable mobility option for people who were previously commuting with private cars as passengers (not as drivers) and people who were already registered users in a bike-sharing system.

USA (New York)	*Pase et al., 2020*	To gain insights on the socio-economic variables behind urban mobility during COVID-19.	Spatio-temporal analysis, connectivity and heat diffusion analysis.	Transit users are wary to return to mass transit after the pandemic. The capacity of the bike system will need to be increased, as well as reach the whole city.
Whole world	*Basu and Basu, 2021*	To examine whether the positive environmental changes could be maintained in the post-COVID world	Literature review and perception studies	For reaping the benefit of the current green environment, sustainable strategies have to be developed to cope with the new normal.
US, China, Germany, France, Italy, Spain, and the UK.	*Bert et al., 2020*	To investigate long-term urban mobility behaviour (mid-2021 through year-end 2021)	Descriptive statistics (April, 2020)	Use of shared mobility and public transit will increase. In the US and Europe, the survey suggests that use of micromobility (mainly bikes and e-scooters) will return to precrisis levels.
India	*Singh et al., 2020*	Investigates the psychological effect of COVID-19 and its impact on post-COVID travel behavior	Descriptive statistics (June, 2020)	During lockdown, 67% of persons started working from home. However, only half of them will continue to do so post-COVID-19. Compared to 70% of persons favoring flexible working hours, only 62% of respondents consented for staggered working hours. people are likely to visit eateries, restaurants, entertainment or religious places to release the tension, to calm the mind, to lessen the anxiety.

Poland (Gdansk)	*Przybylowski, et al., 2021*	To investigate the long-term impact of COVID-19 on mobility behaviours with special regard to public transport users	Descriptive statistics (May-June, 2020)	Almost 75% of the respondents plan to return to using public transport when the epidemic situation will be stabilized. The others have completely lost hope that public transport will ever be safe.
Spain (whole country)	*Awad-Núñez et al., 2021*	To explore the effects of the pandemic on changes in travel behaviour in post-COVID times	Ordered probit model (May, 2020)	The increase of supply and vehicle disinfection, result in a greater willingness to use public transport in post-COVID-19 times. Similarly, the provision of covers for handlebars and steering wheels also significantly increase individuals' willingness to use sharing services.

According to Table 2-2, research shows that when the COVID-19 virus threats will get reduced, public transport ridership may improve, but there are doubts whether the ridership will return to pre-crisis levels. Authors of those papers suggest that governments may have to find solutions to restore the trust of general public on public transit, possibly by reshaping, and restructuring transit systems. Researchers also found that during the pandemic, private car was considered a safe mode of travel, and this perception may trigger increased auto dependency. Private car, bikes and micro-mobility options may gain popularity moving forward. Number of people working from home (telecommuting) may reduce but there will still be a significant amount of people telecommuting once the pandemic is over. Activity participation may increase substantially as people may start making their long due trips to see family, friends, or make holiday travels. This may give rise to traffic congestion, air pollution, noise pollution, and traffic accidents. Experts are concerned whether this gradual shifting of behavior may end up at a level worse than the pre-pandemic condition. However, these possibilities are mainly based on smartphone data stated preference surveys and review studies which are unable to capture the interaction between transport and land-use system transformation, and how people's mobility behavior may evolve in the post-pandemic time. Besides, these studies are not capable of incorporating uncertainties during a pandemic into the behavioral models. A pandemic brings a lot of unreliability in decision making of individuals and it is necessary to observe these aspects while predicting peoples' travel behavior. Further investigation is necessary with sophisticated integrated models to dig more deeper into the changes of transport and land-use systems due to COVID-19 crisis and have a clearer understanding of the emanating travel behaviors from the pandemic. This idea provided motivation for this thesis where synergistic analytical frameworks are proposed considering critical factors of urban systems' environment. Potential of the developed tool is demonstrated through analyzing short-term, medium-term and long-term impacts of the COVID-19 pandemic on transport and land-use. The next section presents the methodological framework of the thesis and description of the study area.

Chapter 3

Conceptual Framework and Study Area

3.1 Framework of the Methodology

Considering the gaps in literature, this thesis develops integrated urban modelling frameworks for assessing impacts of COVID-19 on urban transport systems and land-use dynamics. By combining data mining techniques, questionnaire survey data, and models with uncertainty capturing capacity, it develops integrated urban transport and land-use system frameworks. This study takes a more holistic approach of understanding the impacts of the pandemic on peoples' mobility behavior changes. Figure 3-1 shows the conceptual framework of the study. The developed frameworks can be used to assess transformation of transport and land-use systems in cities because of the pandemic.

This thesis initiated with an in-depth literature review on existing 'COVID-19 and transportation' studies which helped to determine the research questions. Then it delved into identifying critical issues in transport modes and travel behavior that may undergo significant change due to the pandemic. For this, this study applies data mining techniques on Twitter public discourses related to transport modes, reopening challenges, solutions and opportunities to identify the sectors of transport and land-use that are being highly affected by COVID-19. From the learnings of this chapter and the extensive literature review, it conducts a questionnaire survey in Halifax, Canada to get data on people's post-pandemic mobility choices, socio-demographic characteristics, vehicle fleet information. Using these data on individuals' changing mobility decisions this thesis develops Bayesian Belief Network (BBN) models to analyze factors affecting people's mobility choices in the post pandemic time. Through predictive modelling capacity of BBN models, this study captures the uncertainties in decision-making during the crisis. After that, a pandemic scenario simulation is carried out using a long-term decision simulator (LDS) in integrated transport land-use and energy (iTLE) model; to analyze possible long-term changes in households' mobility decisions. To understand likely transformations of urban mobility and land-use more deeply, this thesis finally develops an integrated urban modelling framework (IUMF), by combining BBNs and iTLE. IUMF can be considered as a hybrid model for simulating urban travel behavior in the wake of a pandemic. It is developed as a simple and flexible tool that can be used to assess impacts of COVID-19 outbreaks or any other disease outbreak on transport and land-use systems of cities.

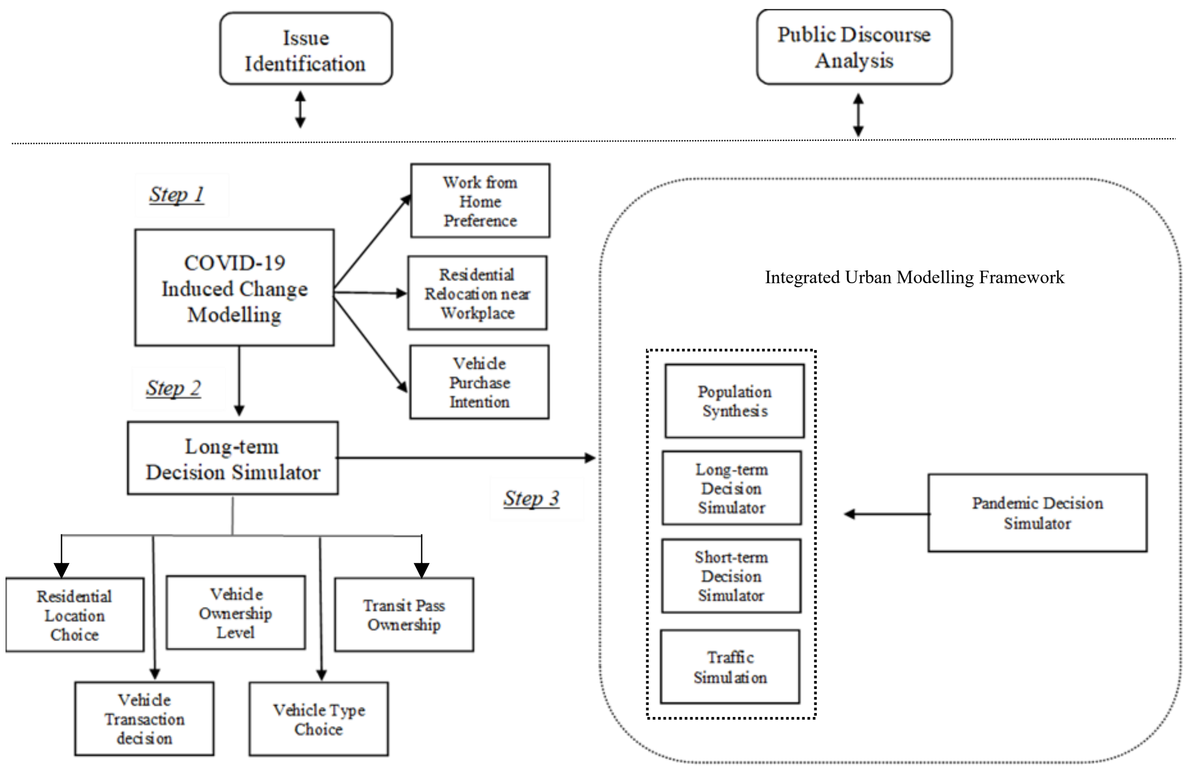


Figure 3-1 Conceptual Framework of the Integrated Urban Modelling Framework (IUMF) for Assessing the Impacts of the COVID-19 Pandemic

3.2 Workflow of the Thesis

The workflow of the thesis can be divided into three parts: a) investigating short-term impacts using Twitter data mining, b) developing Bayesian Network models to assess post-pandemic impacts (medium-term impacts), c) developing integrated urban system tools to examine long-term impacts of COVID-19 on transport and land-use systems. The timeline for short-term impact assessment is considered as the time period in between January-June 2020. Post pandemic impacts indicate approximately behavioral change between the time period of January-June 2021. Finally, the long-term impacts are forecasted for years 2021 to 2030. Figure 3-2 shows the workflow of the thesis.

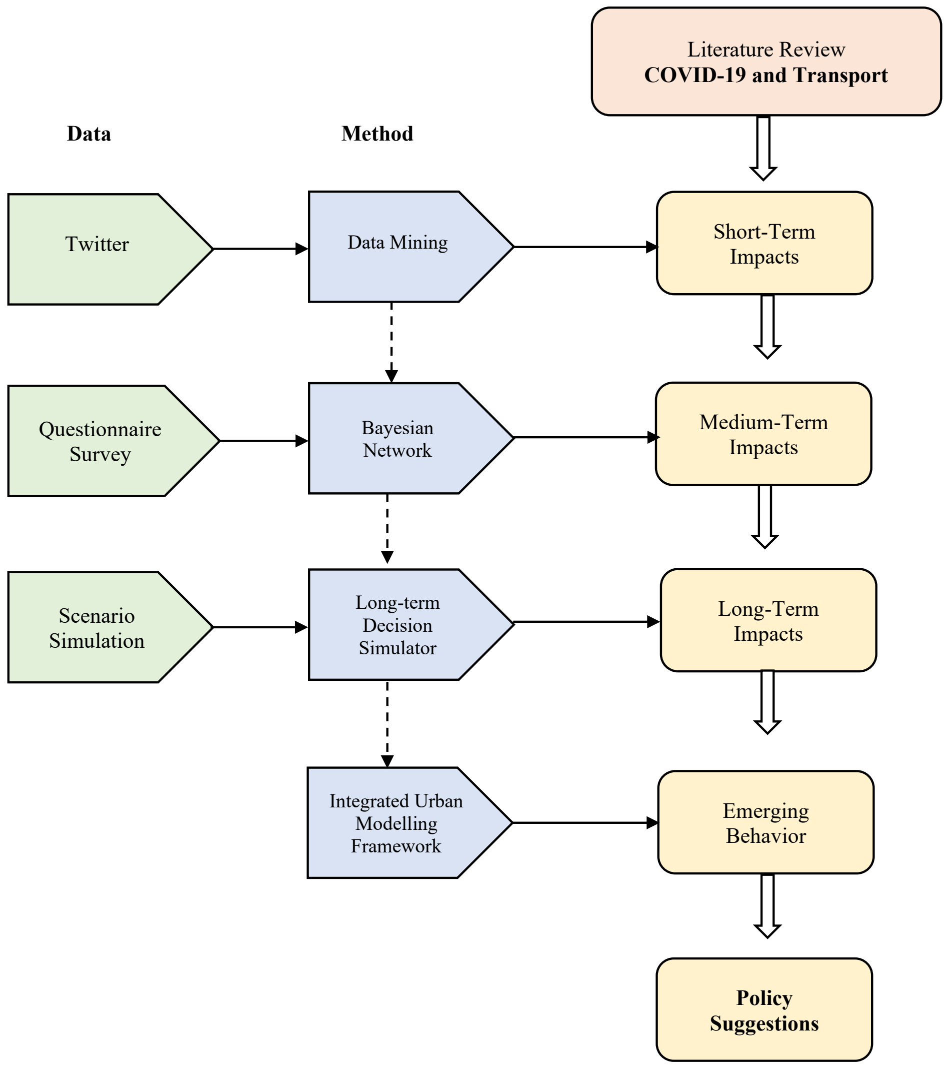


Figure 3-2 Workflow of the Study

According to Figure 3-2, this study initiated with a literature review on COVID-19 and transport. At the beginning, there were not that much available research on this topic.

The author kept updating the literature review section whenever new research became available. To complete the first objective, the short-term impacts of COVID-19 are assessed by applying data mining on social media public discourses (Twitter). Through analyzing general public's real-time experience, concerns, opinions and views related to their daily travel during the pandemic, the impacts on travel modes and mobility behavior are assessed. Following the timeline of COVID-19 pandemic developments in cities, the thesis then delves into investigating peoples' mobility choices in the post-COVID time (approximately after the second wave of the virus in January 2021). For this, it first conducts a questionnaire survey among full-time and part-time working professionals in Halifax, Canada to get data on their socio-demographics, travel choices, household vehicle fleet information and post-pandemic travel attitudes and preferences. Then this thesis develops models based on Bayesian Belief Networks (BBNs) to analyze the relationships between the variables affecting individuals' post-pandemic travel attitudes and choices. Next, the thesis conducts a pandemic scenario simulation using a long-term decision simulator to understand long-term impacts of the pandemic. This thesis simulates travel behavior and choices, such as residential location choice, vehicle transaction decision, vehicle type choice, vehicle ownership level, transit pass ownership of 20,233 households of Halifax up to the year 2030. Finally, it develops an integrated urban modelling framework (IUMF) to analyze impacts of COVID-19 pandemic on transport and land-use systems. To demonstrate the application of IUMF, in the last step this thesis examines long-term impacts of emerging travel behaviors from the pandemic. Particularly, it examines work from home (telecommuting) behavior of individuals with respect to socio-economic characteristics, and travel behavior. These four steps of the thesis are discussed in detail in their associated chapters.

3.3 Study Area

The study area chosen in this thesis is the Halifax Regional Municipality (HRM), the capital of Nova Scotia Province, Canada. Halifax is one of the most rapidly growing cities in terms of population and economic activities in Canada. According to Census (2016), the population of Halifax was 390,328 in 2011, which eventually increased by 3.3% to become

403,390 in 2016. The urban area (34.23 km^2) comprises of downtown Halifax and Dartmouth, which has a mix of land uses, such as commercial, industrial, and residential. The urban area is surrounded by suburban areas (470.24 km^2), which contain mostly residential use and few industrial and commercial uses. Finally, the suburban area is surrounded by rural area of 5349.82 km^2.

After the confirmation of the first presumptive COVID-19 cases, the provincial government of Nova Scotia announced a state of emergency on March 22, 2020 (Province of Nova Scotia, 2020a). Major restrictions were imposed during this lockdown scenario to stop the spread of the COVID-19 disease. Travel was restricted to a certain limit. People were ordered to stay home, and activities such as work, school, shopping, dine out, personal business and recreational activities were suspended temporarily. All parks, provincial trails, and tourists' attractions were closed until further notice. Police were authorized to enforce orders under the Health Protection Act, as well as the Emergency Management Act, and gatherings over 5 people were prohibited. However, after a couple of weeks, the government allowed some small businesses to open but asked to maintain the 2-meter social distance and restrict occupancy to a certain amount of people depending on the establishment. People started working remotely, while schools, universities, childcares were either closed or moved to online (Province of Nova Scotia, 2020b). This situation continued until April 30, 2020. The authorities began reopening business establishments and some recreational facilities starting May 1, 2020. It included the reopening of public parks, trails and sports fishing and people were allowed to visit community gardens and small businesses, e.g., nurseries and garden centres (Province of Nova Scotia, 2020c). On May 15, the provincial government lifted a few restrictions as well. People could attend boating, yachting, or sailing clubs for recreational purposes. Religious activities and travelling within the region were permitted by maintaining a 2-meter social distance after May 15. Restrictions were relaxed on various activity and travel dimension on June 15, 2020. From June 15, provincial campgrounds were opened at a reduced capacity. Individuals were also permitted to gather in close social groups (10 persons), and restaurants were allowed dine in services. In addition, travelling within Atlantic provinces were also allowed starting July 3. The Google's COVID-19 Community Mobility Report states that people participating in shopping activities increased by 3%, whereas people participating in work and recreational activities decreased by 29% and 3%, respectively. The reopening phase-3 began from September 1, 2020 when schools got reopened (Province of Nova Scotia, 2020c).

On December 8, 2021, the Nova Scotia government announced that the first doses of the Pfizer COVID-19 vaccine will arrive in the province by Dec. 15. As of February 23, Nova Scotia reports administering 27,521 doses of either the Pfizer-BioNTech or Moderna vaccines, with 11,533 people having received a booster shot. Cumulative confirmed cases are 1,610 in the province with 65 deaths in total. Compared to other provinces, such as, Ontario (298,800), Quebec (283,666), Alberta (131,336), British Columbia (77,263), Manitoba (31,483), the number of cases and infection rates is significantly low in Nova Scotia (CDC, 2021). Nova Scotia plans to have vaccine available to at least 75% of the population by the end of September 2021.

Chapter 4

Effects of COVID-19 on Transport Modes and Travel Behaviour [1]

4.1 Introduction

One of the many sectors that has been hit hard by the COVID-19 pandemic is transportation. Passenger and freight transport both have suffered severe setbacks from the crisis (*Tardivo et al., 2020*). Daily travel patterns and mobility behaviour of commuters have been significantly affected by the pandemic. Trip-making is significantly reduced during the lockdown period because of the following reasons: mandatory stay-at-home orders, retails/shops are closed, fear of contracting the virus. Public transport in particular has seen an all time low in ridership. People are avoiding public transit in fear of coming in contact with the virus (*Beck and Hensher, 2020*). Crowded public transport is considered a risk for the spread of the virus in urban areas, and as an alternative, people are shifting to private vehicles, bicycles or even walking as their primary modes of transport (*Beck and Hensher, 2020; Vos, 2020*). Some municipalities have responded to this demand by closing streets to vehicles to make more space for pedestrians and cyclists (*Eugene, 2020*). Experts are hopeful for green urban mobility as the increase of 'working from home' may reduce traffic congestion (*Beck and Hensher, 2020*). Specially, the emergence of cycling as an

[1]This chapter is adapted from:

Habib, M. A., and Anik, M. A. H. "Impacts of COVID-19 on Transport Modes and Mobility Behaviour: Analysis of Public Discourse in Twitter.". *Transportation Research Record : Journal of the Transportation Research Board, June 16,* 2021. https://doi.org/10.1177/03611981211029926 alternative for safer mobility may have a long-term implication on green transport policy. Moreover, people are reluctant to participate in activities outside of the home while the demand for telecommuting has increased (*Vos, 2020*). It has been projected that since March 2020, more than 44 million people have been forced to file for unemployment, which in turn reduces travel demand (*Eugene, 2020*). It is necessary to understand these complex reactions COVID-19 has had and continues to have on transportation. Also, impacts on the mobility behaviour of people need to be determined with an aim to assist policy makers to approach the 'new normal', which will follow the current health protocols and be resilient in the case of future outbreaks (*Tardivo et al., 2020*).

The economic fallout from the coronavirus pandemic has been extreme on the transport sector, especially after reducing or closing public transport services. Easing lockdown measures and restarting the economy will have more people on the streets, riding buses, trams, subways, cars, and other modes of transport (*Beck and Hensher, 2020; De Vos, 2020*). In general, the higher the mobility, the more economic activity, and human interactions it will entail. Experts from different sectors including transport, health, business, and social science, need to help developing strategies so that we can safely reopen the urban systems, maintaining public health directives that will help stifle a recurrence of the virus (*Tardivo et al., 2020; Beck and Hensher, 2020; De Vos, 2020*). To make these decisions, it is imperative for us to understand the influence COVID-19 has had on transport modes and travel behaviour from different perspectives.

The general public are the primary users of the transportation services. Their opinions and concerns may help to better understand the challenges and opportunities of the transport system (*Anik et al., 2020*). In addition, the lockdown's implications on people's mobility and activity participation can be more clearly understood. Similarly, public discourse and sentiments on mobility restrictions, their opinion and experiences related to transport modes, and reactions to decisions made by government and transport authorities can also provide useful insights into the impacts of pandemics on the transportation system. Furthermore, an in-depth analysis of people's perspectives will offer directions for countermeasures and reopening of urban spaces.

A social media analysis can be an efficient tool to explore public discourse on transportation during a pandemic (*Gui et al., 2018*). With the rise of the participatory web and social media platforms (‘‘Web 2.0’’) and their resulting proliferation of user-generated content, the general public is playing a larger role in all stages of knowledge translation, including information generation, filtering, and amplification (*Nikolaidou et al., 2018*). Therefore, for transport professionals, it is increasingly important to analyze online public response and perceptions during emergency situations, such as COVID-19, in order to examine the effects and implications of the pandemic lockdown on transport and to produce future plans and their associated reopening strategies. The public are now more actively participating in social media platforms than traditional focus group discussions (FGDs) within planning processes, sharing their concerns, choices, opinions on all trending topics (*Anik et al., 2020*). People share their beliefs, ideas, preferences, and priorities regarding almost every topic through communicating with each other over social networking sites (SNSs). This made SNSs a vast resource of useful information to understand the public and user behavior. Public discussions (posts and comments by users) on SNSs can be extracted and analyzed through different text-analytic methods, such as text mining and topic modelling (*Anik et al., 2020*). These emerging methods can be used to perform both qualitative and quantitative analysis on social media data and elicit general public reactions to the reopening of activity centers, including shops, shopping complexes, schools, community services, and towards government decisions on mobility restrictions.

This chapter uses public discourse data from Twitter, a popular microblogging application that is ideal for conversations and sharing small posts, to identify the effects of the COVID-19 pandemic on the transport system, and also to identify reopening challenges and opportunities for the economy. Conducting a survey is time consuming and requires large costs, particularly at the midst of a crisis. Whereas social media data is free and provides real-time information on topics examined (*Chew and Eysenbach, 2010*). To achieve it’s objectives, first, this chapter collects tweets (text) of Twitter users using keyword-sets related to public transit, cars, bicycles and reopening using TAGS, a free Google Sheet template for collecting Twitter data developed by *Hawksey (2020)*. From May 15 to June 15, 2020, 15,776 tweets are collected on the relevant topics. The scope of the study area is considered worldwide and only the tweets which are in English language are taken into account for analysis. Next, the collected data is uploaded into NVIVO 12 Pro, a widely used Qualitative Data Analysis (QDA) software, categorized into broad themes, and analyzed based on consultation with transportation and planning experts. Next, it applies text mining techniques to the collected tweets to identify keywords and their associations using the aid of NVIVO 12 Pro. Finally, using linguistic analytical approach of topic modelling, it determines topics related to transport modes that are discussed the most, the words associated, along with the probability of association of the words and the topics. The findings of this chapter will offer decision makers an idea about public's concerns, discourse topics, perceptions and opinions regarding the transportation systems, and travel behaviour. Furthermore, the outcomes provide initial understanding of COVID-19 associated impacts on mobility behavior, thereby establishing the base knowledge for the future chapters of the thesis.

4.2 Literature Review

Previous studies have explored potentials of social media data for analyzing travel behaviour and impacts on transport systems. *Nikolaidou and Papaioannou (2020)* investigated whether mining and analyzing social media data can be a powerful tool in the transportation domain. Through an extensive survey of the literature, they found that analysis of social media can provide valuable information regarding incident detection, mobility, and activity patterns as well as **users' opinions about different transport modes.** They also found that advanced data mining and linguistic techniques are required for the extraction of information, the reliability of the data collected, and to reduce the sample bias. Several other studies have examined whether social media can be utilized as an effective communication platform for both public and authorities with an aim to carry out sustainable transportation planning *(Anik et al. 2016; Anik et al. 2017)*. Those studies found that general public opinions and concerns may help policy makers to better understand the challenges and opportunities of the transport system, and social media can be considered a powerful outlet for this information exchange.

Some studies examined the prospects of social networking sites (SNSs) for risk communication during disease outbreaks, also some papers utilized SNSs for exploring public sentiments, concerns during emergency situations. *Abraham (2011)* found that social networking tools, such as, Facebook, Twitter, Instagram can be an effective communication medium for general public, authorities, and other stakeholders during infectious disease outbreaks. *Chew and Eysenbach (2011)* illustrated the potential and feasibility of using social media to conduct 'infodemiology' studies for public health in the time of H1N1 pandemic. They recommended analyzing tweets for real-time content analysis and knowledge translation research, allowing health authorities to become aware of and respond to real or perceived concerns raised by the public. *Yoo and Choi (2019)* examined the effects of potential predictors that might be associated with the expression and reception of information on social networking sites (SNSs) during the South Korea Middle East respiratory syndrome (MERS) outbreak. They suggested that risk communicators and public health officials should pay closer attention to disparities in the engagement of SNS communication. SNS have recently been utilized in order to promote infectious disease awareness because they are known to be cost effective and relatively influential *(Shariatpanahi et al. 2017)*. They concluded saying that SNSs play a critical role in orchestrating and facilitating communication pertaining to a public health crisis, and such communication can have a direct impact on the crisis prevention and management. *Huang et al. (2020)* analyzed over 580 million tweets worldwide to see how global collaborative efforts in reducing human mobility during COVID-19 are reflected from the user-generated information at the global, country, and U.S. state scale. They found that the triggers of mobility changes correspond well with the announcements of mitigation measures, which in return proves that Twitter-based mobility, to some degree, implies the effectiveness of those measures. *Flores-Ruiz et al. (2021)* explored the role of social media in tourist sentiment analysis during COVID-19 and found that tourists placed greater value on safety and preferred to travel individually to nearby, less crowded destinations since the pandemic began. *Das and Dutta (2020)* followed large scale Twitter data analysis to examine the contexts and unknowns associated with sentiments and emotions of Indian people during COVID-19. They used topic modeling and sentiment analysis together to produce topics in different sentiment groups. However, their scope of analysis was broad and not specific to transport as they collected "COVID-19 in India" related tweets only. *Morshed et al. (2021)* examined large-scale Twitter reactions related to shared mobility to perform comparative sentiment and emotion analysis to understand the impact of COVID-19 on transportation network companies (TNCs) in pre-pandemic and during pandemic conditions. One of their findings was that during the pandemic, opinions and expressions of TNC users on Twitter were inclined towards negative sentiment and emotions. However, the scopes of their study did not cover other transport modes, such as, walking, biking, car and public transport.

The abovementioned discussions suggest that social media data has extreme potential to assess impacts on different socio-economic sector, especially transport environment during disease outbreaks. Though there have been studies utilizing the potential of social media data mining to assess mobility dynamics in business-as-usual scenario, very few studies have tried to utilize this emerging method to assess COVID-19 pandemic's impact on transport modes and travel behavior. General public are the primary users of transport services, and people nowadays share experiences related to almost every aspect of their daily lives in social media. This makes social media an excellent platform for analyzing the impacts of COVID-19 on travel behavior of individuals.

4.3 Methodology

The methodology adopted in this chapter is an amalgamation of both qualitative and quantitative research. The study can be divided into the following steps: (i) collecting public discourse data on transport modes and 'reopening' from Twitter (tweets), filtering and preparing them for analysis; (ii) categorizing the tweets into themes (nodes) and sub-themes (sub-nodes); (iii) applying text-mining on the tweets to identify highly-occurring words in public discourse; (iv) using topic modelling, identifying the most discussed topics related to transport system during COVID-19, words associated with those topics, along with their probability of association; and (v) discussion of key findings. Figure 4-1 shows the framework proposed in this chapter.

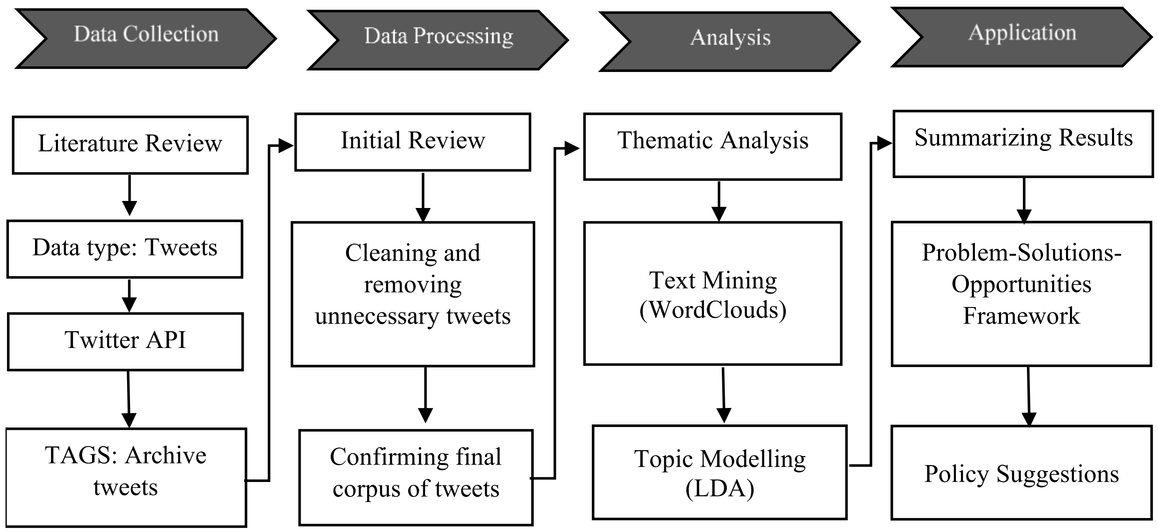


Figure 4-1 Framework for Issue Identification Using Twitter Data Mining

Data collection was conducted with TAGS (https://tags.hawksey.info/). TAGS queries Twitter Search API by user defined search terms and stores the results of the query on a Google Sheet archive. The user can execute the query manually or setup TAGS to update the archive every hour. To extract data from Twitter, TAGS requires an API key from the Twitter Developer website. TAGS offers users the opportunity to extract historical tweets from a defined time period. However, currently there is no text analysis toolkit within the TAGS platform. The extracted tweets must be exported and analyzed separately. Using the geocode option in TAGS, location-specific data can be collected as well. Data was collected using 'public transit and COVID-19', 'car and COVID-19', 'bicycle and COVID-19', 'reopening and COVID-19' as keyword-set search terms between May 15 to June 15, 2020. Within this period, a total of 15,776 tweets were collected involving the aforementioned four (4) keyword-sets. 20 randomly selected tweets for each keyword-sets from every single day during the collection period were manually coded using NVIVO 12 Pro to avoid trend bias associated with posting. As there are no established methodologies for sampling tweets, the authors were unable to perform a formal sample size calculation (*Chew and Eysenbach, 2010*). Therefore, the sample size is chosen based on feasibility and determined that 20 tweets per day (N=600 tweets per keyword-sets) would be sufficient in capturing discussion points and concerns of the general public. Any re-posted or ''retweeted'' tweets using notation ''RT @ username'' or ''RT@username'' were excluded to prevent popular posts or spam from saturating the sample. Non-English tweets were also excluded because translation was outside of the study scope. The categorization or coding process of the tweets into nodes and sub-nodes was guided by consultation with practicing transportation and land-use planners, academicians as well as researcher's constructive judgements. Tweets expressing similar ideas were coded into the same node. After coding all the tweets, nodes and sub-nodes were developed to efficiently observe the issues discussed by the public.

Next, the corpus was created with the tweets used for identifying the nodes and sub-nodes, which were afterwards analyzed through word cloud construction (text mining) and topic modelling. Text mining is the process of analyzing large amounts of natural language text to identify lexical and linguistic usage patterns of significance (*Das and Dutta, 2016*). In text mining, a collection of text documents is represented by a corpus which is then purified by removing redundant words, numbers, punctuations, etc. In this study, the results of text mining were illustrated by word clouds, which is a popular way of visualizing the most frequent terms in unstructured documents. If $P_{u.v}$ is the rate at which word u occurs in document v, and P_v is the average across documents ($\sum_v P_{u,v}$/n), where n is the number of documents then in a word cloud, then the size of each word is mapped to its maximum deviation ($max_u(P_{u,v} - P_v)$), and its angular position is determined by the document where that maximum occurs (*Das and Dutta, 2016*).

With respect to topic modelling, this study adopted Latent Dirichlet Allocation (LDA), which is an autonomous way of discovering topics in unstructured documents. LDA applies bag-of-patterns representation on the text corpus to automatically discover the clusters of topics that are in the unstructured form in the document groups (*Das and Dutta, 2016;Beli et al., 2003*). It represents documents as mixtures of topics that disclose words with certain probability. The algorithm for LDA is as follows:

1) The documents are produced with X number of words following Poisson distribution, i.e., $X \sim Poisson(\mu)$.

2) Documents are a mixture of t topics according to Dirichlet distribution, i.e., $K \sim$ Dirichlet(λ).
3) LDA generates each word p:
   i) by picking up topics following multinomial distribution, i.e., topic $l_{nm} \sim$ multinomial (K), and,
   ii) by using the topic to generate the word (according to the topic's multinomial distribution), i.e., choosing a word p from. $P(p|\lambda, \delta)$.

Here, K is the distribution of topics over document m, l_{nm} is the topic for the n^{th} word in the m^{th} document, δ is the distribution over words over topics t.

Text mining and topic modelling revealed public discussions and concerns on various criteria and components defining private car, cycling and public transport and also on reopening challenges and strategies during COVID-19. In this study, text mining was conducted using NVIVO Pro's built-in features and the topic modelling was carried out using 'tm' package of open source statistical analysis software R.

While preparing the corpus, necessary corrections were made, such as, the abbreviations in tweets were converted to full forms, irrelevant texts were screened out, names of people were expurgated, and synonymous terminologies were standardized into singular words. Also, the searched keywords, such as, 'COVID-19', 'coronavirus', 'transit', 'car, and 'bicycle', were also removed from the corpus of text mining considering their redundancy in the dataset.

4.4 Results and Analysis

Nodes and sub-nodes of talking points were generated after applying manual coding to the collected tweets. A node may or may not have sub-nodes. The results are shown in Table 4-1. In Table 4-1, the percentage of tweets in the whole sample belonging to each node are shown using square brackets ("[ ]"), and the percentage of tweets belonging to each sub-node within their parent node are shown using parentheses ("( )"). The percentage values for all nodes for each keyword-sets ('bicycle and COVID-19', 'car and COVID-19', 'public transit and COVID-19, and 'reopening and COVID-19') sums up to 1 and they are ranked in terms of their percentage values in the Table. However, the percentage values of sub-nodes within a node may or may not add up to 1, as aggregate coding from children (sub-nodes) was checked on for parent (nodes) and parent may have some unique coding references.

Table 4-1 indicates that people were concerned and discussed the most about public transit and it's reopening strategies adopted by transit authorities [40.8%]. Twitter users requested other users to wear face masks while traveling on public transport and also supported the mandatory mask wearing rule announced by different public transit authorities (50%). Countries such as Canada and the United Kingdom imposed a mandatory mask rule on public transport as part of their reopening protocols, which forces transit riders to wear masks even if it is a non-surgical one. Moreover, Google Maps data to alert transit riders about potential COVID-19 clusters (18.8%), social-distancing inside transit (12.5%), pandemic transit plans (6.3%), using UV light (3.1%), not reducing capacity (3.1%), and transit ambulance services (1.6%) were also brought up as effective transit reopening strategies by Twitter users. The second most discussed subject on public transport was the opportunities for improvement [21%]. People discussed and supported the idea that restoring and reshaping transit and increasing safety can significantly increase transit ridership after reopening. The challenges faced by transit workers were also raised by the public [11.5%]. Those who cannot afford a private car or are unable to walk or bike to their destination have to rely on public transit during COVID-19. They have faced difficulties and complained about longer travel times (5.9%), lack of travel freedom (5.9%), and increased fares (5.9%). Some people on Twitter urged to shut down public transit [4.4%]. Amidst the rise of cycling, walking and the use of private automobiles, people were concerned about the uncertain future of public transport [4.4%]. It is expected that after reopening, transit companies will be aiming to recover the economic losses due to COVID-19, which may reduce investments in transit improvement projects. Transport experts think that this approach may have a rebound effect and decrease transit ridership (*Beck and Hensher, 2020; Bucsky, 2020*). Several governments have provided funding to their transit authorities and transit companies to tackle economic losses. Some members of the public welcomed these initiatives and demanded for a safe reopening of public transport [3.2%].

Table 4-1 indicates that, for the mode ‘bicycle’, the subject that was discussed the most was the modal shift to bicycle from other transport modes. This subject matter covered for 24.6% of the total bicycle related tweets. Under this node, people identified cycling as an alternative mode to public transit (34.3%) and car (28.6%) to get to places safely during the pandemic. These results support initial findings of recent studies (*De Vos, 2020*; *Bucsky, 2020*). The second most discussed subject on bicycle was the opportunities of biking to solve mobility problems caused by COVID-19 [22.5%]. Different opportunities were identified, such as, cycling as a solution to mobility restrictions during pandemic (34.4%), possible bike ridership increase after COVID-19 (18.8%), cycling as one of the solutions to fight global warming (15.6%), more walking trips (12.5%), charity rides (9.4%), and cycling races (6.3%). Another prominent discussion matter was the rapid increase of cycle sales across the world [21.1%]. Possibly fearful of public transit, people are using bicycles as their primary mode of transport. This has led to a bicycle boom across cities. The public also discussed the twofold health benefits of biking [10.6%], which are physical well-being (66.7%) and mental health (33.3%) improvement. A study found that 87% of the cyclists rode bicycle during COVID-19 to improve their physical and mental health (*BikeRadar, 2020*). The public demanded the needs of cyclists [9.9%] during and after COVID-19. They urged cyclists to wear a mask (57.1%) and asked for improved cycling infrastructure (21.4%) and safety (21.4%). Public discourse on bicycles also included bike infrastructure projects implemented by different transport authorities across cities to meet the increasing cycling and walking trip demand. Another interesting fact that came out of the analysis was that bicycle shops sold out of products and failed to meet the sudden huge demand of cycles [4.2%]. Each day, more and more bicyclists are on the road and facing challenges, such as, difficulty to share the road with cars on shared roads, long distance trips, insurance issues, torrid weather, etc. These cyclists’ challenges were also discussed in the tweets analyzed in this study [2.1%].

Table 4-1 postulates that, ‘Consequences on Car’ due to COVID-19 is the highest discussed subject matter on private car [34.7%], followed by ‘Strategies for Using Car Safely’ [23.8%], ‘Reopening Car Services’ [14.3%] and ‘Preference of Car than other Modes’ [8.2%]. Due to COVID-19, car sales have decreased abruptly, car rental companies and car sharing services are suffering from economic losses, car thefts and accidents have increased, and gas prices have decreased. Interestingly, people were discussing that the introduction of autonomous vehicles may be delayed due to the uncertainties in the transport industry. Under safe car usage strategies, people discussed eyesight testing (31.4%), disinfecting cars regularly (28.6%), wearing a mask (20%), car inspecting protocols (5.7%), limiting the number of passengers (2.9%), social-distancing inside cars (2.9%), maintaining the 2-metre distancing rule (2.9%), driving less (2.9%), and proper rescue plans (2.9%). Another important finding from the tweet analysis is that people felt safer to use cars [8.2%] rather than transit (50%), trains (16.7%) or planes (16.7%). This perception is analogous to the discussion themes of 'bicycle' and 'public transit' related tweets, indicating that people are considering bicycle, walking and private car the safest modes of transport during COVID-19. Before the spread of COVID-19, different countries undertook special projects to reduce the mode share of cars and increase walking, biking, and transit trips, in order to tackle traffic congestion, air pollution and climate change. As more people are shifting to private cars now, people are concerned about the future of those projects [5.4%]. Another subject matter that was discussed frequently is the risk associated with leaving hand sanitizer in cars [4.8%]. There were discussions of hand sanitizer bottles exploding due to high temperatures inside a car, and people were expressing their concerns over Twitter. Literature review have suggested that on a very hot day, significant pressure could build up inside a bottle of hand sanitizer, causing it to rupture, but it would not result in fire (*Gillespie, 2020*). Other subject matters discussed by people related to cars were, the use of parking during Eid prayers [4.8%], anti-lockdown car protests [2.7%], and fear of a probable second wave of COVID-19 [1.4%].

Apart from analyzing the tweets related to 'bicycle, 'public transit', and 'car', 'economy restarting' related discourses were also analyzed (Table 4-1). 'Reopening Consequences' was the most discussed subject matter [22.6%] followed by 'Strategies for Safe Reopening' [20.4%]. People showed their anger and frustration on the record increase of COVID-19 cases following the reopening of cities (78.6%). Interestingly, some areas (e.g. Georgia, Saskatchewan) found that reopening did not increase the number of cases. Mixed opinions on reopening were found among the public, some were in support of a safe reopening [5.9%], while others wanted to wait until a vaccine arrives [3.2%]. Under the strategies for safe reopening, wearing a mask (23.7%), phased reopening (15.8%), containment zones (5.3%), state of emergency (5.3%), mobility-data driven approach (5.3%), telecommuting (2.6%), hand sanitation stations (2.6%), social distancing (2.6%), and obeying traffic rules (2.6%) were all discussed. Challenges associated with reopening were also highly discussed on Twitter [19.4%]. People were calling for employee (22.2%) and customer protection (19.4%) strategies, especially for transit workers and riders. People were worried for a probable second wave of the virus (16.7%) and were concerned about the global unemployment increase (13.9%). People were anxious that after reopening, staff may not join workplaces due to the fear of coming in contact with COVID-19 (11.1%). People also pointed out the lack of guidelines from the government on reopening protocols (5.6%). People's perceptions were that it would be difficult for authorities to reopen public bathrooms (2.8%) and public transit (2.8%) while maintaining health measures. Consensus were found among the public about 'not reopening the schools'. These tweets constituted 10.8% of the total reopening related tweets. Some countries reopened schools but closed them again after COVID-19 clusters were found in school areas (*Kwon and Jeong, 2020*). Another compelling finding was the 'forced reopening' idea [9.7%]. Discourses were found on the issue that some countries initiated the reopening project to save their economies even though they knew that it would increase spread of the COVID-19 and potentially further deaths.

Table 4-1 Nodes and sub-nodes of tweets with global percentages for nodes (in square brackets) and local percentages for sub-nodes (in round brackets)

Public Transit and COVID-19		*Bicycle and COVID-19*		*Car and COVID-19*		*Reopening and COVID-19*	
Node and Sub-Node Names	**Percent of Tweets (%), N=600**	**Node and Sub-Node Names**	**Percent of Tweets (%), N=600**	**Node and Sub-Node Names**	**Percent of Tweets (%), N=600**	**Node and Sub-Node Names**	**Percent of Tweets (%), N=600**
1. Reopening Strategies	[40.8]	1. Prefer Using Cycle than Other Modes	[24.6]	1.Consequences On Car Usage	[34.7]	1.Reopening Consequences	[22.6]
1.1 Wearing Mask	(50.0)	1.1 Using Cycle to Avoid Transit	(34.3)	1.1 Car Sales Decreased	(25.6)	1.1 Cases Increased after Reopening	(78.6)
1.2 Use Google Maps Data	(18.8)	1.2 Using Cycle to Avoid Car	(28.6)	1.2 Car Rentals	(25.6)	1.2 Reopening not that Bad	(11.9)
1.3 Social-distancing	(12.5)			1.3 Car Theft Increased	(15.7)	1.3 Church Closed after Reopening	(7.1)
1.4 Pandemic Transit Plan	(6.3)			1.4 Car Accidents Increased	(11.8)	1.4 No New Cases	(2.4)
1.5 Ultraviolet Light	(3.1)			1.5 Car Buying Increased	(9.8)		
1.6 Do not Reduce Capacity	(3.1)			1.6 Cycling Revolution	(3.9)		
1.7 Transit Ambulance	(1.6)			1.7 Car Mode Share Increase	(2.0)		
				1.8 New Car Parking	(2.0)		
				1.9 Petrol Price Decreased	(2.0)		
				1.10 Rule Breaking Increased	(2.0)		
				1.11 Car Sharing Services	(2.0)		
				1.12 Autonomous Vehicles	(2.0)		
2. Opportunities	[21.0]	2. Opportunities	[22.5]	2. Strategies for Using Car Safely	[23.8]	2. Strategies for Safe Reopening	[20.4]
2.1 Restore Transit System	(24.2)	2.1 Solution to COVID-19 Mobility Restrictions	(34.4)	2.1 Eyesight Testing	(31.4)	2.1 Reopen Safely	(34.2)
2.2 Increase Ridership	(12.1)	2.2 Continue Using after COVID-19	(18.8)	2.2 Disinfecting Car	(28.6)	2.2 Wear Mask	(23.7)
2.3 Increase Safety	(9.1)	2.3 Tackling Climate Change	(15.6)	2.3 Wearing Mask	(20.0)	2.3 Phased Reopening	(15.8)
2.4 Reshape Transit	(6.1)	2.4 More Walking	(12.5)	2.4 Car Inspection	(5.70)	2.4 Containment Zones	(5.3)
				2.5 Occupancy Restriction	(2.90)	2.5 State of Emergency	(5.3)
						2.6 Data-driven Approach	(5.3)

		2.5 Charity Rides 2.6 Cycling Races	(9.4) (6.3)	2.6 Social-distancing Inside Car 2.7 2 Metre Distance Rule 2.8 Drive Less 2.9 Rescue Plan	(2.90) (2.90) (2.90) (2.90)	2.7 Work from Home 2.8 Hand Sanitizer Station 2.9 Social-distancing 2.10 Obey Traffic Rules	(2.6) (2.6) (2.6) (2.6)
3. Transit Worker Challenges 3.1 Transit COVID-19 Cases 3.2 Drivers Strike	[11.5] (11.1) (5.6)	3. Cycle Sales Increased 3.1 More Cycling 3.2 New Cyclists	[21.1] (23.3) (6.7)	3. Reopening Car Services 3.1 Showroom Reopen 3.2 Car Wash Reopening 3.3 Car Repairing Shops Reopen	[14.3] (81.0) (14.3) (4.8)	3. Reopening Challenges 3.1 Protecting Employees 3.2 Protecting Customers 3.3 Second Wave 3.4 Unemployment Increased 3.5 Staffs May not Come 3.6 Reopening Dilemma 3.7 Lack of Guidelines from Government 3.8 Public Bathrooms 3.9 Public Transport	[19.4] (22.2) (19.4) (16.7) (13.9) (11.1) (5.6) (5.6) (2.8) (2.8)
4. Rider Challenges 4.1 Transit Cases 4.2 Public Health Crisis 4.3 Lack of Freedom 4.4 Longer Travel Time 4.5 Increased Fare	[10.8] (29.4) (11.8) (5.9) (5.9) (5.9)	4. Benefits of Cycling 4.1 Improves Physical Health 4.2 Boost Mental Health	[10.6] (66.7) (33.3)	4. Prefer Car than Other Modes 3.1 Use Car not Train 3.2 Use Bicycle or Car 3.3 Use Car not Plane 3.4 Use Car not Transit	[8.20] (16.7) (16.7) (16.7) (16.7)	4. Do not Reopen Schools	[10.8]
5. Shut Down Transit	[4.4]	5. Cyclist Demands 5.1 Wear Mask 5.2 Increase Space 5.3 Improve Safety	[9.9] (57.1) (21.4) (21.4)	5. Climate Change	[5.4]	5. Forced Reopening	[9.7]
6. Uncertain Future of Transit	[4.4]	6.Cycle Infrastructures Built	[4.9]	6.Leaving Sanitizer in Car	[4.8]	6. Guidelines	[8.1]

7. Economic Impact on Transit	[3.8]	7. Bicycle Shortage/Sold Out	[4.2]	7. Parking Used	[4.8]	7.Restarting Economy	[5.9]
8. Funding Awarded	[3.2]	8. Cyclist Challenges	[2.1]	8. Anti-Lockdown Car Protest	[2.7]	8. No Reopening Until Vaccine Arrives	[3.2]
				9. Second Wave	[1.4]		

4.4.1 Text Mining Results

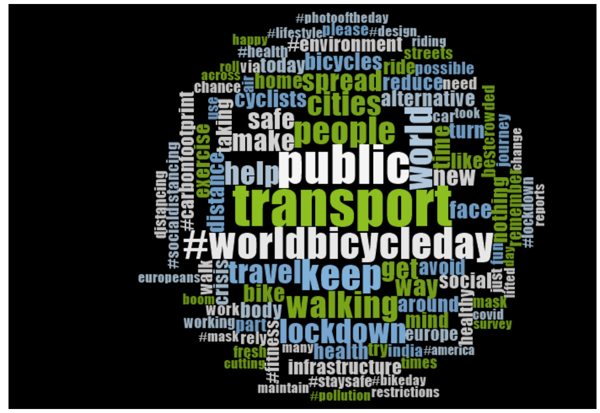
The finalized four corpuses – one for each of the keyword-sets, were used to generate word clouds as presented with Figure 4-1 (a, b, c, d). The size of the word indicates it's usage on Twitter, i.e., larger sized words infer more frequent occurrence, suggesting that these words came up in discussions more often.

Figure 4-1 (a) represents the word cloud derived from the tweets containing the 'public transit and COVID-19' keywords. The highly occurring words in these tweets were 'masks', 'mandatory', 'people', 'mass', 'new', 'face', 'cities', 'workers', 'riders', and 'wear'. To understand the underlying ideas of these words, tweets containing these words were extracted from the corpus. Those tweets narrow down the following ideas shared by the public: a) masks should be made mandatory as face coverings for travelling in mass transit. One relevant post opined: "*Please! Make masks mandatory in schools, libraries, community centres, stores, and restaurants. Crowded areas, both indoors and outdoors, including protests and busy parks or trails. Public transit…*"; and b) city authorities should identify strategies to protect the transit workers and riders from COVID-19. For instance, one user wrote: "*…begins to partially reopen, some public transit workers say safety measures are not in place to protect them or their riders from #Coronavirus infection".* Another post read: *"City administrators have to figure out how to restart buses and trains safely…".*

It can be inferred from Figure 4-1 (b) that, the ten terms (words) with the largest dimensions are 'public', 'transport', 'worldbicycleday', people', 'keep', 'cities', 'travel', 'walking', 'safe', and 'world', indicating that these were the most common points on 'bicycle and COVID-19' posted by Twitter users. To obtain a clearer picture of the messages that the users wanted to convey, all the tweets containing these words were extracted and evaluated. This revealed that the words used in the tweets contained the following ideas: a) people across cities considered biking and walking as safe modes of travel, and as an alternative to public transit. For instance, one post said: "*Need to make a journey? Protect public transport for those with no alternative. Walking & cycling is a safe way to travel. Reduce the spread of #coronavirus…*"; and b) the celebration of world bicycle day can thrust the cycling revolution in the world. One post read: "*May the world be free with pollution and be fit by using Cheapest mode of transport. "HAPPY CYCLE DAY" #worldbicycleday…".*

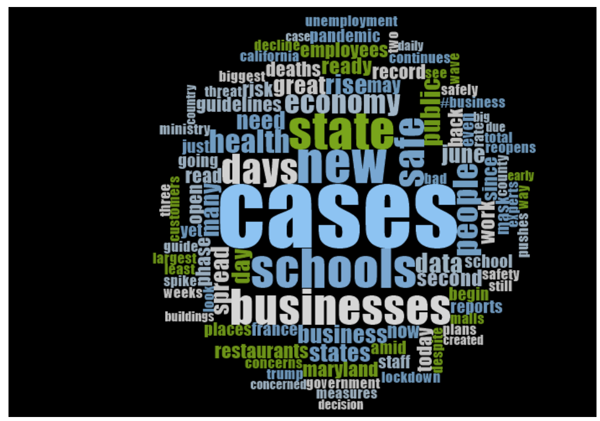
Figure 4-1 (c) presents the word cloud of words having high occurrences in tweets with the keywords 'car and COVID-19'. The most frequently used terms were 'safe', 'open', 'travel', 'keep', 'drive', 'mask', 'reopen', 'showrooms', 'sales', and 'rental'. The tweets corresponding to these words were extracted and it revealed that they were associated with the following themes: a) commuters are considering private cars as a safe mode of transport but also at the same time, are urging to wear a mask while driving or traveling in a car. One of the relevant tweets opined: "*Do not use public transport during the #Coronavirus outbreak – it is not safe, and the risks to yourself are too great. Go by car instead…".*; b) car showrooms are reopening and offering new deals to increase sales, and to cover for the economic loss. One user wrote: "*Lots of car companies are offering good financing deals right now to make up for poor #coronavirus sales…"*; and c) car rental companies are suffering from great financial loss due to COVID-19 mobility restrictions. One relevant post read: "*Struggling rental car companies expected to sell vehicles at deep discounts. They don't need them. And they need the cash…".*

(a) Public Transit and COVID-19



(b) Bicycle and COVID-19

(c) Car and COVID-19



(d) Reopening and COVID-19

Figure 4-2 Word clouds of the most frequently occurring words in tweets

Figure 4-1 (d) indicates that the most frequently used words in ‘reopening and COVID-19’ related tweets were, ‘cases’, ‘new’, ‘schools’, ‘state’, ‘businesses’, ‘economy’, ‘safe’, ‘health’, ‘days’, and ‘people’. Tweets containing these words were extracted from the corpus and evaluated. They revealed the following ideas: a) after reopening the economy, a record spike in new positive COVID-19 cases was found in some of the states of the US, such as, Florida, Maryland, California, New Jersey, and also in countries like India and Bangladesh. One relevant post read: “*Florida sets new single-day record for #coronavirus cases since reopening economy, over 4,000 in three days…*”. Another post read: “*India reported a record 9,887 new #coronavirus cases in one day on Saturday and overtook Italy as the world’s sixth-biggest outbreak, two days before the relaxing of a* *lockdown with the reopening of malls, restaurants and places of worship…*"; and b) schools should not be reopened but considering the economic crisis, businesses can be restarted maintaining health and safety protocols. One of the posts said: "*No to the reopening of schools! Build action committees to safeguard children and teachers...".* While, another user wrote: *"Slowly but surely! We celebrate the reopening of our community. Support local businesses...".*

4.4.2 Topic Modelling Results

As the third phase of analysis, topic modelling was conducted with the Twitter posts-separately for each of the four keyword-sets. The most prominent eight topics related to bicycle, car, public transit, and reopening were extracted and listed in Table 4-2 in chronological order based on the conditional probability of each topic. Word clusters for each topic and their associated probabilities presenting their influence within the topic are also illustrated in Table 4-2. To gain a full understanding of these co-occurring words, sentences having these word clusters were extracted from the raw database of tweets and reviewed. Since the remaining topics either did not convey any new information or were not found to make any notable rational sense to the authors, they were not listed.

Table 4-2 Top 8 topics from Twitter for Each Keyword Obtained through Topic Modeling on Respective Tweets (Probability Value of Each Word is Given in the Parenthesis)

Topic number	Topic word clusters and their associated probabilities
	Public Transit and COVID-19
1	Pandemic (0.029), Required (0.010), Masks (0.008), Guidelines (0.008), Employees (0.008)
2	Public (0.052), Wear (0.024), Cities (0.016), Revenue (0.016), Mandatory (0.013)
3	Maps (0.016), Google (0.014), Related (0.014), Alerts (0.011), Restrictions (0.011)
4	Riders (0.016), Protect (0.014), Stores (0.012), Workers (0.012), Reopen (0.010)
5	Transit (0.046), Mask (0.023), Shopping (0.012), Community (0.010), Schools (0.010)

6	Mass (0.027), Transportation (0.019), Trains (0.019), Masks (0.010), Buses (0.010)
7	Workers (0.029), Transit (0.025), Spread (0.017), Systems (0.015), Risk (0.007)
8	Coronavirus (0.026), People (0.020), Mandatory (0.014), Masks (0.014), Coverings (0.008)
	Bicycle and COVID-19
1	People (0.029), Cycling (0.019), Transport (0.019), Coronavirus (0.011), America (0.008)
2	Mask (0.015), Coronavirus (0.012), Wearing (0.009), Journey (0.006), Spread (0.006)
3	World (0.012), Activetravel (0.009), Cyclists (0.009), Demand (0.009), Wise (0.006)
4	Distance (0.014), Exercise (0.015), Social (0.012), Alternative (0.01), Pandemic (0.01)
5	Public (0.016), Boom (0.011), Sales (0.011), Cycling (0.01), Months (0.01)
6	Worldbicycleday (0.019), Lockdown (0.016), Health (0.016), Public (0.014), Avoid (0.014)
7	Cycling (0.074), Walking (0.017), Safe (0.010), Regularly (0.01), Rely (0.01)
8	Cities (0.022), Crisis (0.020), Infrastructure (0.016), Compassionate (0.014), Extended (0.014)
	Car and COVID-19
1	Car (0.009), Safe (0.009), Lockdown (0.007), Spain (0.007), Autos (0.007)
2	Car (0.033), Public (0.014), Drive (0.014), Test (0.012), Outbreak (0.010)
3	Coronavirus (0.01), Death (0.007), Pollution (0.007), Thefts (0.007), Eyesight (0.005)
4	Car (0.094), Customers (0.011), Inside (0.008), Government (0.006), Experience (0.006)
5	Coronavirus (0.026), June (0.023), Car (0.017), Showrooms (0.011), Retailers (0.009)
6	Rental (0.017), Bankruptcy (0.015), Hertz (0.013), Shops (0.01), Mask (0.008)
7	Park (0.018), Ikea (0.016), Reopen (0.014), Lockdown (0.009), German (0.008)
8	Coronavirus (0.030), Sales (0.013), Lockdown (0.009), Showrooms (0.009), Post (0.007)
	Reopening and COVID-19
1	Reopening (0.026), Bad (0.011), Total (0.009), Public (0.009), Threat (0.009)
2	Schools (0.014), Business (0.012), Record (0.010), Employees (0.008), Wave (0.006)
3	Reopening (0.075), Economy (0.017), Schools (0.015), Florida (0.010), Maryland (0.010)
4	Businesses (0.012), Safe (0.012), Schools (0.010), Restaurants (0.008), Health (0.006)

5	Health (0.011), Deaths (0.009), Experts (0.009), Months (0.009), Rate (0.007)
6	Government (0.009), Economy (0.007), Continues (0.007), Ministry (0.007), Reopens (0.007)
7	Coronavirus (0.074), Reopening (0.045), Safe (0.012), Business (0.011), Spread (0.007)
8	Reopening (0.049), Spike (0.010), Rise (0.008), India (0.008), Malls (0.008)

Topic modelling on 'public transit and COVID-19' tweets were conducted, and the results are shown in Table 4-2. It can be seen from the results that, the words with highest probabilities in Topic 1 are pandemic (0.029), required (0.010), and masks (0.008), indicating the urgency of a mandatory mask rule on transit. The other two words in Topic 1 are guidelines (0.008) and employees (0.008) from the tweets expressing the need for proper safety measures to protect transit employees. Topic 2 also supports the idea of a mandatory (0.013) mask wearing rule and adds the news of public transport revenue (0.016) collapse. After evaluating the tweets involving the Topic 3 word clusters, it was found that Google Maps was alerting transit riders about COVID-19 clusters, and the initiative was saluted by the general public. The fourth topic is on protecting transit workers (0.012) and riders (0.016) after reopening. Similar to Topic 1, Topic 5 brings the mask wearing (0.023) rule into discussion and additionally, it talks about safely reopening shopping centers (0.012) and schools (0.010) for communities (0.010). The sixth and eighth topics again cover mask wearing habits on trains and buses while the seventh topic considers transit systems as risky (0.007) because they are enclosed areas and users are more exposed to other riders.

In the 'bicycle and COVID-19' Topic 1, the word 'people' achieved the highest probability value of 0.029, followed by cycling (0.019), transport (0.019), coronavirus (0.011) and America (0.008), indicating that the talking points of Topic 1 circles around the fact that people are considering cycling as a safe mode of transport during the coronavirus outbreak, especially in the United States. The second topic is on wearing a face mask (0.015) while making bicycling journeys (0.006) to help control the spread (0.006) of the coronavirus (0.012). The third topic related to promoting active travel options

(0.009) such as, cycling (0.009) and walking around the world (0.012). The need for maintaining social distancing (0.014) while biking is discussed in Topic 4 and it also covers the health benefits (0.015) of cycling. Topics 5 and 6 are on the boom of cycle sales (0.011) and avoiding public transport (0.016) for health safety. The seventh topic, again, indicates that cycling (0.074) and walking (0.017) are considered safe modes of transport, and people can rely (0.01) on them. Finally, the last topic involves the infrastructure (0.016) projects undertaken by cities (0.022) to extend (0.014) their bicycling networks.

According to Table 4-2, Topics 1 and 2 of 'car and COVID-19' tweets deal with considering private cars (0.009) as a safe (0.009) mode of transport. In most of the cities, people were avoiding public transport and instead chose to travel in a car when lockdown restrictions were eased. During the COVID-19 outbreak, air pollution (0.007) has decreased but car thefts (0.007) increased significantly. People rejoiced at the greener environment but cursed the car thieves and burglars (Topic 3). In the fourth topic, people were demanding that governments (0.006) should come up with a safety plan to protect customers (0.011) of businesses. Also, staying inside (0.008) a car was considered quite safe by Twitter users. The fifth and seventh topics deal with the news of car showrooms (0.011) reopening. The sixth topic is on the financial sufferings of car rental (0.017) companies such as Hertz (0.013), which went bankrupt (0.015) during the COVID-19 outbreak. Additionally, this topic covered the urge made by the public for wearing a mask (0.008) inside a car. The final topic is on the discussion of car sales declining (0.013) and post-lockdown car showrooms (0.009) reopening.

According to Table 4-2, Topic 1 of 'reopening and COVID-19' related tweets has the following word clusters: reopening (0.026), bad (0.011), total (0.009), public (0.009), and threat (0.009). After extracting and evaluating the tweets containing these words, it was found that people predicted that restarting the economy may be a threat to public health. They were concerned that reopening businesses and public transport may exacerbate the whole COVID-19 situation. Topics 2 and 3 cover the public's stance on not wanting to reopen schools (0.014). These two topics also highlighted the record increase in new COVID-19 cases after reopening (0.075) the economy (0.017) in Florida (0.010) and Maryland (0.010). Though most Twitter users opposed the reopening of the economy, others advocated for it to be restarted with safety protocols maintained. The reopening of businesses and restaurants following health safety measures were discussed in Topic 4. The fifth and sixth topics are on the angers and frustrations expressed by the public thinking that governments and ministries are forcing the 'economy reopening project' against experts' counsel. Finally, while Topic 7 warrants for a safe (0.012) reopening (0.045) of economic activities, Topic 8 includes the spike (0.010) of new COVID-19 cases after the reopening of shopping malls (0.008).

4.4.3 Problems-Solutions-Opportunities Framework

The findings of this chapter have high policy implications. Through analyzing real-time public discourse this study identifies COVID-19 challenges in priority areas, such as, public transport, workplaces, business centers, retails, that need to be addressed. This study also developed a problems-solutions-opportunities framework to illustrate the identified issues and proposed solutions by the general public. This framework also includes the future potentials of those solutions (Table 4-3). Demand for more resilient, more equitable mobility was evident in the public discourse, not only to fight the current storm, but to prepare for future catastrophes. The general public identified bicycling as a green solution to mobility problems during and after COVID-19 world. One encouraging finding from this study was that people are concerned about the environment and welcomed the surge of the new enthusiasm for cycling as a blessing to save the world from global warming. Restoring, reshaping, and enhancing transit systems were proposed as solutions to increasing transit ridership and to make up for the economic losses suffered due to COVID-19. Use of advanced technologies to monitor disease spread, pandemic transportation plans for cities, transit ambulances (free ambulance service for the public), were identified as effective reopening strategies. However, most Twitter users were against reopening schools. Instead of in-person schools, an online school system was proposed by public.

Table 4-3 The Problems-Solutions-Opportunities Framework

No.	Problems	Solutions	Opportunities

1	Public transit is risky to use during pandemic	Use bicycle or walk	Embracing active travel options as an integral part of urban transport systems planning
2	Not enough space for cyclists and pedestrians	Extend existing cycling networks, improve sidewalk facilities	Potential modal shift from car to bicycle and walking
3	Travelling to and from workplaces increase chances of getting infected with COVID-19	Work from home (telecommuting)	One or two days per week can be allocated for telecommuting in post COVID-19 workplace schedule which in turn may reduce travel demand, air pollution, and traffic congestion
4	Lockdown has adverse effects on humans' physical and mental health	Walking and biking may significantly improve health of both mind and body	More active individuals and connected communities, promoting mixed-land use and sustainable cities
5	Economic loss of public transit companies	Restore, reshape, and improve transit systems	May increase transit ridership
6	Not enough guidelines from government on safety protocols to maintain while using bicycle, private car, or public transport	Formulation of Pandemic Transportation Plan for each city	Cities will be more prepared in the case of any future contagious disease outbreaks
7	Not enough research or information on effects of transport modes on pandemic spread	Use of advanced technologies like artificial intelligence (AI) and mobility data collected by apps such	More informed decisions can be made for controlling disease spread due to travelling

		as, Google Maps, Uber, etc.	
8	Risks involved in reopening schools	Online schools	May increase flexibility of the school schedule and offer increased instructor-student time

4.5 Conclusion

This chapter analyzed Twitter posts through text mining and topic modelling to assess public discourses in order to clearly understand the impacts of COVID-19 on transport modes and likely changes in mobility behavior. It also evaluates the efficacy of analyzing social media data to understand public concerns, demands, and feelings about transport systems during an emergency pandemic situation. The results revealed that people are avoiding public transport, and shifting to private car, bicycle, and walking in fear of COVID-19. Bicycle sales have increased remarkably, even some cycle shops have been sold out failing to meet the huge demand. People are making recreational trips on bicycles in order to improve their physical and mental health. Cycling and walking has been identified as green solution to COVID-19 mobility problems, and to tackle climate change in the post COVID-19 world. To meet the rise in number of active transport users, transport authorities across cities have extended cycling network, improved walking facilities, and made way for micro-mobility options, such as, electric scooters, bikes. Interestingly, though the world is experiencing a cycling boom, car sales have declined notably during the lockdown period. Car thefts, car crashes, and traffic rule breaking has increased while petrol price have decreased strikingly. People requested each other through Twitter to drive only when necessary, wear a mask inside a car, maintain social distancing, not to leave sanitizers in car, and to disinfect their private vehicles regularly. They also advised each other to use face coverings and maintain social distancing while travelling in public transit. People urged governments and transit authorities to use advanced technologies, such as, Google Maps data to alert transit riders and operators about COVID-19 risky zones. Moreover, they advocated for a pandemic transportation plan for protecting the shop customers, staff, transport workers and riders. In addition, people applauded governments' decision to allocate funding to public transport companies for covering up the economic losses, also at the same time asked for the reshaping, restoring and safe reopening of public transport. Some tweets were identified that demanded for the immediate shut down of public transport while some showed concern on the uncertain future of transit. Mixed opinions were found among the general public on restarting economical activities. One group of people supported the idea of reopening maintaining the safety protocols, while the other group wanted to wait until a vaccine arrives. The group in support of reopening identified mask wearing, phased reopening, social distancing, telecommuting, public hand sanitizer station, data driven approach as effective reopening strategies. They also demanded for protecting employees, customers of shops, restaurants, shopping malls, and other business outlets. The group of people in opposition of reopening pointed out the record spike in new COVID-19 cases after reopening, and the lack of guidelines from government on how to reopen safely. They figured that governments are forcing the 'project restart' prioritizing the economy and not the general public's health. Though these two group's opinions differed in reopening business activities, they agreed in opposing the reopening of schools. Online schools were proposed by them as an alternative to in-person classes.

We need to be cautious while using Twitter data as it represents unfiltered and diverse opinions from general public. Analyzing public discourse can be considered as the first step of the total policy decision making process. We need to combine priorities and concerns of general public along with behavioral models and analytical frameworks to develop a significant policy guideline. One of the limitations of this research is that it considers the opinions of Twitter users only. Opinions of transport users who do not have access to Twitter were not considered. Another limitation is the lack of a well-defined study population. It was beyond the scope of this study to retrieve every user profile for determining the demographics of the sample. Although it can be noted that, Twitter is predominantly used by Americans, accounting for 50.8% of all users (*Sysomos, 2009*). Additionally, it is estimated that in the US, 55% of Twitter users are female, 45% are aged 18–34, 69% are Caucasian, 49% have less than a college degree, and 58% make over $60K a year (*Quantcast, 2010*). These numbers may provide a sense of population demographics;

however, those who tweet about COVID-19 may not necessarily be representative of the Twitter population, and the Twitter population is not representative of the general population. In addition, because TAGS collect tweets from users across the globe, it is difficult to narrow down the study context and compare results with COVID-19 studies that report on a certain geographic region (*Chew and Eysenbach, 2010*). This methodological issue also exists in traditional studies that attempt to compare their results with papers from different cities or countries (*Balkhy et al., 2010*). In the future, it may be possible to take advantage of geocoding to address this problem and sort tweets based on location. This study did not consider the non-English tweets in the analysis. This may exclude potentially minority and underrepresented communities who often are not represented in studies or planning processes. As a future scope of this study, tweets which are in languages other than English can be translated and used in the analysis. Furthermore, this study included manual classifications and preliminary automated analyses. More advanced semantic processing tools can be used in the future to classify tweets with more precision and accuracy. Nevertheless, the results of this study will allow transport authorities and planners to become aware of and respond to real or perceived concerns raised by the public about transport modes. Also, the outcomes will assist in understanding the impacts of COVID-19 on transport systems, to identify effective reopening strategies, and comprehending future potentials of those strategies.

The results of this chapter provide the early understanding and helps to determine a specific set of behavioral aspects that may undergo a significant transformation in the post-pandemic time. The insights gathered from this chapter set up the foundation for the next chapters which develop models to assess medium-term and long-term changes. The next chapter presents the development process of Bayesian models to assess post-pandemic travel behavior.

Chapter 5

Assessment of Post-Pandemic Travel Behaviour[2]

5.1 Introduction

COVID-19 pandemic has brought unprecedented changes in our day-to-day activities, travel behaviour, and shopping habits (*Anik et al., 2021; Habib and Anik, 2021a*). During the initial lockdown phases, due to the combination of 'stay at home' orders and fear of contracting the virus, trip making outside home has seen an all time low (*Habib and Anik, 2021a*). In a research by *Barbieri et al. (2021)*, different transport modes were considered for investigating the effect of localized travel restrictions for three main travel purposes, namely, work/education, free-time and leisure, and the socio-economic predictors connected to perceived risks. Ten countries (Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa and the United States) were taken into consideration. It was found that the reduction in use of any mode is highest in Italy (+27.3%) and Iran (+22.1%) where the pandemic hit hard relatively early. On the other hand, the smallest decreases in travel were registered in those countries with the lowest pandemic-related death toll per 100,000 inhabitants, which are, China (+5.7%) and Ghana (+3.1%). Public transport ridership had been decreased to a minimum, while private car, bicycle and walking trips increased. Telecommuting, virtual classes, online shopping, food delivery services gained popularity which acted as catalyst for further reduction of travel demand. With time, these changes got normalized a bit, while some behaviours still continue to exist, such as work

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[2] This Chapter is adapted from:

Anik, M.A.H., and Habib, M.A. "A Bayesian Belief Network Approach to Examine the Long-term Impacts of COVID-19 on Travel Attitudes and Preferences". *Accepted for presentation at the 2021 World Symposium on Transport and Land Use Research (WSTLUR),* A Virtual Conference, 2021.

from home, e-shopping and food delivery. According to some experts, some behavior adopted during the pandemic may persist in the long-run *(Murray, 2020)*. Public transport ridership is slowly improving. The active transport infrastructures built during the pandemic stays and continues to encourage people to use bicycle and walking more with an aim to reduce car trips. The introduction of COVID-19 vaccine may add a new dimension to these mobility changes and may affect how people perceive risk of the virus. These in turn may affect people's post-pandemic travel choices, such as, residential mobility to live near workplace, vehicle purchase intention or attitude towards working from home *(Habib and Anik, 2021b).*

As of 18 February 2021, vaccines of seven different manufacturers have been rolled out in different countries of the world. At the same time, more than 200 additional vaccine candidates are in development *(WHO, 2021)*. The arrival of vaccines is starting to influence people's daily activities and travel choices, with millions of newly inoculated individuals anticipating a return to long-postponed activities. Some may consider visiting sorely missed colleagues, friends and relatives, while schools may get reopened in cities. When vaccines become widely available to people from all sectors, new cases and deaths are expected to decrease at a higher rate. Furthermore, health experts are hopeful that through vaccinating significant amount of people, herd immunity can be achieved, which may further reduce COVID-19 transmission *(WHO, 2020)*. As a result, daily trips may increase again because residents will start feeling safer. Experts say that personal practices like mask wearing and social distancing may fade with the introduction of vaccines, other industrywide changes introduced during the pandemic will likely prove durable. However, if governments lift restrictions and become easy on mask requirements, even with vaccine rollout for high-risk populations, the pandemic would still be much harder to contain *(Truong and Truong, 2021)*. It will be interesting to see whether general peoples' experiences and habits adopted during COVID-19, such as, fear of using public transport, inclination towards using car, bicycle or walking, preference for doing work from home (telecommuting) may continue or get back to pre-COVID form once the threat of the crisis is over.

Though the mobility restrictions are expected to be removed slowly after vaccination, experts and researchers fear that the mobility behaviour will not be back in its prior form all on a sudden. As mobility is closely connected to regular habits and reproducible patterns *(Bohte et al., 2009)*, a permanent shifting of behavior may bring important changes in travel modes as well as mobility behaviour *(Schoenduwe et al., 2015)*. Thus, the restrictive measures taken for COVID-19 and habituation of using technologies for telecommuting and online services might play a significant role for impacting the mobility behavior of people even after the arrival of vaccines. Although it is quite clear that the pandemic has heavily affected travel behavior during the crisis, it is still unclear to what extent individuals will continue to modify their attitude once the pandemic is considered no longer a life-threat. Research works exploring this particular topic is rare.

This chapter of the thesis explores individuals' mobility choices, such as, mode choice, vehicle purchase intention, residential mobility and attitude towards working from home in the post-pandemic time (medium-term impacts). This scenario is assumed to develop through vaccination of individuals or by development of herd immunity in the following months. To achieve its objectives, this chapter conducts a questionnaire survey among the workers/ employees in Halifax, Canada. The survey collects data on their socio-demographic characteristics, such as, age, gender, vehicle fleet information, mode choice, working status. It also collects data on their preference towards working from home, purchasing new private vehicle, and intention to relocate to live near their workplace once COVID-19 threat is reduced. Bayesian Belief Network (BBN) models are developed to analyze and determine the relationship between the variables affecting individuals' future mobility choices, and finally for predictive modelling purposes.

5.2 Literature Review

Bayesian Belief Networks (BBNs), also known as Bayesian Networks have been extensively used in travel behavior research, especially under uncertainty where individuals have limited information. With the combination of relational network structure and conditional probability table, BBNs are capable of capturing the uncertainty in behavior modelling. *Arentze and Timmermans (2005)* developed a model of dynamic activity-travel behavior under conditions of uncertainty. They found that expected information gain can have an impact on both the location choice and route choice in cases where the individual has limited information about the environment. *Parvaneh et al. (2012)* had similar outcome to justify that pre-trip information can significantly affect individual commuters' travel choices and decision-making. Using the data from Fuyang Resident Travel Survey in 2012, *Wu and Yang (2013)* examined commuters travel behavior by BBN, in which the elements of residential location and commute distance were incorporated. The conditional probability table (CPT) of each node was achieved through the method of Maximum Likelihood Estimation. They found that commute distance has a direct influence on commuters travel mode choice while the residential location has an indirect effect on it. *Li et al. (2016)* used BBN to model the car use behavior of drivers by time of day in Japan. They chose BBN as it can represent complex relationships between multiple random variables. They argued that behavior analysis in their study depended on inferences and evidence sensitivity analysis of the estimated BBN model. *Wang et al. (2018)* uses the Bayesian network approach to study the dynamic relationships among residential events, household structure events, employment/education events, and car ownership events. Using retrospective data obtained from a web-based survey in Beijing, China, first structure learning is used to discover the direct and indirect relationships between these mobility decisions. They found that households' residential location choice has significant impact on vehicle purchase decision. *Wang et al. (2017)* studied the main factors affecting city residents' public bicycle choice behavior using BBN. In their research, K2 algorithm combined with mutual information and expert knowledge was proposed for Bayesian network structure learning. Bayesian estimation method was used to estimate the parameters of the network, and a Bayesian network model was established to reflect the interactions among the public bicycle choice behaviors along with other major factors. The authors concluded that the resident travel mode choice may be accurately predicted according to the Bayesian network model.

Use of discrete choice models are popular method of investigating commuters' travel behavior, such as, mode choice, residential location choice, vehicle purchase behavior. However, some studies have shown that Bayesian Networks have some advantages over these conventional choice models and may yield more accurate prediction of peoples' mobility behavior. For example, BBNs can incorporate 'uncertainty' in behavioral dynamics and through probabilistic modelling may provide somewhat accurate prediction results. *Chen (2014)* examined travel mode choice of residents to determine the set of factors which can influence mode choice of residents and analyze the influence factor characteristics using BBN. The author found that BBNs has a high accuracy prediction for actual travel mode choice of residents. Results highlighted the advantages of BBN over multinomial logit models in travel behavior analysis considering the fact that it can make prediction of based on its network structure and conditional probability. *Ma (2015)* utilized a rule-based approach based on Bayesian Networks to capture the non-linear effects of related determinants on individuals' mode choice behavior. They found that Bayesian network has a competitive performance compared with classical discrete choice models with reasonably good, corrected prediction rates.

It is evident from the above discussion that existing studies have used Bayesian Networks in examining individuals' travel behavior, like mode choice, residential location choice, vehicle ownership behavior, and such method have specific advantages over conventional discrete choice analysis (i.e., includes critical factors like uncertainty). Research works utilizing BBNs in travel behavior analysis under emergency situations that imposes uncertainly among human lives is rare. Thus, this chapter of the thesis contributes uniquely to the 'travel behavior' research by incorporating pandemic uncertainty into mobility choices while developing the behavioral models.

5.3 Data and Methods

This study uses a 'COVID-19 and Travel Behavior Survey' that collected information from commuters in the Halifax region, Canada during January 5 to February 5, 2021. Respondents were asked to state the following information: socio-demographic information, such as, age, gender, employee status, car ownership; general travel choices, like mode choice, number of vehicles, vehicle type choice, household location; travel behaviour during the pandemic, such as, mode choice, travel time, work from home status and possible changes in mobility behaviour in the post-pandemic times, such as, attitude towards working from home, intention to purchase new vehicles, residential relocation to live near workplace. In total, 339 individuals participated in the questionnaire who are involved either in a full-time or part-time job. Necessary data screening and cleaning was conducted once the data collection was completed. At the end, data from 338 respondents were taken as input for analysis.

Bayesian Belief Network (BBN) models are developed in this study to understand the factors affecting peoples' mobility decisions in the post-pandemic periods. Bayesian Belief Network is also known as Bayesian Network, Belief Network, or even Causal Network. Bayesian Network consists of a directed acyclic graph (DAG) and a conditional probability table (CPT). The DAG is supported with parent nodes and child nodes. CPT facilitates and analyzes the uncertainty using Bayesian interface (Zhang, et al., 2014). The Bayesian hypothesis is based on conditional probability distribution among parent and child nodes, which forms the general Bayesian framework. The equation below illustrates the fundamental notions of the Bayesian hypothesis:

$$p(A|B) = \frac{P\ (B|A)\ p\ (A)}{p\ (B)} \tag{5-1}$$

In this equation, p(A) is the probability of event A to occur, whereas p(B) is the probability of event B's occurrence. p(B|A) is the probability of B event's occurrence when event A has already taken place, and p(A|B) is the probability of A event's occurrence when B has occurred already.

In this paper, events A and B denote socio-demographic characteristics, mobility choices and work-arrangement preferences of individuals. For example, if p(R) is the probability of an individual's residential relocation to live near the workplace and p(V) is the probability of that person purchasing a vehicle, then p(V|R) is the probability of that individual purchasing a vehicle given that he/she wants to relocate to live near their workplace. The equation can be formulated as follows:

$$p(R|V) = \frac{P\ (V|R)\ p\ (R)}{p\ (V)} \tag{5-2}$$

Bayesian network can be framed utilizing the following three principles: an expert can layout the network where the dependencies between the parent and child nodes can be intellectually defined, or otherwise, applying the structural learning technique, or combining structural learning and expert opinion. In this study, GeNIe 3.0 Academic Version was used for structure and parameter learning. Expectation Maximization (EM) algorithm was implemented in GeNIe for parameter learning which can deal with both complete and incomplete datasets. EM algorithm works similar to the maximum likelihood estimation (MLE), except, if there are any missing responses in the dataset, EM will follow an iterative procedure using current parameters to estimate the necessary sufficient statistics and then perform MLE again. EM algorithm first predicts the missing values based on assumed values for the parameters, then uses these predictions to update the parameter estimates (*Nelwamondo et al., 2007*) This process is repeated until convergence is achieved. The EM algorithm is described as follows:

Let y_{obs} be the vector of observations, y_{mis} the vector of missing data, y_{obs}, y_{mis} the complete data, Θ the vector of unknown parameters and $p(y_{obs}, y_{mis} |\Theta)$ the likelihood function, which is regarded as a function of Θ for given y_{obs} and y_{mis}. To apply the maximum likelihood estimation, it is often analytically easier to maximize the natural logarithm of the likelihood function so that it is possible to work with $\log p(y_{obs}, y_{mis} |\Theta)$.

EM algorithm is generally carried out in two steps: a) expectation and b) maximization. The E (expectation) step of the EM algorithm determines the conditional expectation, usually called $Q(\Theta, \Theta(t-1))$, of the log-likelihood function $\log p(y_{obs}, y_{mis} |\Theta)$ given yobs and the current estimate $\Theta(t-1)$ of the unknown parameters (*Little and Rubin, 2000; DasGupta, 2011*).

$$Q(\Theta, \Theta(t-1)) = E[\log p(y_{obs}, y_{mis} |\Theta)| y_{obs}, \Theta(t-1)]. \tag{5-3}$$

The M (maximization) step of the EM algorithm determines the new estimate $\Theta(t)$ by maximizing equation (5-3).

$$\Theta(t) = \arg \max\Theta\ Q(\Theta, \Theta(t-1)). \tag{5-4}$$

These two steps are repeated until Θ(t) converges (*Wu, 1983*).

A sensitivity analysis is conducted afterwards with the objective to visualize and quantify the impacts of parameters' variations on the target node. Tornado diagrams are produced incorporating the algorithm by *Kjaerulff and van der Gaag (2013)*, which illustrates the most significant parameter for a target node state. The color of the bar indicates the extent of change in the target node state. The red color symbolizes negative changes, and the green color stands for positive changes. Overall, this chapter produces the BBN network from the survey data, computes marginal probabilities, conducts sensitivity analysis to understand the choices of workers to change their residence, purchase new vehicles and preference towards working from home in the post-pandemic time.

5.4 Model Development, Analysis and Results

Bayesian Search (BS) is used for structural learning from the complete survey dataset. After developing the Bayesian networks (connection between nodes), marginal probabilities of all nodes are generated. This is done using the built-in Expectation Maximization (EM) algorithm. Figure 5-1 is the optimal constructed network structure with strength of influence of the nodes. The thickness of the arrows represents the strength of correlation and influence among the connected nodes. Total 100 iterations are conducted, and the best score (-2652.2) is achieved in iteration 96. EM Log Likelihood came out as -2321.91.

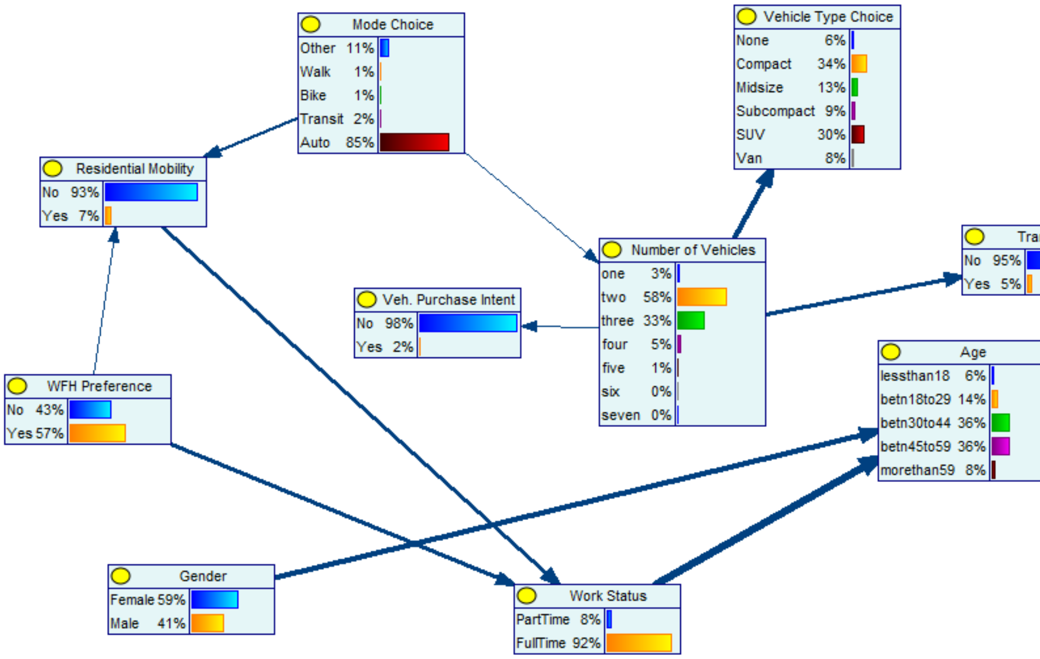


Figure 5-1 The BBN Reflecting Marginal Probability Values for Factors Related to post-COVID mobility behavior change

According to Figure 5-1, when COVID-19 will no longer be a threat, 'residential mobility' will highly depend on 'mode choice' and will be weakly connected to 'work from home (WFH) preference'. Whether a person will buy a new vehicle will depend on 'number of vehicles' owned by them and their households. 'vehicle type choice' will heavily depend on 'number of vehicles', whereas 'number of vehicles' will depend on 'mode choice'. Whether a person will work full-time or part-time will depend on 'residential mobility' and 'WFH preference'. Furthermore, probabilities for owning a transit pass will depend on 'number of vehicles' owned. For further analysis, 'residential mobility', 'vehicle purchase intention' and 'WFH preference' are set as target node (each of them has two states: 'yes' and 'no'). For each target node, both of their states are set as evidence and the marginalized probabilities are calculated. These results are summarized in Table 5-1.

Table 5-1 Marginal Probabilities for the Three Target Nodes when Different States are Set as Evidence

Attribute	Attribute Category	Evidence					
		Work from Home		Residential Mobility		Vehicle Purchase Intention	
		Yes	No	Yes	No	Yes	No
Age	a. Less than 18	4	10	**32**	4	7	6
	b. Between 18 to 29	14	13	13	14	13	14
	c. Between 30 to 44	**38**	**34**	19	**37**	**36**	**36**
	d. Between 45 to 59	**38**	33	17	**37**	**36**	**36**
	e. More than 59	7	10	20	7	8	8
Gender	a. Male	41	41	41	41	41	41
	b. Female	**59**	**59**	**59**	**59**	**59**	**59**
Work Status	a. Full-time	**97**	**85**	39	**95**	**90**	**92**
	b. Part-time	3	15	**61**	5	10	8
Transit Pass	a. Yes	5	5	10	4	21	5
	b. No	**95**	**95**	**90**	**96**	**79**	**95**
Mode Choice	a. Auto	**85**	**85**	27	**89**	**72**	**85**
	b. Transit	2	2	6	1	6	2
	c. Walk	1	1	3	1	4	1
	d. Bike	1	1	6	1	4	1
	e. Others	11	11	**58**	7	14	11
Vehicle Type Choice	a. Compact	**34**	**34**	**33**	**34**	**30**	**34**
	b. Midsize	13	13	13	13	10	13
	c. Subcompact	9	9	9	9	7	9
	d. SUV	30	30	27	30	23	30
	e. Van	8	8	7	8	10	8
	f. None	6	6	12	6	20	6
Number of Vehicles	a. One	3	3	9	2	17	2
	b. Two	**58**	**58**	**59**	**57**	**35**	**58**
	c. Three	33	33	24	33	18	33
	d. Four	5	5	6	5	9	5
	e. Five	1	1	1	1	8	1
	f. Six	0	0	1	0	7	0
	g. Seven	0	0	1	0	7	0
WFH Preference	a. Yes	**100**	0	25	**59**	**57**	**57**
	b. No	0	**100**	**75**	41	43	43

Residential Mobility	a. Yes	3	12	**100**	0	9	7
	b. No	**97**	**88**	0	**100**	**91**	**93**
Vehicle Purchase Intention	a. Yes	2	2	2	2	100	0
	b. No	**98**	**98**	**98**	**98**	0	**100**

For example, when 'WFH preference' is taken as the target node and 'yes' state is fixed as the evidence (Figure 5-2), full-time work status probability becomes 97%. This means that if an individual worker has a positive preference towards working from home, there is 97% chance that the individual is a full-time employee. There is 59% chance that the individual is female, 5% chance of owning a transit pass, 85% probability of using auto as travel mode, 58% chance of owning two vehicles, 97% chance of relocation of residence and 2% chance of new vehicle purchase.

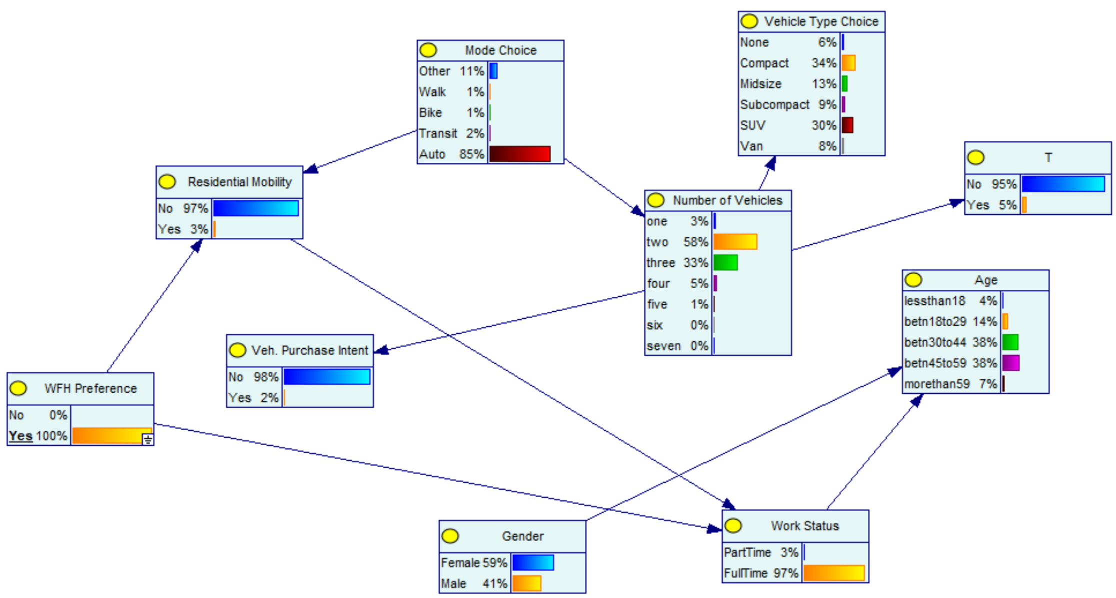


Figure 5-2 The BBN which Reflects Marginal Probability Values for Factors when 'Yes' is Set as the Evidence for 'WFH Preference'

Again, according to Table 5-1, when 'residential mobility' is set as the target variable and 'no' state is fixed as the evidence, positive preference for work from home becomes

59%. In contrast, when ‘yes’ state if fixed as evidence for ‘residential mobility’, positive preference for work from home reduces to 25%. These findings postulate that if an employee wishes to relocate his residence to live near workplace, he/she is less likely to work from home and vice versa. For both the states (‘yes’ and ‘no’) of ‘vehicle purchase intention’ variable, non-ownership of transit pass, auto mode ownership, compact type vehicle choice, positive preference for working from home (57%) and negative attitude towards residential mobility (around 91%) prevails. Interestingly, amongst all the state of the three target nodes, only for the state ‘yes’ (positive preference) for ‘residential mobility’, the prevailing mode choice is not ‘auto’. The reason behind this behaviour can be the disinterest in using private cars if someone relocates to live near workplace If an individual has positive preference for ‘residential mobility’, it is highly likely (61%) that individual to be a part-time worker.

Sensitivity analysis is performed using the GeNIe software to explore variables with the greatest influences on the target nodes (‘WFH preference’, ‘residential mobility’, and ‘vehicle purchase intention’). The Tornado Diagram in the sensitivity analysis (Figure 5-3) shows the most sensitive parameters for a selected state ‘yes’ (positive preference) for ‘residential mobility’ sorted from the most to least sensitive. In the Tornado Diagram, the color of the bars indicates the direction of change of probability in the set target state. According to Figure 5-3, the most sensitive parameters to positive preference for ‘residential mobility’ are auto mode ownership and positive preference for WFH. This finding indicates that if a person owns a private car and has a positive attitude for working from home, that individual is less likely to change his residential location when the COVID-19 pandemic is no longer deemed a threat.

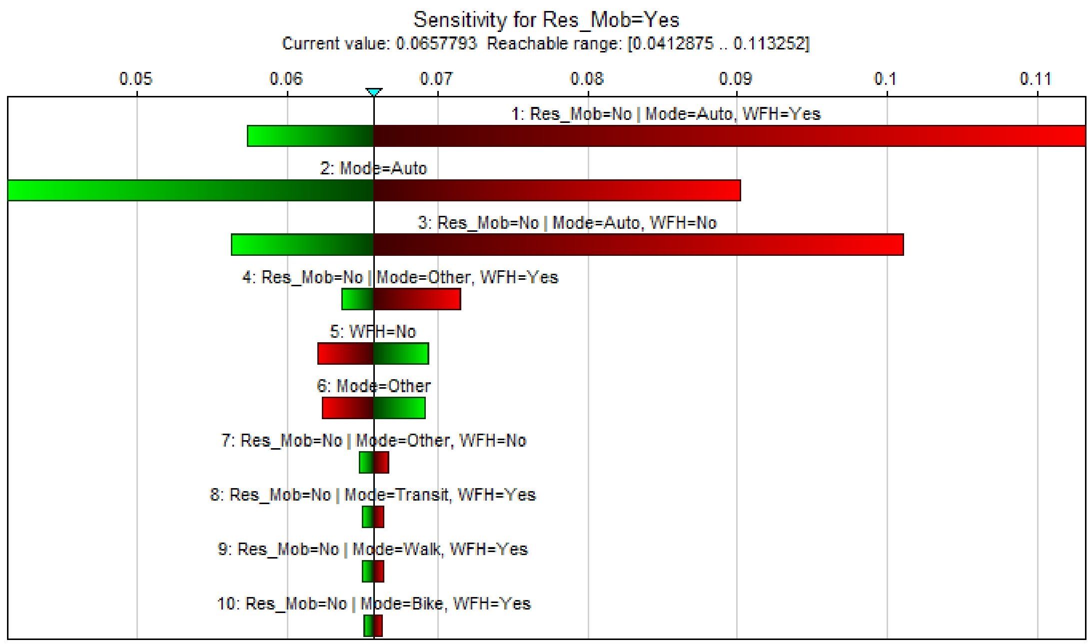


Figure 5-3 Tornado Diagram in Sensitivity Analysis on the State of "Yes" for Residential Mobility

Figure 5-4 illustrates the Tornado Diagram for the state 'yes' (positive preference) for 'vehicle purchase intention' in the post-COVID time. The figure suggests that, individuals/households owning two-four vehicles are highly sensitive to purchasing new vehicle in the post-pandemic time. Results indicate that they are less likely to purchase new vehicles. Individuals owning one vehicle and having auto as their daily travel mode are also sensitive to 'vehicle purchase intention'.

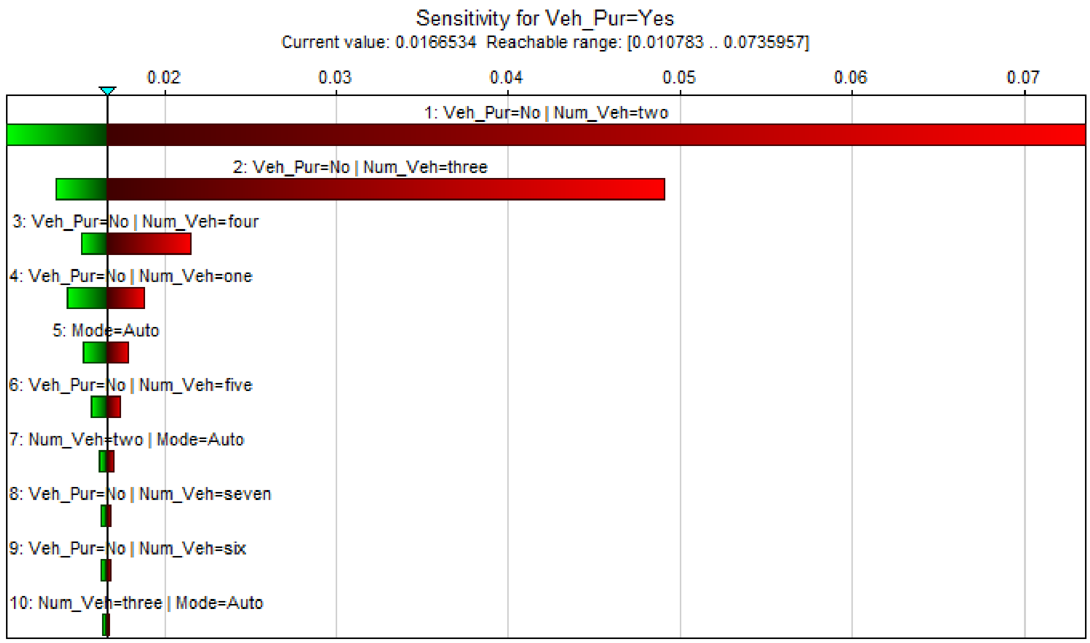


Figure 5-4 Tornado Diagram in Sensitivity Analysis on the State of "Yes" for Vehicle Purchase Intention

5.5 Discussion

In order to utilize fully the benefits of the positive changes in mobility behavior during the pandemic, such as, more active transportation usage, less trips due to work from home, virtual schools and online services like e-shopping, food delivery, it is necessary to reconfigure policies for the post-pandemic period so that some positive changes become long-lasting. For that, it is crucial to understand whether and how people may transform their mobility choices when COVID-19 virus threat will be reduced. The outcomes of this chapter shed lights on this topic and has high policy implications. Results indicate that once the pandemic situation gets better, people who have full-time jobs will mostly have positive preference for working from home, but less likely to change their residential location to live near workplace. This finding supports the existing literature on WFH and COVID-19 (Remote Work Statistics, 2020) where full-time workers are more eager to WFH during the pandemic. Nevertheless, this thesis adds that these group of people will continue to show positive attitude towards WFH in the post-pandemic time. Full-time workers not intending to relocate supports the well-established fact that they are more settled cohort of the society and less likely to take major household decisions, such as, residential relocation frequently. Another interesting finding in this study is the negative correlation between residential mobility and working from home. This finding postulate that after all the COVID-19 pandemic experiences and learnings, it is more convenient for a person who lives near his/her workplace to go to there in-person. This explains individuals' attitude to work from home who lives far from workplace, if given the opportunity. Sensitivity analysis showed that in the post-pandemic time, if an individual/household owns two or more vehicles, they are less likely to purchase a new vehicle. COVID-19 has caused uprise in bicycle sales, but car sales got reduced. As a result, price of private cars got increased in most of the countries *(Edmunds, 2020)*. Besides, economy has taken a massive hit, average household income got reduced and unemployment rate increased in major cities. Under these uncertain times, it is less likely that people will be intending to purchase new vehicles if they already have any. However, during the pandemic, a good number of public transport users shifted to other modes such as shared car, walking, bicycles, and they may intend to purchase private cars for themselves and their family members in order to prepare for a new outbreak. This finding is critical from a sustainable transport perspective. As a result of 'stay at home' orders by government, lockdown and fear of contracting the virus, people made less trips during the crisis. These resulted in less traffic, less air and noise pollution and less traffic accidents. It is necessary for the city administrators and planners to restructure policies for the post-COVID periods, in order to avoid a return to auto-dependent society.

5.6 Conclusion

This study delves into investigating a major topic of interest to the practitioners and research community is that whether the travel behaviour changes during the pandemic will be permanent or will return to the pre-COVID scenario once the virus threat is reduced. For achieving its objectives, this study conducts a questionnaire survey among working individuals in Halifax, Canada, to get data on their socio-economic condition, pre-COVID and possible post-pandemic mobility choices, and attitude and preference towards working from home, residential mobility to live near workplace and vehicle purchase intention. Results show that a very few percentages of people want to purchase new vehicle (2%), wants to relocate near workplace (7%) but a high percentage wants to do telecommuting or work from home (57%). There is higher probability that full-time workers will be doing telecommuting but less chances of them to relocate their households. Auto mode ownership prevails for all the cases except for the scenario when positive preference for residential mobility is set as evidence. Compact vehicles are found to be most popular vehicle type followed by SUV and midsize vehicles. Another significant finding is the negative correlation between residential mobility and work from home which indicates that people wishing to relocate near workplace are less likely to telecommute. Individuals or households having two or three vehicles are less likely to purchase new vehicles than other groups. One of the limitations of this study is that it considers the responses of only the people involved in workforce. However, considering the high impact of this group of individuals' mobility choices on transport and land-use systems, the sample is deemed significant and rational. This chapter utilizes and advances the predictive modelling capacity of Bayesian Belief Networks (BBNs) under uncertainty and applies to the case of COVID-19 pandemic that brought massive uncertainties in our day-to-day travel choices. The results of this study will offer transport and land-use planner insights on possible behavioral changes in the post-pandemic periods and help them make policies focusing on promoting sustainable travel habits.

Along with assessing the post-pandemic impacts, it is also worth investigating into possible long-term changes in individual travel choices because of the pandemic. The models developed in this chapter are unable to forecast future travel behavior, and not inclusive enough to study transport and land-use interactive transformation. The next chapter utilizes a long-term decision simulator consisting of necessary sub-modules to inspect emerging travel choice and trends in the following years.

Chapter 6

Examining Long-term COVID-19 Impacts [3] [4]

6.1 Introduction

The impacts of COVID-19 on transport and land-use systems in terms of time segments can be divided into 4 stages: i) during lockdown; ii) reopening-phase-1; iii) reopening-phase-2; iv) and long-term impacts *(Monash University Public Transport Research Group, 2020)*. One aspect of long-term impacts are the changes caused by COVID-19 in household decision making such as, mobility tool ownership (i.e., vehicle ownership and transit pass ownership), vehicle type choice, and mode choice after 5-10 years. Up until now, COVID-19 has affected all forms of transport, including cars, public transport, and planes all across the world. One of the biggest impacts has been the reduction in passenger travel demand, due to a combination of lockdowns and fears of contracting the virus while travelling. Global road transport activity was almost 50% below the 2019 average at the end of March 2020 *(Global Energy Review, 2020)*. This trend contributed to a 5% decrease in oil demand in the first quarter of 2020. Passenger transport sector contributes to around 40 percent of the total oil demand and 15 percent of energy-related carbon emissions worldwide *(Sung and Monschauer, 2020)*. Therefore, COVID-19 induced changes to our long-term travel

[3] This chapter is adapted from:

Habib, M. A., and Anik, M. A. H. "Examining the Long-Term Impacts of COVID-19 Using an Integrated Transport and Land-Use Modelling System", International e-Conference on Pandemics and Transport Policy (ICPT2020), A Virtual Conference, December 7-11, 2020.

[4] Habib, M. A., and Anik, M. A. H. "Examining the Long-Term Impacts of COVID-19 Using an Integrated Transport and Land-Use Modelling System", *International Journal of Urban Sciences, June 30* 2021. https://doi.org/10.1080/12265934.2021.1951821

and household decisions will continue to have significant implications on global energy sector if these changes become permanent in the post COVID-19 world.

A key question for researchers is whether changes to transport behaviour during COVID-19 may result in a permanent change in behaviour and/or affect households' long-term decisions. A few studies have questioned if mobility patterns and energy use will revert to 'business as usual' when the crisis ends *(Sung and Monschauer, 2020)*. Previous studies have shown that disruptions can cause shifts towards more sustainable transport behaviours, such as the.. use of bicycles *(Williams, 2012)*. Moreover, the adoption of telecommuting strategies may become more popular in the post COVID-19 time, as suggested by the previous two chapters. As a result, work-trips to downtown may be significantly reduced. This trend may influence people to move their residences away from downtown as they will be able to work from home *(Sampson and Compton, 2020)*. To avoid a return to pre-crisis auto-oriented travel behaviours, governments need to take proactive actions and formulate policies accordingly *(Sung and Monschauer, 2020)*. For that, the policy makers first need to have a clearer understanding of how peoples' long-term choices will change due to the COVID-19 crisis. COVID-19 is unprecedented in terms of the scale of impacts and government responses. Forecasting long-term impacts, such as, residential mobility, household location choice, vehicle ownership level, travel tool transaction decision (acquire, dispose, trade, etc.), and vehicle type choice, can be useful in informing policy makers how peoples' decisions may transform. Additionally, this knowledge will assist city administrators in determining what sort of policy options are available for governments to incentivise certain behaviours and discourage others, all while focusing on sustainable travel behaviour.

After the London terrorist attacks in July 2005, bike usage increased substantially. Biking trips remained high until the end of 2005, with a 9% annual increase in registered trips compared to 2004, whereas car, bus and underground rail use decreased. Surprisingly, in terms of long-term changes to transport energy demand, bicycles had only 2.5% mode share of all trips in London in 2018 despite the 2.6-fold increase in bike rides since 2000 *(Ayton, 2019)*. However, the scale of the COVID-19 crisis could stimulate even larger and longer lasting effects on mobility patterns compared with crises like the London Bombings, depending on how the public perceives risk. Meaning that, if the perceived risk of catching the virus on public transit outweighs the safety risks associated with other transport modes, travelers might choose to change transport behaviour for a longer period *(Global Energy Review, 2020)*. To understand general public transport behaviour in long-term scale, governments need to accurately assess the risks associated with peoples' transport choices and consider virus exposure, transport accidents, and unstable economic conditions. To do which, households' socio-demographic characteristics, such as age and income, should be taken into account. As uncertainties emerge with COVID-19 (e.g. whether the crisis persists or not), predicting long-term decisions of households under different scenarios can give policy makers an idea of how transport and land use systems may look like in future. Previous crises, such as 9/11, the 2005 London Bombings, SARS, and H1N1 show that supporting policies are needed to promote sustainable behaviours and avoid negative consequences that can flow from peoples' calculation of risk in the wake of a crisis *(Sung and Monschauer, 2020)*. At a time when people are feeling vulnerable, policies that increase trust in the safety of sustainable transport options are particularly important. To develop those policies, it is necessary to predict and analyze how people may change their longer-term decisions under the effects of the pandemic. Crises make people show risk averse behaviour meaning that they are more likely to choose the sure outcome *(Habib, 2009)*. This type of behaviour is quite complex and may be difficult for decision makers to determine. Additionally, research works that simulated long-term decisions of households following a crisis are quite rare.

To address this issue, this chapter develops an Integrated Urban Model (IUM) to predict changes in households' future decision making in the context of COVID-19. The previous two chapters of the thesis developed tools and processes to analyze short-term and medium-term impacts whereas the focus of this chapter is examining long-term impacts. This chapter incorporates pandemic behavioral changes within an Integrated Transport Land-Use and Energy (iTLE) model to develop the IUM framework. Then it simulates residential location choice, travel tool ownership and vehicle transaction decisions, as well as vehicle type choice up to the year of 2030 for Halifax, Canada. The novelty of iTLE is that it is a life-oriented agent-based microsimulation tool which can predict transport and land-use changes of a future year based on any given scenario. iTLE can be utilized effectively as a decision-support tool for testing alternate scenarios against the baseline. To achieve its objectives, this segment of the thesis first uses the data of the 2016 NOVATRAC Household Survey of Halifax Regional Municipality, Canada to develop the heuristic and statistical models, then determines the behavioral results for year 2020. Next, it simulates decisions of 20,233 households between the years of 2020 and 2030 under two scenarios associated with COVID-19. The scenarios are developed through learnings from COVID-19 mobility report by Halifax Regional Municipality, Nova Scotia *(Halifax Regional Municipality, 2020a)*, Google mobility reports *(Google, 2020)*, review of the published papers related to 'COVID-19 and travel behavior' and consultation with transport and land-use system experts. The scenarios are as follows: a) without COVID-19 pandemic and b) with COVID-19 pandemic. Comparative analysis between the scenarios provides critical insights into the long-term impacts of COVID-19 on transport and land-use systems.

6.2 Literature Review

6.2.1 Integrated Urban Models for Estimating Land-Use Change

For estimating and simulating urban travel and land-use behavior change, integrated models have been widely used by the researchers. *Johnston and Barra (2000)* demonstrated the feasibility of linking an integrated urban model and GIS to produce a spatially detailed set of land use maps. Their objective was to evaluate regional transportation and land use policies' impacts on changes to user welfare, mobile emissions, energy use in buildings and vehicles, greenhouse gases, important habitats, prime agricultural lands, and water pollution. Later, *Seto and Kaufmann (2003)* integrated remotely sensed land use data with socioeconomic data to develop statistically meaningful models of urbanization. More recently, *Guan et al. (2011)* used data on land use maps of four years along with natural and socio-economic data to combine Markov-Cellular Automata model with GIS in order to simulate land use changes in Saga, Japan. Simulation was carried out up to the year 2042 to identify land-use changes. Results indicated a decrease in agricultural and forest land and increase in built-up land. There were signs that urban built-up land would expand to suburbs. *Puertas et al. (2014)* added logistic regression in the integrated models with Markov Chain and Cellular Automata to spatially represent the simulated urban dynamics in Santiago Metropolitan Area (SMA), Chile. The model was used to make predictions for the years 2030 and 2045, using two datasets of urban and non-urban explanatory variables. The results principally corresponded to peri-urban development of the widespread boundaries and higher fragmentation. Forecasting for 2030 land use change estimated that around 15% of the predicted urban expansion will occur outside the boundary set by the Regulatory Plan by the Municipality. To establish a systematic indicators model for integrated urban land-use zoning, *Peng et al. (2014)* used Shenzhen City in China as a case study. The authors focused on both current intensity and structure of land-use system as well as transformation potential derived from socioeconomic system.

6.2.2 Operational Agent-Based Integrated Urban System Platforms

Agent-based models (ABMs) are comprehensive, dynamic, and disaggregate representations of individual decision-making processes *(Miller et al., 2004).* ABMs are compatible for land-use change modeling because they are able to capture dynamic human behavior within the land-use transformation processes *(Rodrigues et al., 1998)*. Except iTLE, there are few other agent-based integrated urban systems which are capable of simulating travel and land-use change based on any given scenarios. Few of these systems/packages are described within the following subsections:

The **METROSIM** package is intended to forecast the interdependence effects of transport and land use at the metropolitan level for US Metropolitan Planning Organisations. The model consists of the subsequent seven sub-models: Basic industry, Non basic industry, Property, Vacant land, Households, Travel, Traffic assignment *(Pfaffenbichler, 2003)*. **TRANUS-J** is another software package having a highly integrated architecture. It relies on the random utility approach. **TRANUS-J** has two main modules: the activity module and the transport module. Both modules interact back and forth until a general equilibrium is achieved *(Pfaffenbichler, 2003)*. **ITLUP**, another integrated urban model, was developed by Professor Stephen H. Putman in the early 1970s. The **ITLUP** model has two main model components: a land use model and a transportation network model. The land-use component is based on a modified Garin-Lowry model whereas the network model is a conventional capacity-restrained incremental-assignment model. **UrbanSim** is one among the foremost comprehensive urban land use modeling packages available *(Waddell, 2002)*. The planning of **UrbanSim** is significantly different from most of the prevailing integrated models. The census data to be utilized in the model have to be converted to grid cell data. Synthesized households are probabilistically assigned to parcels. In total, eight models are used within the **UrbanSim** package to predict the household, employment, and land characteristics for every 150 square meter grid cell covering a region. Although **UrbanSim's** comprehensiveness is deemed useful to several land use modelers, others are averted by the huge data requirements. **MATSim** is another open-source integrated urban model for implementing large-scale agent-based microsimulations. The primary outputs of the simulation model include optimal daily plans, traffic flow and facility occupation *(Zhuge et al., 2019)*. More recently, **MATSim** has been employed by the researchers to look at the consequences of the COVID-19 pandemic on transport and land-use systems. Researchers modified the base model to assess the impacts of COVID-19 pandemic on travel behavior in USA. Using Apple Mobility Trends Reports and transit data, they differently calibrated mode choice to fit updated ridership information and examine the probable shifts to auto during the COVID-19 pandemic period *(C2Smart, 2020)*. Another leading integrated urban model developed to-date is **ILUTE** (Integrated Land Use, Transportation, Environment model). **ILUTE** simulates the activities of individual objects (agents) as they gradually change over time. These objects comprise of persons, transport networks, the built environment, the economy, firms, as well as the job market. As an integrated full-feedback model, **ILUTE** allows long-term decisions, such as, residential mobility to influence short-term decisions, such as daily travel behaviour, and vice versa *(Salvini & Miller, 1998)*.

Though there are a plenty of operational integrated urban models existing, except MATSim, no other models have attempted to assess and simulate the impacts of COVID-19 on transport and land-use system components. The disaggregate modelling approach and interaction capabilities between submodules make iTLE a perfect fit for conducting the research. Considering these factors, this study delves into simulating and predicting long-term changes in urban travel and land-use behavior based on the developed COVID-

19 scenario to compare with the baseline scenario and gather useful insights on urban transformation in the wake of the pandemic.

6.3 Scenario Generation

Scenario 1 is considered the baseline scenario (business-as-usual scenario of land use and transportation), while scenario 2 is considered the COVID-19 scenario where peoples' travel behaviour is influenced by the pandemic. In this chapter, for each scenario, multiple long-term decisions are simulated such as residential mobility decision, residential location choice, travel tool ownership and type choice, among others. The short-term decision simulation results (e.g., activity type choice, mode choice, shared travel decision, etc.) can be found here: *Shahrier et al. (2020)*.

6.3.1 Scenario 1: Business as Usual (Without COVID-19)

This is the scenario in which it is assumed that COVID-19 never came into existence. This scenario acts as baseline to compare to scenario 2. Behavior of both households and individuals are simulated without the effects of COVID-19 from years 2020 to 2030. This scenario can be termed as the optimistic scenario, in which, COVID-19 crisis is assumed not to affect people's long-term travel choices.

6.3.2 Scenario 2: Pandemic Scenario (With COVID-19)

In this scenario, it is assumed that the changes caused by the crisis on people's travel behaviour, perception of risk, and decision making will persist through 2020 to 2030. This scenario can be termed as the pessimistic scenario in which COVID-19 pandemic is assumed to have significant impacts on people's long-term mobility decisions. Residential mobility and location choice is one of the key indicators of urban land-use behavior. According to the data of Google mobility report, up to the reopening-2 phase in Nova Scotia, 6% households changed their residences *(Google, 2020)*. This change in residential mobility behavior is considered in this study while simulating from 2020 to 2021. One of the primary travel behaviours shifts during and after lockdown is that people are trying to avoid public transit and shifting to private car, bicycle, and walking. People who do not own a car are using public transit anyway but staying fearful of contracting the virus *(Beck and Hensher, 2020)*. Transport experts have opined that this group of people may intend to buy a car after reopening economy, which may eventually increase the number of cars on the road, and thereby increase traffic congestion *(De Vos, 2020)*. However, due to COVID-19, a lot of people have lost their jobs, small businesses have undergone major financial loss. Therefore, it is highly unlikely that these people will acquire private vehicles immediately after lockdown is lifted. In scenario 2 of this study, similar to residential location choice behaviour, it is assumed that people's vehicle transaction behaviour will change after 2 years of introduction of COVID-19 in 2020 and persist up to the last year of simulation (year 2030). The reason behind selecting 2 years time-interval to impose this behaviour is that previous researches found households change their house location or make vehicle transaction decision 2 years following a major event in their lives *(Fatmi, 2017)*.

In order to avoid the risk involved in collecting transit fare by drivers, and to ensure a safe environment to both transit operators and passengers, governments have made public transit free for people in cities across the world, including in Halifax *(Halifax Regional Municipality, 2020b)*. Keeping this in mind, it is assumed that people will no longer buy transit pass for the year 2020. However, it is presumed in this scenario that once the crisis is normalized and transit start functioning like before (or in slightly reduced capacity), the authorities will start collecting fare from passengers, and people who depend on transit will buy transit passes. While simulating for this scenario in iTLE, this particular behavior is considered in the mode choice submodule of iTLE. The travel activities are assumed to the restrictions imposed by the Government of Nova Scotia on June 15, 2020 *(Government of Nova Scotia, 2020)*. Individuals were also permitted to gather in close social groups (10 persons), and restaurants were allowed for dine-in services. In terms of short-term travel decisions in scenario 2, for year 2020, transit is considered as limited, school trips are restricted, but shared travel is allowed. However, starting from year 2021, these three restrictions are lifted supposing that transit will be fully functioning, and schools will be opened as COVID-19 will no longer exist. For scenario 2, household decisions are simulated for year 2020 to 2030.

6.4 Modelling and Simulation Platform

The integrated transportation, land use and energy model (iTLE) is a multi-level urban system microsimulation platform which integrates long-term (yearly) household and individual decisions and processes, short-term (daily) travel behaviour and traffic simulation, leading to estimates of traffic flow and transportation emissions. The iTLE model operates on a microsimulation model-building platform, iTLE Sim, developed simultaneously to the model. iTLE Sim achieves its simulation functionality through the implementation of modular algorithms, the building blocks with which users can build a simulation model. The varying temporal resolutions define the three primary modules shown in Figure 6-1: the long-term decision simulator (LDS), the short-term decision simulator (SDS), and the traffic simulation system (TSS). Currently, the LDS and SDS are implemented on the iTLE Sim framework and traffic simulation is performed on third-party commercial software. The LDS updates the simulated population from one year to the next, performing the transitions necessary to generate a realistic updated population. The SDS generates a schedule of activities for each individual, determining travel details such as mode choice and vehicle assignment. This study presents only the LDS results of the scenario simulations. iTLE Sim was designed in C# .NET Framework in Visual Studio 2019. The codebase follows the model-view-viewmodel (MVVM) framework, an established software architecture pattern that separates the user interface from the program logic, allowing for more efficient implementation. The 'model' part of the framework centres on the Algorithm abstract class, which all types of algorithms extend directly or indirectly. When a user builds a simulation model, the program creates an instance of the AlgorithmChain class, which contains a list of algorithms and has methods to run them sequentially *(Habib and McCarthy, 2021)*. Furthermore, algorithm chains handle serialization and deserialization so users can easily save and share models.

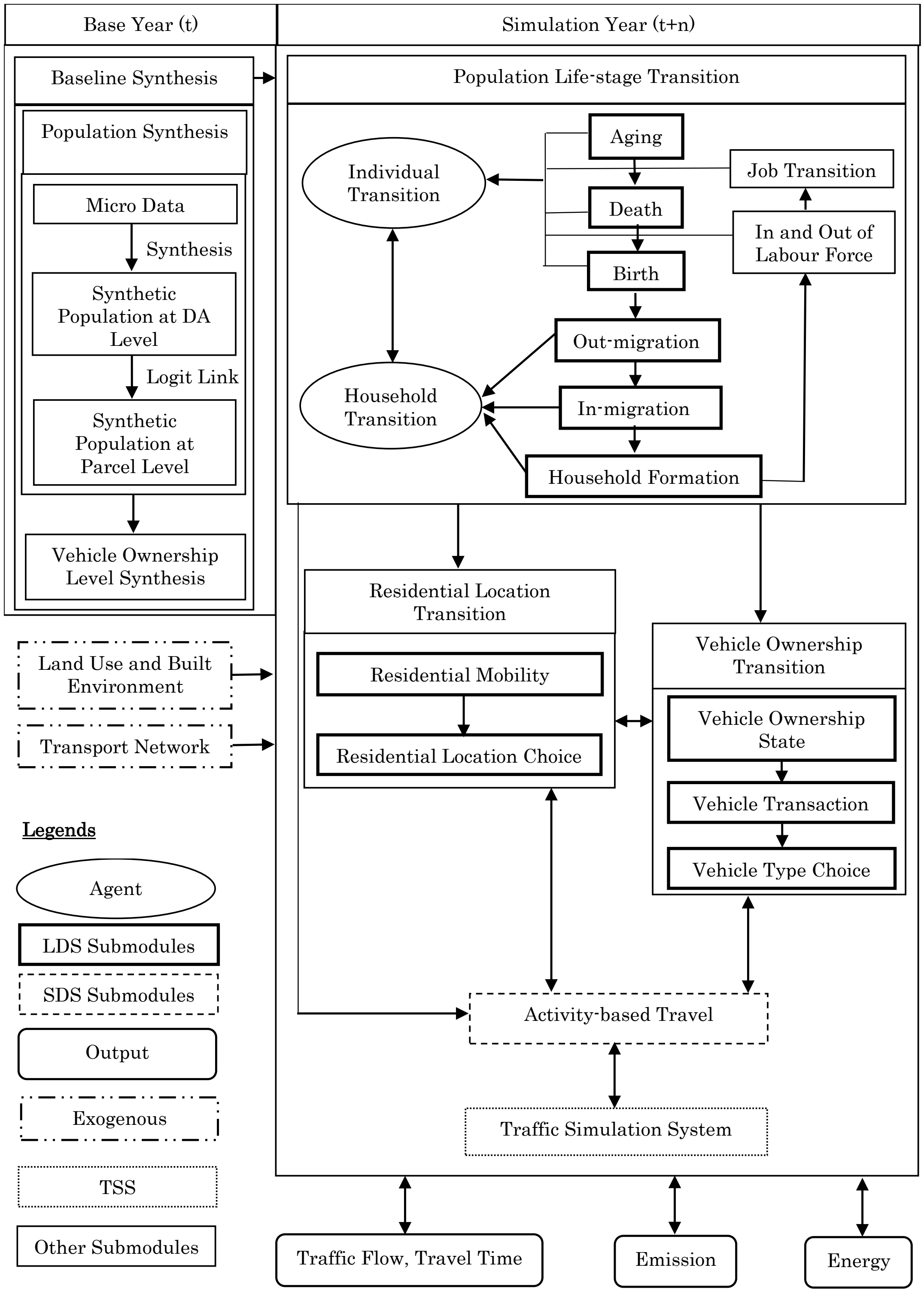


Figure 6-1 Modelling Framework of the Integrated Transportation, Land Use, and Energy (iTLE) Modeling System

From Figure 6-1, only the results from the LDS submodules (**bold outlines**) are discussed in this study although both LDS (long-term decision like residential location, vehicle ownership) and SDS submodules (day-to-day travel decisions such as mode choice, shared travel decisions) are run and integrated for feedback in the simulation process. The iTLE model uses a relational data structure to maintain relationships among various agents and objects in the model, such as individuals and activities. Figure 6-2 shows the structure of these data relationships, shown in information technology engineering notation. The LDS uses only the four left-most data tables (Residences, Households, Individuals, and Vehicles). The remainder are generated by the SDS for each simulation year. To avoid overtaking residential supply with household demand, the LDS performs a uniformly distributed expansion of residences at a rate which matches household growth *(Habib and McCarthy, 2021).*

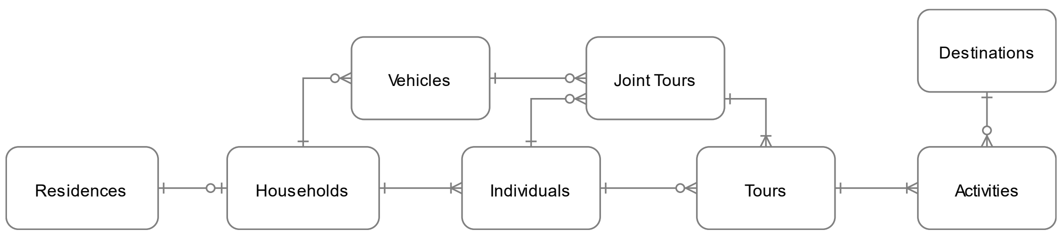


Figure 6-2 Relational Structure of Data Tables in the iTLE Model

The following subsections describe the operational details of the LDS module, describing the various submodules, such as, life-stage transitions, residential mobility, and travel tool ownership, within the system. This chapter focuses on the LDS, as it deals with households' long-term decision making. As mentioned in the previous sections, SDS modelling, and simulation results are not covered in this thesis.

6.4.1 Life-stage transitions

The life-stage transition submodule illustrates the longitudinal nature of the iTLE model, reflecting the trajectories of individuals' lives by moving the simulated population of individuals forward from one year to the next. It deals with updates to individuals' age, employment, education level, and income, as well as the socio-demographic characteristics of population: births, deaths, and migration. It also handles the processes by which individuals form, move between, and dissolve households. The life-stage transition processes are heuristic and stochastic, with probabilities calibrated using recent Nova Scotian and Canadian data. Birth rates by age were taken from Nova Scotia 2016 birth rates *(Statistics Canada, 2019a)*. Death rates were obtained from Nova Scotia 2015-17 life tables *(Statistics Canada, 2019b)*. The migration component uses the average Halifax net migration rate between 2014 and 2018 *(Province of Nova Scotia, 2019)*. The probabilities for student status were calibrated to 2017 Canada-wide education participation rates, and those for employment status were calibrated to 2018 Nova Scotia labour force data *(Statistics Canada, 2019c)*. Individual income is generated by a stochastic process based on employment status and calibrated to 2016 Canadian Census data for Halifax *(Statistics Canada, 2019d)*. Household income is the sum of members' incomes. The household transitions component simulates the moves that individuals make into and out of households and the formation of new households. The model explicitly considers three processes: nest-leaving, household formation and dissolution by couples, and household formation and dissolution by roommates. Each of these use a probabilistic approach calibrated using 2016 Halifax family characteristics data *(Statistics Canada, 2017)* and 2004 Canada marriage and divorce rate data *(Statistics Canada, 2011a, 2011b).*

6.4.2 Residential Mobility and Location Choice

The residential mobility submodule simulates households moving from one residence to another. It evaluates households' decisions to move, performs a search for compatible available locations and assigns locations to the households. This process builds upon the previous iTLE research to establish behavioral, repeated choice models of decision-to-move, and location choice processes that use advanced econometric models, such as a latent segmentation-based logit model *(Fatmi and Habib, 2015, 2018)*. For the operational version of iTLE, binomial and multinomial logit models are developed and used. These simulation models retain the basic specifications and respect the life course perspectives that incorporate the effects of life cycle events on residential mobility decisions. They also demonstrate the integration of travel behaviour modeling into the land use decision processes of the LDS, as the residential location choice model dynamically links the utility of the micro-level decision of home-to-work mode choice with the consumption process of home ownership via modal accessibility (mode choice logsum term). For homeowners, residential selection is done using a multinomial logit model first developed by *Fatmi et al. (2017)*. In this study, while simulating for scenario 2, the 'residential location choice' submodule was controlled to observe the pandemic residential mobility behaviour.

6.4.3 Travel Tool Ownership and Transactions

The final submodule within the LDS deals with household vehicle ownership and individual's transit pass ownership. While simulating for scenario 2, these two submodules are controlled to observe households' vehicle ownership, vehicle type choice and transit pass ownership behaviour under pandemic effects. Whether a household or individual has access to a travel tool is an important factor in determining the modes of travel available to them. This submodule therefore significantly influences households' travel behaviour. The vehicle transactions models of iTLE were developed by *Fatmi and Habib (2016a)* and the simplified models used in implementation are described in *Khan et al. (2019)*. Households without vehicles decide whether to acquire a vehicle using a binomial logit model. Households which own vehicles decide first whether to perform a transaction using a binomial logit model, and then whether the transaction will be to acquire, trade or dispose of a vehicle using a multinomial logit model. If the household trades or disposes a vehicle, a random vehicle is removed from its fleet. If the household acquires or trades a vehicle, its type is determined by a multinomial logit model including five types of vehicles: subcompact, compact, midsize, SUV and van/truck. Individuals can also have driver licences and transit passes. The processes for acquiring and losing these are defined by binomial logit models developed in *Fatmi and Habib (2016b).* Transit pass updates combine a probability with a binomial logit model. The probability that individuals will run the update model depends on their age and whether they had a transit pass last year. In this study, for scenario 2, it was assumed that people will not buy a transit pass for the months of April to July, 2020 as transit was made free by the Halifax Municipality. However, as fare collection was started by the Municipality from August 1, 2020, people started buying transit pass again. The abovementioned impacts of COVID-19 on behaviour related to transit pass purchase decision was imposed on the ‘transit pass’ submodule, and vehicle purchase behaviour was imposed on the ‘first time vehicle purchase’ and ‘vehicle transaction decision’ submodules of iTLE while simulating for scenario 2. While simulating for scenario 1 (baseline), these behavioral changes are not imposed.

6.5 Results and Analysis

The following subsections explain the prediction results under the two scenarios considered in this study. Descriptive analysis as well as spatial distribution of results show significant differences in households’ long-term choices under the two scenarios.

6.5.1 Residential Mobility and Location Choice

Spatial distribution of the percentage change of household density in 2025 and 2030 between scenario 1 (baseline) and scenario 2 is shown in Figure 6-3.

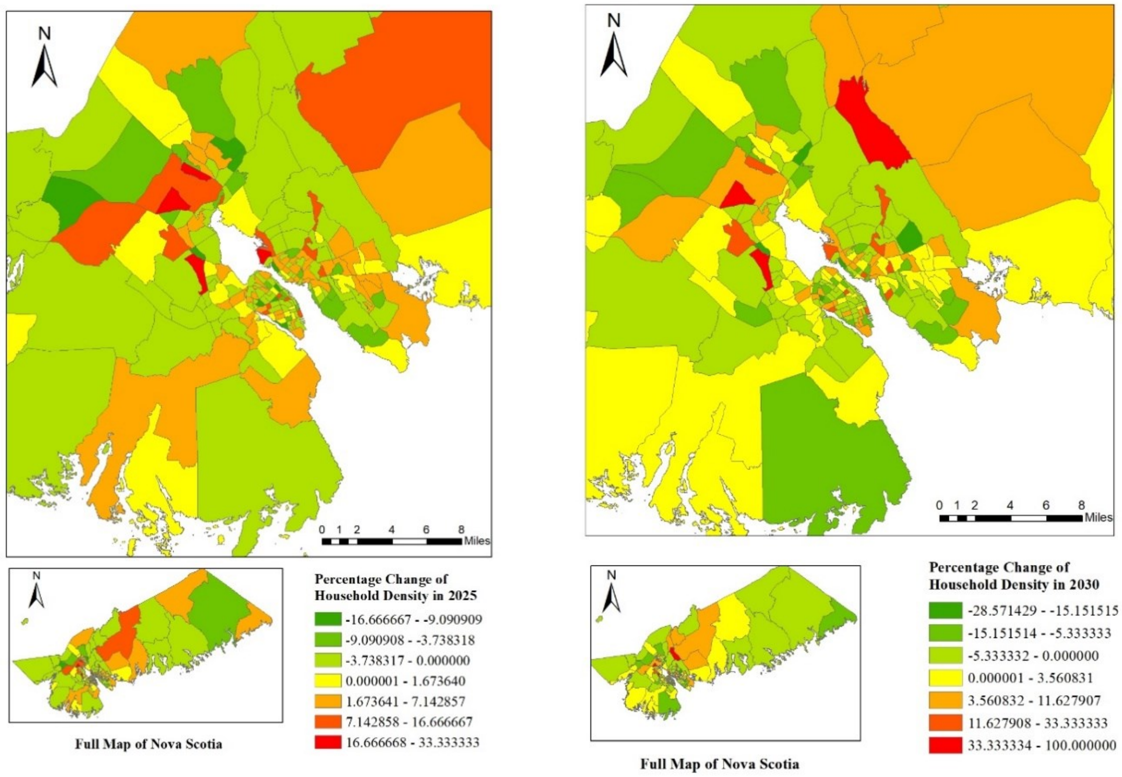


Figure 6-3 Predicted Percentage Change of Household Density in 2025 (a) and 2030 (b)

The figure focuses on the urban core and surrounding suburban traffic analysis zones (TAZs) in the Halifax Regional Municipality, provincial capital of Nova Scotia for the years 2025 and 2030. Figure 6-3 (a) shows that most of the downtown urban core area will mostly undergo an increase in household density by 2025. However, suburban areas (i.e. Clayton Park, Bedford, and Sackville) will experience a decrease in density. Further away from downtown (rural areas), the household density decreases. Sprawling is expected to happen by 2030 according to Figure 6-3 (b) as downtown household density decreases while in suburban zones it increases. Urban sprawl is defined as the physical pattern of low-density growth of large urban areas, mostly into the surrounding suburban areas *(European Environment Agency, 2006)*. These results indicate that having the opportunity to 'working from home', 'virtual school', 'e-shopping', and online medical services, people are not as inclined to live downtown and rather prefer to live in surrounding suburban areas.

This behaviour may not occur by 2025 but is likely to come into effect by 2030. It should also be noted that, although most people may choose to live in suburban areas, rural areas will not attract density as the housing supply is not adequate to allow for residential relocation within the LDS module of the iTLE model. The prediction results postulate that sprawling may happen gradually in future but in a medium scale. To observe the results through the years 2020-2030, the percentage change in number of households in downtown Halifax (urban core) under scenario 2 is shown in Figure 6-4.

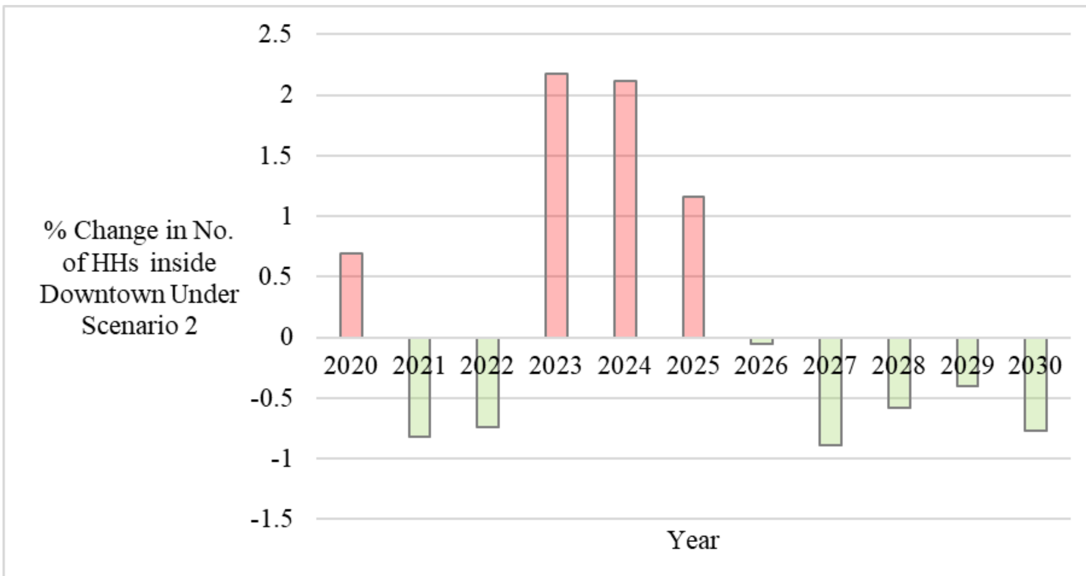


Figure 6-4 Percentage Change (%) in Number of Households Inside Downtown Halifax

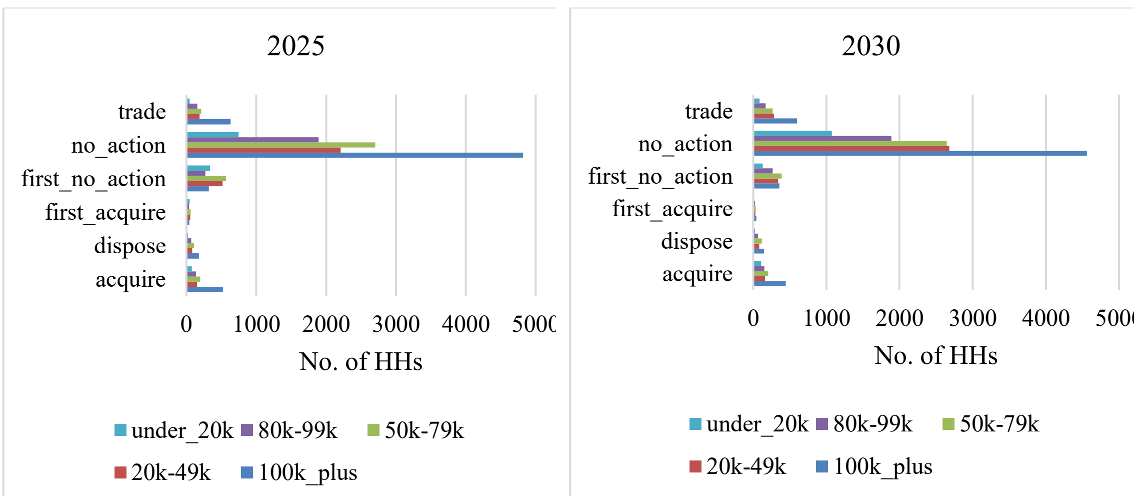
As illustrated, household density in the downtown is expected to decrease in years 2021-2022 (0.78% on average per year) but will increase in years 2023-2025 (1.80% on average per year). Interestingly, in between 2026-2030, the household density in downtown is predicted to decrease again (0.53%). According to the model specifications, residential location choice of households is highly linked with their mode choice and during the years when household density decreases notably within downtown (2027-2030), auto ownership level increases significantly (high rate of new car owners). These findings support the results illustrated in Figure 6-3 postulating that overall increase in vehicle ownership level in HRM may decrease household density in downtown Halifax.

6.5.2 Travel Tool Transactions, Ownership, Type Choice

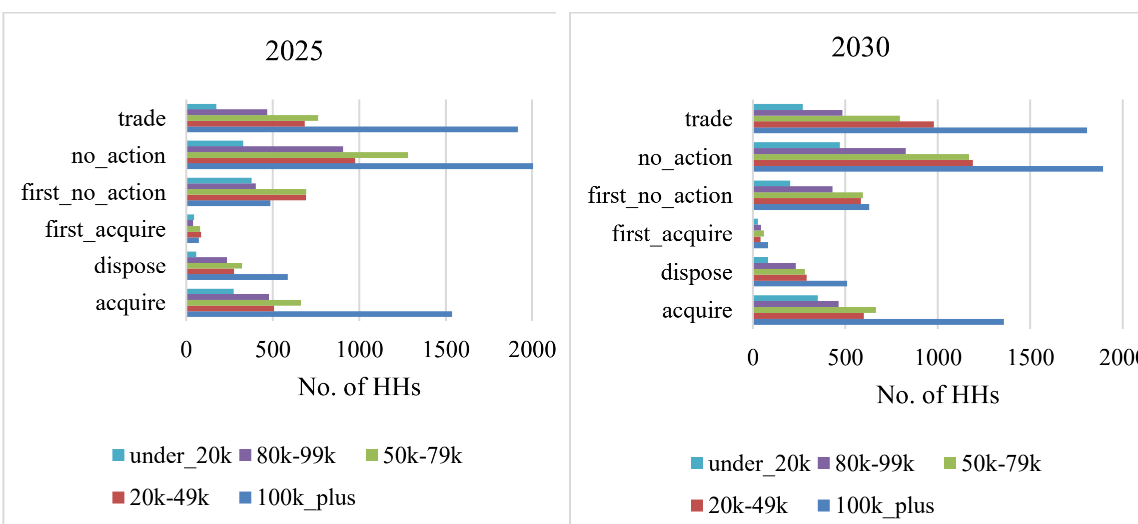
6.5.2.1 Vehicle Transaction Decision

There are six types of vehicle transaction decisions considered in this study. The decisions are as follows: i) 'acquire'- a household which had a vehicle in the past or has purchased another vehicle; ii) 'dispose'- a household getting rid of their vehicle; iii) 'first_acquire'- household which has never owned a vehicle and is purchasing their first one; iv) 'first_no_action'- a household which has never owned a vehicle and chooses not to purchase one; v) 'no_action'- a household which has a vehicle and chooses not to make any transactions; vi) 'trade'- a household that has a vehicle, gets rid of it, and acquires another vehicle.

The yearly trends of scenario 1's vehicle transaction decisions do not show many changes throughout the years. In contrast, under scenario 2, vehicle acquiring is doubled between 2021 and 2022 and remains that way up until 2027 but decreases by almost 50% in 2028. This is interesting as in those two years, the HH density in the downtown area also decreases. 'first_acquire' is quadrupled in 2028 and falls back again in 2029 to the levels seen in 2027. Vehicles trades is tripled in 2022 and remains similar up to 2030. 'No action' decision increases by about 33% in 2021 but decreases by 50% in 2022. Dispose of vehicles is increased by around 25% in 2021 and is almost doubled in 2022. These results indicate that most people who do not have private vehicles may continue restraining themselves from purchasing one up until year 2027. In 2028, possibly because of the improved economic conditions, households may prefer to purchase automobiles. Dispose of vehicles increasing in years 2021-2022 gives insight into the behaviour shift to bicycle, walking or public transit while moving away from car use following the COVID-19 crisis. However, the percentage of population that displays this particular behaviour is not that high (8.55%). Vehicles trading increasing in 2022 postulates that many people may want to change their vehicles once the uncertainties of the transport industry are more resolved. The percentage of households acquiring vehicles increasing in 2022 shows diverging behaviour from a sustainable transportation perspective. This indicates that households which already own vehicles will purchase more. ‘HH income’ and ‘vehicle transaction decision’ variable interaction illustrates interesting results (Figure 6-5). According to Figure 5, for scenario 2, vehicle acquiring, trade, and dispose decisions are mostly shown by households that have an income higher than $100,000 per year (high income). ‘first_no_action’ behaviour is displayed mostly by medium income HHs (yearly income $50,000-$79,000) in 2025 but is surpassed by high income HHs in 2030. The ‘no_action’ behaviour is more evident in medium income HHs than in low-medium income HHs in 2025 (yearly income $20,000-$49,000).



(a) Scenario 1



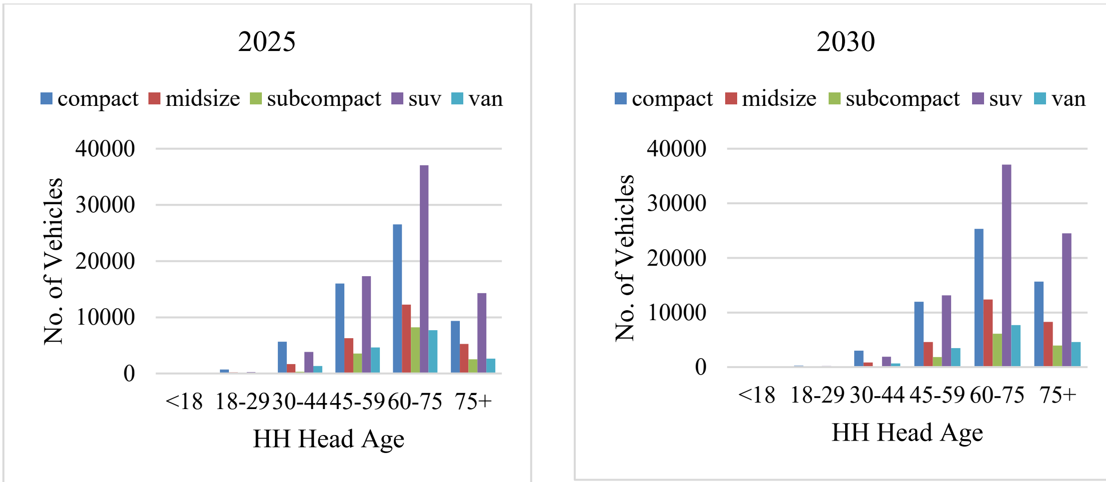
(b) Scenario 2

Figure 6-5 Predicted Household Income vs Vehicle Transaction Decision

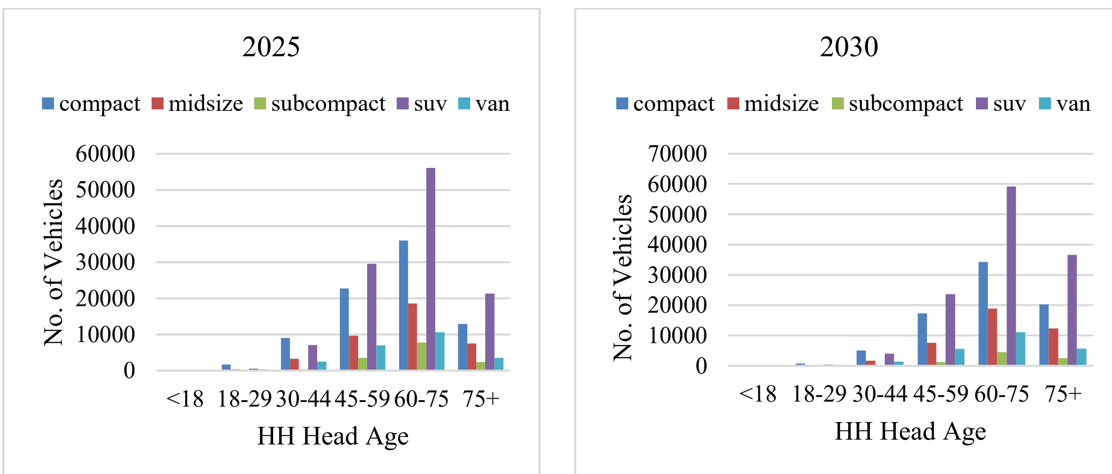
6.5.2.2 Vehicle Type Choice

Five vehicle types are considered in this study: i) compact; ii) midsize; iii) subcompact; iv) SUV; v) van. Results show that under both scenarios, the most common type of vehicle for households is SUV, followed by compact and midsize vehicles. Under scenario 1, the number of SUVs increase by about 22% between 2025 and 2030. The comparison between scenario 1 and 2 shows that, under scenario 2, households will be owning approximately 25% more SUVs than under scenario 1 in 2025. SUVs are eventually increased by almost 27% by 2030 in scenario 2. These **results indicate that SUVs will become more popular among people in the post COVID-19 period.**

Under both scenarios, households that have a high yearly income (over $100,000 per year) will mostly own SUVs, compact size, and midsize vehicles. HHs having low income (below $20,000 per year) will prefer to own SUV and compact size vehicles. Midsize vehicles will mostly be owned by high income HHs, followed by HHs that have a yearly income between $50,000-$79,000. Subcompact and van type vehicles will not that high in demand among these households, accounting for only around 3 and 6% of total vehicles in Nova Scotia in the year 2025. 'Household (HH) head age' and 'vehicle type choice' variable interaction results show that SUVs are mostly owned by the HHs which have a household head between the ages of 60-75 years (Figure 6-6). A comparison between the two scenarios shows that SUVs will become more popular among 45-59 and 75+ year old HH head age groups over time.



(a) Scenario 1

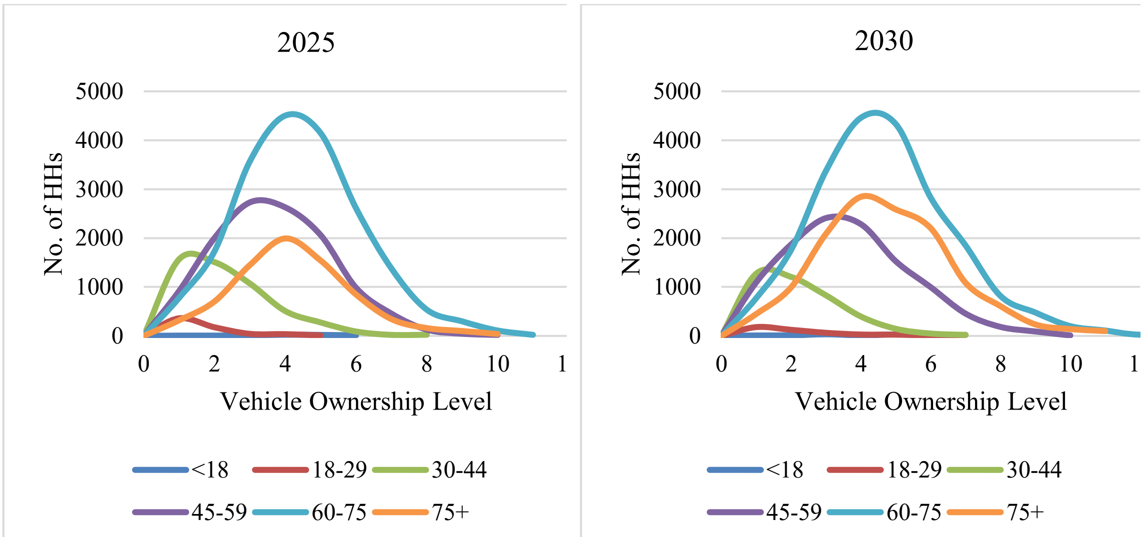


(b) Scenario 2

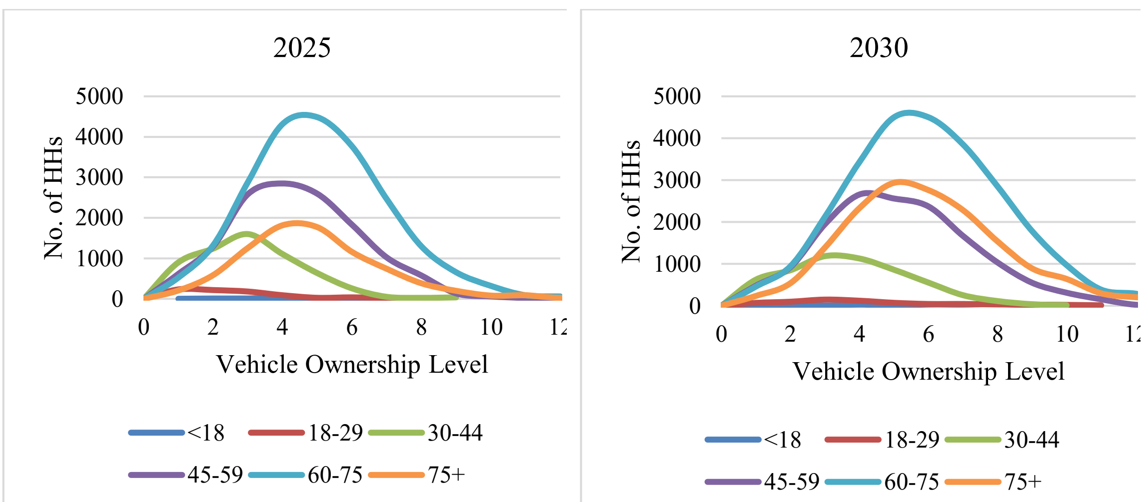
Figure 6-6 Predicted Household Head Age vs Vehicle Type Choice

6.5.2.3 Vehicle Ownership Level

Simulation results show that the average number of vehicles owned by households increase with time under both scenarios. Under scenario 2, the rate of increase is higher. 'HH income' and 'vehicle ownership level' variable interaction shows that high income HHs will mostly own 4 vehicles in 2025 under the baseline scenario. In contrast, under scenario 2, high income HHs will mostly own 5 vehicles, which eventually increases to 6 vehicles within 2030. HHs that have a yearly income below $100,000 may not behave differently in the case of vehicle ownership level in scenario 2 within 2025 but may prefer to have one more vehicle by 2030. Further analysis shows that, HHs with heads aged 75+ and owning 4 vehicles will increase by 20% under scenario 1 from 2025 to 2030. These results are displayed in Figure 6-7. According to Figure 6-7, HHs heads aged 60-75 and 30-44 will prefer to own more vehicles in scenario 2 than in the baseline scenario.



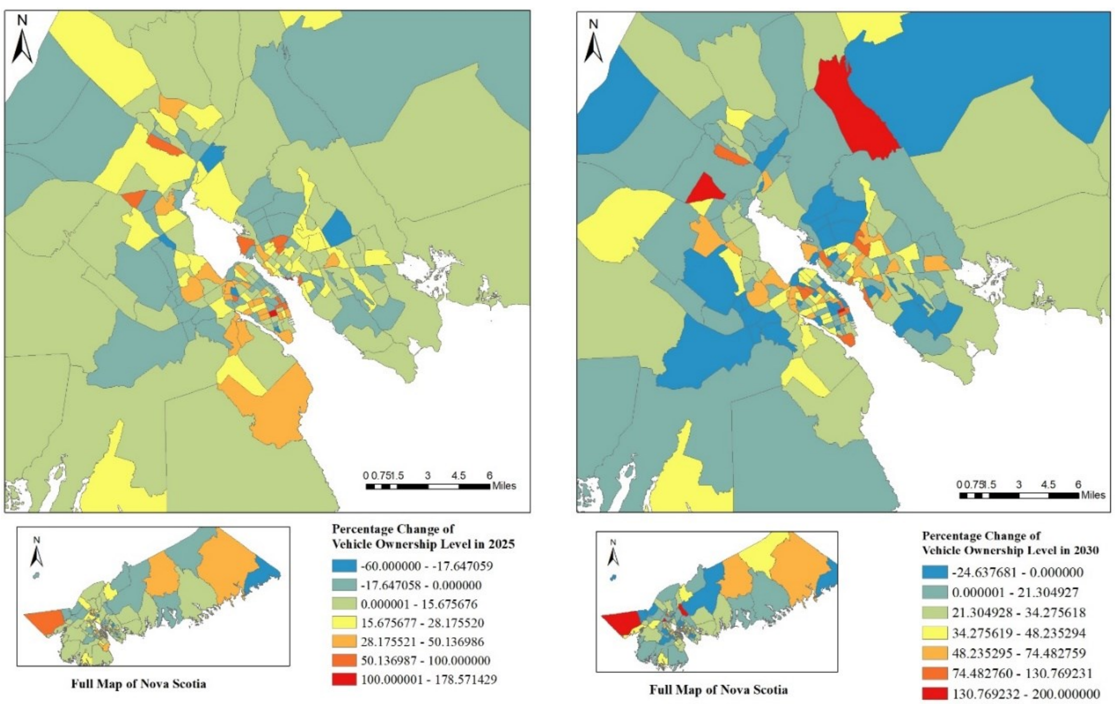
(a) Scenario 1



(b) Scenario 2

Figure 6-7 Predicted Household Head Age vs Vehicle Ownership Level.

Figure 6-8 adds another dimension by representing the spatial distribution of the percentage change of vehicle ownership for years 2025 and 2030. While comparing scenario 1 and 2, The figure shows that in most of the downtown Halifax areas, vehicle ownership will be reduced in the range of 0 to 17% by 2025, eventually reducing to be in the range of 0 to 24% by 2030. In 2025, a higher proportion of vehicle ownership increase is predicted in the suburban areas, experiencing vehicle increase in the range of 0 to 50% (Figure 6-8(a)). By 2030, this may increase to above 74% for these areas (Figure 6-8(b)). Some areas within downtown Halifax will experience a significantly high percentage of vehicle increase (74-130%) by 2030. To identify the socio-economic information of the HHs of these areas, the HHs living in those TAZs are separated from the raw data and analyzed. Results show that most HHs of these areas have higher incomes (above $100,000 per year) and mostly have HH heads aged between 45-75 years. Figure 6-8 (a) and (b) also show that some areas furthest from downtown (rural areas) will see a 0-50% increase in vehicles by 2025 and a 21-74% increase by 2030.



(a) (b)

Figure 6-8 Predicted Percentage Change of Vehicle Ownership Level Under Scenario 1 and 2 in 2025 (a) and in 2030 (b)

6.5.2.4 *Transit Pass Ownership*

The percentage of individuals owning a transit pass between years 2020 to 2030 is shown in Figure 6-9. In Figure 6-9, S1 Male stands for scenario 1 male, S1 Female stands for scenario 1 female, S2 Male stands for scenario 2 male and S2 Female stands for scenario 2 female behavior.

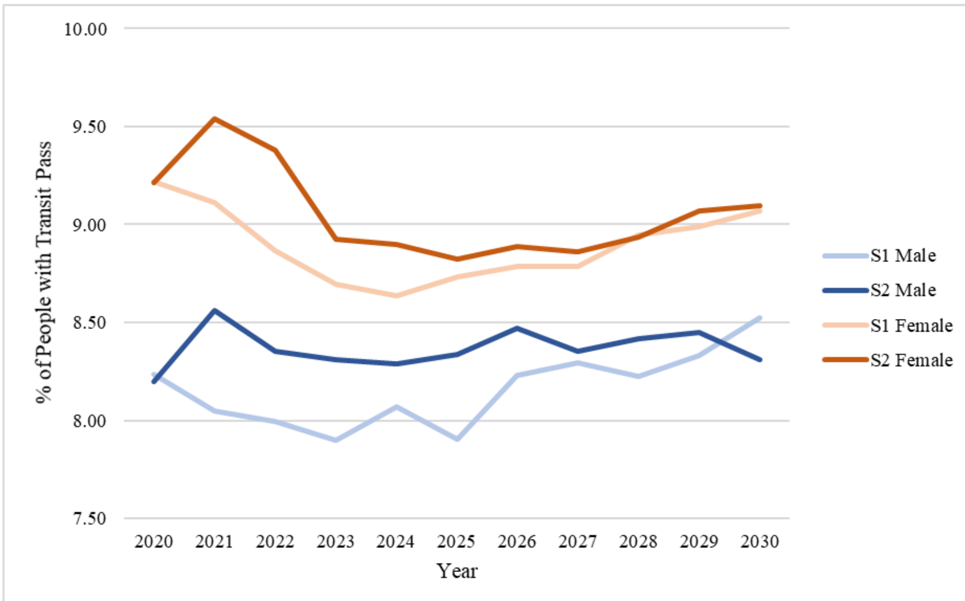


Figure 6-9 Percentage (%) of People with Transit Pass with Respect to Gender from 2020 to 2030

The figure indicates that generally females tend to purchase transit pass more that males. Under the pandemic scenario, both men and women are projected to purchase more transit passes than the baseline scenario throughout years 2021 to 2029. For men, the greatest difference in transit pass ownership between the two scenarios is in 2021 (0.51%), whereas for female it is also in 2021 (0.52%). The pandemic scenario presents that peoples' intention to purchase a transit pass increases substantially from 2020 to 2021. This finding is interesting as it was expected that people may not be as willing to purchase transit passes following the pandemic reopening period due to the likelihood of shifting to other modes. Although Figure 6-9 does not imply that transit ridership will increase in future, it gives a notion that people may not drastically switch their modes from public transport to private car, bicycling, and/or walking.

6.6 Policy Discussions

This chapter is an attempt to develop tools to forecast long-term changes on transport and land-use systems due to the COVID-19 pandemic based on initial reports and knowledge. Although this study develops a prototype model for Nova Scotia, Canada, its outcomes can be applied to cities with similar geographic and population characteristics. The framework developed in this research can be used as a scenario building and impact forecasting tool for other areas. The findings of this chapter have significant policy implications.

The simulation results show significant changes in household behaviour between the baseline and the pandemic scenario. In terms of residential location choice, results show that under pandemic effects, a significant proportion of people may move their home away from downtown areas by 2030 (Figure 6-3). *Patino et al. (2021)* conducted a research to examine the migration patterns in the US cities during the COVID-19 pandemic. They found similar results indicating that urban areas are losing residents, whereas suburban areas are gaining. They also found that age, education and income were key factors in pandemic movement out of urban centers. This particular behaviour of leaving downtown areas may stem from the ability to 'work from home' in the future and even the fact that in-person education may adapt to online (*Coons et al., 2021*). Additionally, the opportunity to perform e-shopping and have purchases delivered to a residence as well as having access to online medical services may also influence this decision. People are also getting laid off because of the pandemic economic fallout which may motivate people to leave metro areas and move to cheaper suburbs. The findings of this chapter suggest that sprawling will increase, but they also suggest that it will take place gradually and primarily after 2025. Though there are some benefits of urban sprawl, this issue finally leads to major problems in cities, like traffic congestion, long travels, increase in infrastructure costs, reduction of environment quality and social interactions *(Habibi & Asadi, 2011)*. Necessary steps should be taken by the governments to decrease the negative effects of the probable sprawling. Strategies such as, creating urban boundaries, betterment of low income households' living conditions, supporting smart growth, creative and efficient management strategies can be utilized based on the characteristics of the region *(Sustainable Proseprity,* *2012; Sag and Karaman, 2014)*. Figure 6-4 indicates that in the pandemic scenario, HH density in downtown will decrease following the year of 2025 and continue to decrease up to 2030. In the vehicle transaction results, it was found that HHs on average will intend to purchase new (or more) vehicles following the years of 2025. These findings postulate that as people shift away from living downtown, their vehicle ownership level are likely to increase. This result supports the existing literature that HHs living in suburban areas are more car dependent than people living in downtown *(Fatmi et al., 2017)*. This outcome has significant policy implication. More private car dependency may lead to more peripheral uncontrolled growth of the city. Existing research shows that reducing the number of private auto ownership is one of the main strategies for controlling sprawl *(Habibi and Asadi, 2011)*. Policy makers should come up with a combined solution on how to control the possible increase in urban sprawl and also at the same time, reduce car dependency.

Model prediction results show that under the pandemic scenario, vehicle purchasing will be doubled in 2022. This shows signs of getting back to previous auto-oriented travel behaviour. Disposing of vehicles will increase by almost 25% in 2021. It is then almost doubled in 2022, while vehicle trading is tripled. This indicates that some people may get rid of their private automobiles due to COVID-19 and shift to alternative modes such as biking, walking or public transit in the upcoming years. However, this cohort belongs to a small percentage of the whole population (8.55%). One interesting finding is that most people who do not already own any private vehicle will continue restraining themselves from purchasing one up until year 2027. These outcomes are positive in terms of sustainable travel behaviour. However, decision makers need to make plans to improve sustainable travel mode infrastructure and formulate strategies to attract new users to those modes. They need to devise and implement a plan of action right now focusing on sustainable mobility to see its impact in the longer run. As cities around the world are restricting car traffic to make way for active transportation, Halifax Regional Municipality (HRM), the provincial capital of Nova Scotia has taken strategies to promote cycling, such as, organizing Bike Community Events program *(Halifax Regional Municipality, 2020c)*. Similar to this, more projects should be initiated, for example, extending cycling networks, enhancing cyclists' safety as well as sustained promotion and education for cycling throughout the year. These initiatives will compliment the broader cycling promotion projects with an aim to increase bicycle ridership in the post-COVID times.

Results indicate that 'no_action' behaviour in vehicle transaction decision is evident in medium income HHs in 2025 but is passed by low income HHs in 2030, which indicates that low income HHs may not be interested in owning more vehicles or performing any other vehicle transactions in the near future after getting settled. This is another positive sign for sustainable mobility in the long-term. However, iTLE predicts that the average number of vehicles owned by the high income HHs will increase with time under both scenarios. This is especially apparent under pandemic scenario. Under the baseline scenario, high income HHs will mostly own 4 vehicles in 2025. On the other hand, under pandemic scenario, these HHs will mostly own 5 and 6 vehicles on average in 2025 and 2030, respectively. This is an alarming indication that vehicle ownership level of high income HHs may increase in such an unprecedented manner. Efforts should be made by the transport policy makers for attracting high income HHs to walking, biking and public transport so that they are less dependent on their private vehicles for trip planning. In terms of the 'vehicle type choice' decision, prediction results show that under pandemic scenario, HHs will be owning around 25% and 27% more SUVs in 2025 and 2030 respectively, compared to the baseline scenario. SUVs becoming more popular can be due to their current popularity (especially as the first car of a HH), and when more people are intending to purchase new vehicles, they are likely to prefer buying an SUV. Another reason may be because as people move further away from downtown, their vehicle size increases (i.e. trucks, vans and SUVs are all popular in rural and suburban areas). As urban sprawl increases so do SUV sales *(Khan et al., 2019)*. This finding is also crucial for other North American cities where SUVs are the most popular vehicle type. A study from the International Energy Agency found that from years 2010 to 2018, SUVs were the second-largest contributor to rising carbon emissions. If demand for SUVs continues to grow like this, the amount of oil required to fuel these larger vehicles will offset the environmental benefit of 150 million electric cars *(Stevens, 2019)*. To solve this issue, governments as well as private organizations may consider taking initiatives for promoting environment-friendly cars (e.g., electric vehicles) *(Bennett et al., 2016)*.

The transit pass ownership results show that under the pandemic scenario, people will be buying slightly more transit passes than under the baseline scenario (Figure 6-9). Loss of income due to COVID-19, and thereby shifting to public transport as well as trust in the transit authority safety protocols may be reasons as to why people will continue to be reliant on transit. Transit planners should formulate plans to reconfigure and improve public transport, with an aim to keep the existing riders as well as to attract new passengers. Regarding this, the introduction of mobile phone apps which alert potential transit passengers to overcrowding in real-time and suggest alternative routes could be helpful. In addition, emphasis on active transport modes through Government emergency funding to reshape road space and bringing forward trials for e-scooters and their safe use can only serve to improve public transport ridership *(Budd and Ison, 2020).* To solve the first-mile last-mile issue, micro-transit services, e-scooters, e-bikes have been found to be effective in urban areas across the world *(Rankin, 2019)*. E-scooter represents one of several emerging travel modes that have appeared to serve for transportation needs in urban areas. E-scooters are already available in Nova Scotia but only in a small scale and under private ownership. Support from the city authorities, promotional campaigns and proper operational guidelines are necessary for utilizing the benefits of this innovative mode of transport *(Button and Reaves, 2020).* Findings of this chapter also indicate that men tend to be less likely to own transit passes than women. Promotional campaigns for using public transit should be geared toward attracting more male passengers (e.g., incentives or rewards for renewing transit pass ownerships). From the vehicle ownership level results, it can be presumed that people aged greater than 60 tend to be more dependent on private vehicles than others age groups. Mass transit authorities may take necessary steps to attract these groups of people to public transport. Federal, provincial, and municipal governments, as well as private organizations, should work together to form policies and plans to incentivise sustainable travel behaviour among households and avoid returning to an auto-oriented society.

6.7 Conclusion

This research utilizes the integrated transport, land-use, and energy (iTLE) model, an agent-based urban microsimulation model to develop an Integrated Urban Model (IUM) that predicts the long-term impacts of COVID-19 on transport and land-use systems. iTLE is already validated with the Canadian Census Survey 2016. iTLE consists of different stochastic and deterministic algorithms, as well as statistical and econometric models, such as a latent class model, a multinomial logit model, and a binary logit model to simulate household decisions and life-stage transitions for the future. To achieve its objectives, this study first develops two scenarios related to COVID-19: a) scenario 1: baseline scenario (without COVID-19), and b) scenario 2: COVID-19 pandemic occurs. The scenarios are developed based on regional data on mobility and behaviour change due to pandemics, literature review, and consultation with transport and land-use experts. Both the scenarios are then implemented and simulated within iTLE framework to observe how people may change their long-term decisions, such as, residential mobility decisions, residential location choice, vehicle transaction decision, vehicle type choice, and vehicle ownership level.

The overall goal of this study is to determine the long-term impacts of the pandemic on transport and land-use systems. One limitation of this study is that its assumptions in the developed scenarios may or may not reflect the actual future behaviour of households. Human behaviour is complex and difficult to predict, and it is even more hard to presume the behaviour of people amidst a crisis *(Bavel at al., 2020).* In the future, the inclusion of a workplace location choice model within the framework, may provide more insights into how the pandemic has influenced people in changing their work locations. Nevertheless, the findings of this study will offer transport and land-use planner as well as policy makers a greater understanding of how households' long-term decision making may evolve in the future as a consequence of the COVID-19 pandemic. The results of this study will also assist in developing policies to promote sustainable mobility choices among communities in order to avoid returning to non-sustainable travel behaviour in the post COVID-19 world.

Though the model developed in this chapter can analyze transport and land-use system interactive transformation, it does not allow to observe the uncertainty in individuals' mobility choices. Keeping this in mind, this thesis develops an integrated urban modelling framework (IUMF) by combining BBN models developed in the previous chapter and the IUM model in this chapter.

Chapter 7

Extending the Integrated Urban Modelling Framework (IUMF) for Pandemic Scenarios

7.1 Introduction

This thesis develops a novel framework of IUMF where the BBN models and the IUM are merged into one model to make it more representative of the behavior of individuals during and after the COVID-19 pandemic. The developed model is named as integrated urban modelling framework (IUMF). IUMF advances conventional integrated urban models for transport and land-use systems by developing behavioral sub-modules representative of peoples' travel behavior during the COVID-19 virus outbreak. This tool can be used to simulate travel behavior of individuals under business as usual scenario as well as in the wake of a disease outbreak. As mentioned in previous chapter, in some US cities, socio-economic characteristics of people were key factors influencing their intention to relocate during the pandemic *(CBRE, 2021)*. IUMF model can be utilized to analyze the spatial distribution of people migrating with respect to their demographics. It is crucial from urban planning perspective to understand this migrating behavior since migration patterns can affect traffic demands, housing prices, tax revenue, job opportunities, and retail markets in cities *(WEF, 2017)*. Existing literature indicate that individuals' post-pandemic travel behavior may not be affected by one single factor, rather it will be a constellation of variables influencing the changing patterns urban mobility choices. To clearly understand how the pandemic may accelerate the transformation of cities, it is pivotal for the researchers to bring together and integrate all the factors into their prediction models that may play key roles in reshaping built-up environment (*Coons et al., 2021*). Considering this objective, this thesis develops IUMF as a urban travel behavior simulating tool that embeds modules and sub-modules within its framework significantly representing post-pandemic mobility patterns. Another novelty of this agent-based microsimulation model is that it incorporates the life-history of individuals with choices while longitudinally simulating their mobility decisions under the effects of the pandemic. This makes the prediction more accurate and representative of the real world.

To demonstrate the capacity of the developed IUMF tool, peoples' decision to work from home and associated travel behavior are simulated up to the year 2025 for Halifax, Canada. Comparative analysis is conducted to examine whether and how 'work from home' decision may affect peoples' short-term as well as long-term travel behavior. The reason for selecting the 'work from decision' as dependent variable is that existing COVID-19 researches have identified WFH as the major transport lever for travel demand management and tackling climate change going foreword (Hook et al., 2020). How peoples' socio-demographic characteristics, and daily travel choices, such as, mode choice, shared travel decision, activity participation decision of the households varies with the decision to work from home is analyzed using IUMF in this chapter.

7.2 Literature Review

7.2.1 Bayesian Networks and Agent-Based Modelling

Studies coupling models for developing integrated urban frameworks to simulate transport and land-use changes are not abundant. *Kocabas and Dagiecevic (2013)* combined the major physical and social drivers of land-use transformation using Bayesian networks (BNs) coupled with agent-based modeling (BNAS). The authors obtained CPT values from census data. Their goal was to develop a spatial model that simulates land-use change under the influence of individuals' land-use choice behavior. Their model was developed with historical data and then used to simulate 20 years of future population and land-use change for the City of Surrey, Canada. Results indicated that BNs can grasp reasoning under uncertainty and therefore represent human behavior. In addition, the integration of BN and agent-based model was flexible and elicited accurate results. *Nascimento et al. (2020)* combined a land use/cover change (LUCC) model with BNs to simulate the impacts of environmental governance mechanisms on LUCC in the states of Pará and Mato Grosso, Brazil through 2030. The authors explored the effects of changes in major LUCC drivers in a baseline (BAU) and an improved governance scenario. Results showed that their model allows users to explore policy-relevant scenarios in a probabilistic setting and thus identify critically knowledge gaps that require further research to reduce uncertainty. *Pope and Gimblett (2015)* combined Bayesian and agent-based models to simulate complex feedbacks between human decisions and environmental conditions in the Rio Sonora Watershed, Mexico. They use cognitive mapping in combination of stakeholder participation to develop the Bayesian model conditional probabilities of individuals' behavioral processes resulting in changes to water demand. Next, the authors integrated the probabilities created in the Bayesian model into the agent-based model so that each individual gets a unique probability to make a decision. By using this hybrid approach, they were able to capture the uncertainty in human decision-making process and simulated changes in hydrologic systems through simulating individual agents' behavior.

Although these studies combine Bayesian and agent-based models to simulate environmental or in some cases land-use dynamics, no other studies merged Bayesian and agent-based urban models to simulate transport and land-use system transformation. It is crucial to incorporate the uncertainties in peoples' decision making in behavioral models, especially during a sudden disruptive event, and Bayesian networks are capable of doing that. Therefore, combining BNs and agent-based urban micro-simulation models can be an efficient approach to represent individuals' travel behavior during a pandemic.

7.2.2 Work from Home as an Emerging Behaviour

One of the many behaviors that have emerged from the COVID-19 pandemic is working from home (also termed as telecommuting or teleworking). Although working from home existed in the pre-COVID-19 times, the pandemic has fast-tracked adoption of this practice. Up to half of American workers shifted to working from home in year 2020, which is more than double the fraction who worked from home (at least occasionally) in 2017-18 (Guyot and Sawhill, 2020). Possible reasons why teleworking gained much popularity during the pandemic are: commute to work became too much of a risk due to rapid virus spread, advancement and affordability of telecommunication technologies, employers investing in tools and management practices to operate tele-workforce, among others. It has been widely discussed in print and electronic media, as well as in research papers that a lot of people are likely to continue working from home even after the pandemic (Mielck, 2021).

Studies exploring peoples' work from home (WFH) decision before and during the pandemic or intention to continue after the pandemic are limited but growing in number. Deloitte (2020) conducted a survey in Switzerland among 1,500 people all over the country to collect data on their work-arrangements before and during the pandemic. Also, they have asked the respondents to state their preference of working from home after the pandemic. Results showed that around 50% of people who are employed or self-employed are working from home. Before the crisis, 25% of respondents were working from home at least once a week. After the crisis, however, 34% believe that they will be working from home at least once a week. Work from home decision and daily travel behavior are interrelated and this interrelationship have been investigated by a lot of research papers. Rubin et al. (2020) carried out an online survey distributed internationally to investigate people's perceptions and experiences of working from home as an alternative to commuting. People who regularly travelled to their workplace before the pandemic, but who since the pandemic (try to) work from home and therefore do not commute at all, were taken as respondents. Data were collected in between 31 March- 27 April, 2020, and 1,014 individuals participated in the survey. 69% of respondents stated they miss at least some aspects of commuting. The main aspects missed by respondents include the activity of commuting itself (53%), the ability to spend some time alone (25%) and feeling independent (24%). Conway et al. (2020) used descriptive statistics to analyze long-term changes in telework, daily travel, restaurant patronage, and air travel. The authors conducted an online survey among US residents in Spring 2020. However, their sample strongly over-represented highly-educated, high-income households. Based on 1,545 responses, results indicated that around half of the people who were not working from home before the pandemic, but are now, expect to continue teleworking at least a few times a month once the pandemic subsides. One interesting finding was that about 80% of the respondents identified 'no commuting time' as the major reason for increased work productivity. Although the study collected data on their mode choice during and after the pandemic, it was unclear how their travel behavior may get affected because of working from home.

Pre-pandemic studies indicate that home-based teleworking has significant effects on individuals' mobility behavior, residential location choice, and subsequent effects on land-use (Moeckel, 2017; Silva and Melo, 2018). However, very few papers have considered the timeframe and context of a sudden disease outbreak. Given the uncertainty associated with the pandemic, it is still quite unknown how urban mobility dynamics may transform if there is a permanent shift to work from home. Habib and Anik (2021b) suggested that work from home (WFH) assures to be one of the major levers for transport policy makers to reduce traffic congestion and crowding that the sector has ever had. Their research in Australia during COVID-19 demonstrated that at least a 10–15 percent improvement in the metropolitan transport networks can be achieved due to reduced traffic congestion on the roads and crowding on public transport. Studies have found that older and high-income people are more involved in WFH than low and medium income households, since most of the low-medium income people are daily workers and have to go to their workplaces physically (Beck and Hensher, 2020). Existing travel behavior studies indicate that older high-income individuals are more auto-centric, and less willing to use public transport. Also, this subgroup practices work from home more than other groups of the society. This specific subgroup being more inclined to WFH points to a silver lining: car trips to workplaces can be reduced. However, pre-pandemic travel behavior studies have found that vehicle miles travelled (VMT) on average per day for telecommuting people is higher than people not-telecommuting. Besides, WFH cohort travel more distance on average than non-WFH cohort (Silva and Melo, 2018). It is important to understand how WFH decision may affect peoples travel behavior under the effects of the pandemic; to see whether large-scale shift to teleworking in cities will decrease trip-making or have a rebound effect to increase to the level more than ever before. Studies exploring this topic is rare. Besides, if businesses and cities have most of their employees working from home, they may consider giving up office spaces in metro areas, which leads to the opportunity to reconfigure downtown cores. Marsden et al. (2021) conducted a panel survey in 10 city-regions across England and Scotland to gather insights into how people's travel patterns have adapted over the time of the pandemic and why.

They have also explored mode choice and residential relocation decision of people working from home, and not working from home to determine how much impact the decision of WFH making on the urban environment. The wave 1 data were collected in between 3rd – 22nd June 2020 (sample size: 9,632) and wave 2 data were collected between 1st – 11th December 2020 (sample size: 6,209). Results indicated no greater tendency for people who work from home to say they have an increased desire to move home. One interesting outcome from their results was that people working from home are more inclined to use bike and public transit than private cars. Individuals who continue to never work from home are disproportionately dependent on auto and less likely to live within city centres. However, their study did not focus on the pressing questions: "What is next? "What are the long-term implications on individuals' travel behavior if they choose to work from home" "How working from home may affect urban transport and land-use going foreword". Although answers to these questions are critical to plan for metro areas if businesses and workplaces goes even partly online, it is extremely difficult to accurately forecast peoples' future behavior in this respect – provided the variability of the pandemic situation. Already giant businesses and tech companies, such as Pinterest, Twitter, Facebook, Microsoft have adapted to work from home culture and gave up their office spaces in urban downtowns (Barth, 2021). Nevertheless, efforts should be made with appropriate urban frameworks to examine how the resurgence of 'work from home' may change urban transport and land-use systems (Liu, 2021). Considering these gaps in the literature, this thesis develops IUMF as a sophisticated urban travel behavior simulating tool that generates 'work from home' submodule within its structure to simulate peoples' WFH decision and travel behavior – thereby assisting to have a clearer understanding on how WFH may change urban dynamics in the future. The next section discusses the methodological framework of the IUMF model.

7.3 Methodology

This study advanced IUMF by integrating Bayesian Network Models representing pandemic mobility choices of individuals within an Integrated Urban Model into a single framework. The conceptual diagram for the IUMF is shown in Figure 7-1.

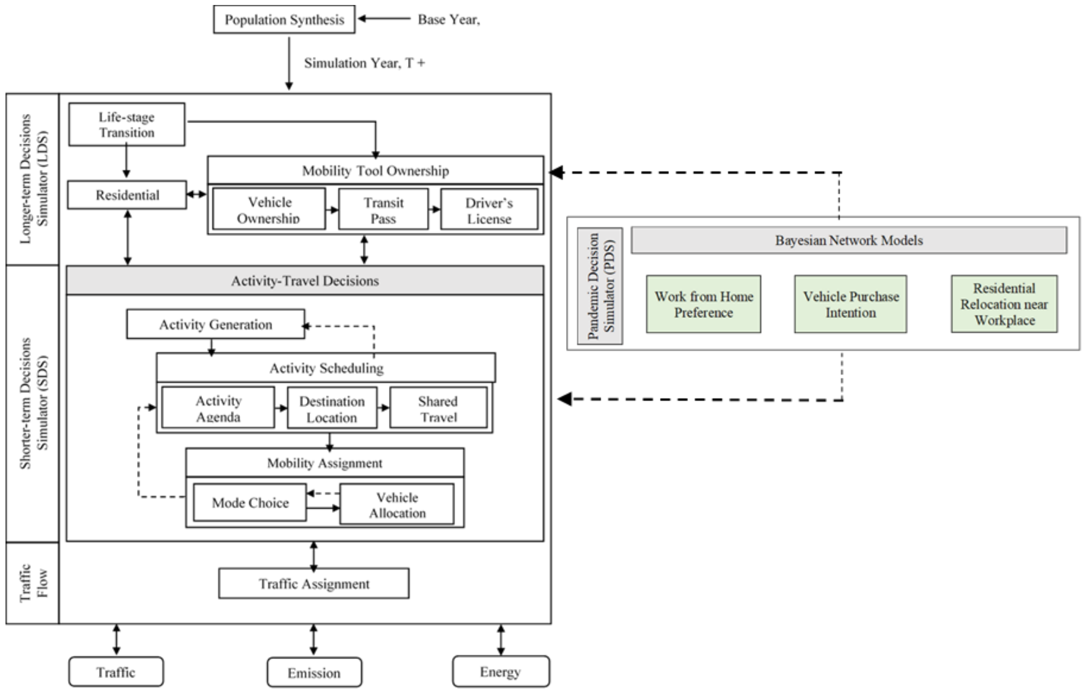


Figure 7-1 Conceptual Diagram of Integrated Urban Modelling Framework (IUMF) to Predict COVID-19 Impacts

Table 7-1 illustrates the modelling components shown in Figure 7-1, methods adopted within the components as well as input variables and output.

Table 7-1 Methods, Input Variables and Output of Integrated Urban Modelling Framework (IUMF) Modelling Components

Modelling Component	**Method**	**Input Variables**	**Output**
Population Synthesis	Iterative Proportional Updating (IPU) technique	*Household-level control variables* Household income and size Tenure type and dwelling type *Individual-level control variables* Age, sex, marital status, and employment status.	100% synthetic population
		Long-Term Decision Simulator (LDS)	
Residential Mobility	Binomial logit model	Child born in household this year Death of a household member this year Age of household head below 40 Age of household head above 55 Household income below $50,000 Household owns at least 1 vehicle	Decision to move or stay

		Distance from residence to CBD > 10km Distance from residence to bus stop < 1km	
Residential Location Choice (residence owners)	Multinomial logit model	Mode choice logsum × household owns only one vehicle Mode choice logsum × household owns two or more vehicles Land use index of DA × household owns at least one vehicle Proportion of residences owned in DA DA average property value × household income $100,000+ Area of property × child born in household this year Auto travel time to nearest bus stop Auto travel time to CBD Auto travel time to CBD × household does not own any vehicles Auto travel time to CBD × child born in household this year Auto travel time to CBD × dwelling is single detached Travel time to nearest school × household has children Household head auto travel time to work Travel time to nearest business park	Location choice of households
Vehicle Transaction Type	Multinomial logit model	*Acquire* Income, household head age, number of adults in household, number of vehicles in household, residence distance to CBD *Trade* Income, household head age, years since moved to current residence *Dispose* Household head age, years since moved to current residence, number of vehicles in household	Decision whether to purchase, trade or dispose vehicle
Transit Pass Ownership	Binomial logit model	Age, sex, income, employment status, household size and tenure type, residence distance to CBD	Decision to own a transit pass
Driver's License	Binomial logit model	Age, sex, income, employment status, number of vehicles in household, residence dwelling type, residence distance to CBD	Decision to own a driver's license
		Short-Term Decision Simulator (LDS)	
Activity Participation and Time Allocation	Multiple Discrete Continuous Extreme Value model	Age, income, number of vehicles in household, employment status, transit pass ownership, driving license ownership, residence distance to CBD, residence distance to closest bus-stop, residence distance to closest shopping mall, DA land use index	Decision to participate in any mandatory/ maintenance/ discretionary activity and time allocated for that activity
Mode Choice	Multinomial logit model	*Auto* Household head age Household head auto travel time to work Household head is full-time employed Household income is $100,000+ Land use index of DA	Choice of primary travel mode

		Residence in an urban area × household head age 25-40 Number of vehicles owned by household *Transit* Household head age Household head transit travel time to work Number of people in household Household head is student *Bike* Household head travel distance to work Residence in an urban area Residence in an urban area × household head age 25-40 Number of vehicles owned by household *Walk (Reference choice)* Household head travel distance to work Household head is student Land use index of DA Household head age	
Shared Travel	Mixed logit model.	Age, number of activities, employment status, density of DA, household size, income, number of vehicles, travel duration, land use index of DA, residence distance to CBD, residence distance to shopping mall	Choice of traveling alone/ with roommate /partner/parents/ children
		Pandemic Decision Simulator (LDS)	
Work from Home, Residential Mobility, Vehicle Purchase Intention	Bayesian network models	Age, sex, work status, transit pass ownership, mode choice during pandemic, vehicle type choice, number of vehicles in household	Choice of working from home, residential relocation near workplace and intention to purchase a vehicle in the post-pandemic time.

The connection between the BBN and IUM model is established using stochastic conditional probability algorithms. Conditional probability tables calculated in the fifth chapter of the thesis are utilized as input in these algorithms. For constructing the connections, a common variable ('employment status' of individuals) between the two models is employed. Figure 7-1 shows that the three sub-modules developed in this thesis to represent the changing mobility choices in the post-pandemic time are 'Work from Home Preference', 'Vehicle Purchase Intention' and 'Residential Relocation near Workplace'. These three sub-modules are conceptualized to be under a novel module named as ‘Pandemic Decision Simulator (PDS)’. The architecture of the sub-module implementation are shown in Figure 7-2.

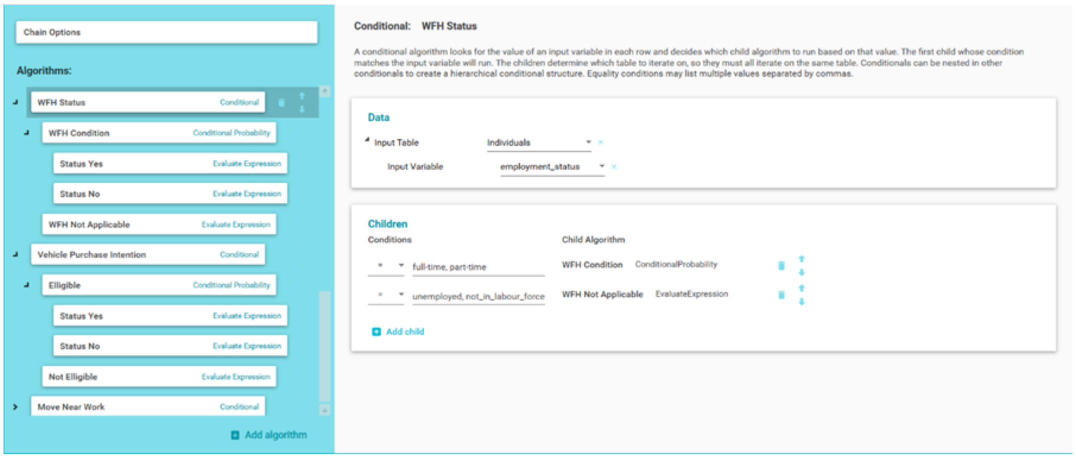


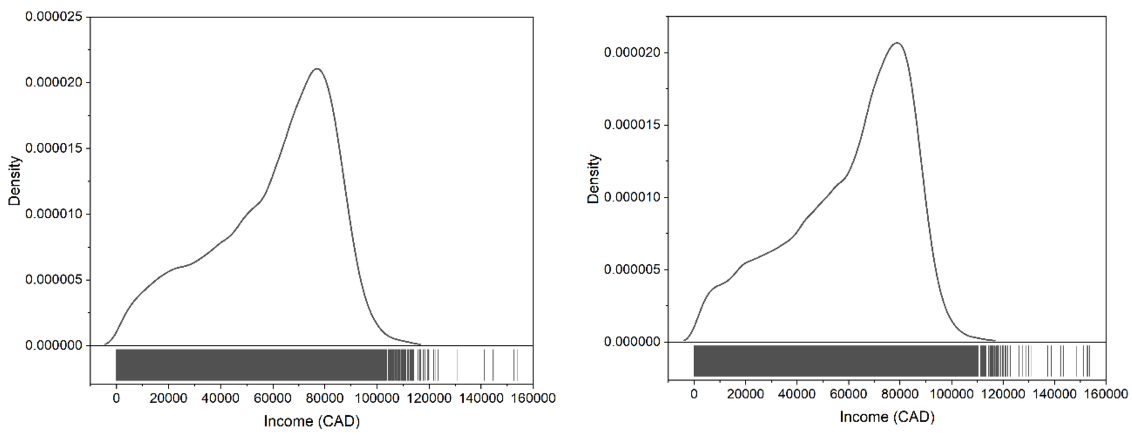
Figure 7-2 Pandemic Decision Simulator (PDS) Module Architecture

It is worth mentioning that this thesis only reports the results from the ‘work from home’ submodule considering WFH as one of the key instruments for travel demand management and tackling climate change going foreword IUMF is developed as a comprehensive and flexible agent-based micro-simulation tool to simulate households’ short-term as well as long-term choices under the effects of the COVID-19 pandemic. It can be used to examine socio-demographic characteristics, daily travel choices, such as, mode choice, shared travel decision, activity participation decision of the households who wants to work from home, intends to purchase new vehicles or migrate to live near their workplace in the post-COVID times. The aim is to enable a more in-depth understanding of the transformation of transport and land-use systems. For demonstration purposes, this chapter simulates mobility behavior of individuals’ in Halifax, Canada for the years 2021 to 2025 taking ‘work from home preference’ as the differential variable. The results are shown in the next section.

7.4 Analysis and Results

7.4.1 WFH and Income

Figure 7-3 shows the relationship between individuals' income and their positive preference to work from home for years 2021 and 2022.



2021 2022

Figure 7-3 Density Plot of Individuals' Income who are Willing to Work from Home

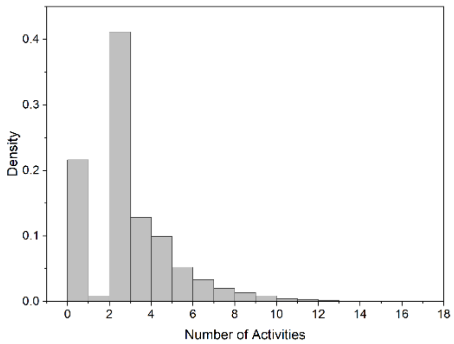
According to 2021 and 2022 results, medium and high-income households will be more actively working from home – the peak is found on around 75,000 \$. However, low-income households or day-workers may not have that much opportunity of telecommuting and may have to go to their workplaces.

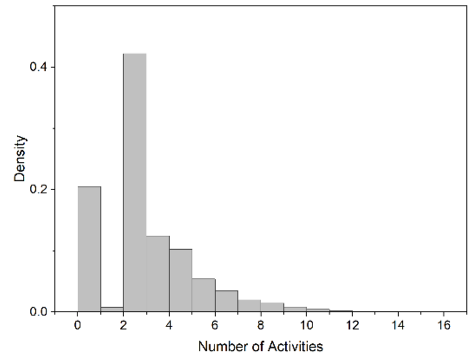
7.4.2 WFH and Number of Activities

Figure 7-4 plots number of activities for 'individuals working from home' and 'not working from home' for years 2021-2025. The results are similar for 2021 for both groups of people suggesting that working from home may not affect peoples' number of trips in this year. In addition, most of the people will be making two trips per day.

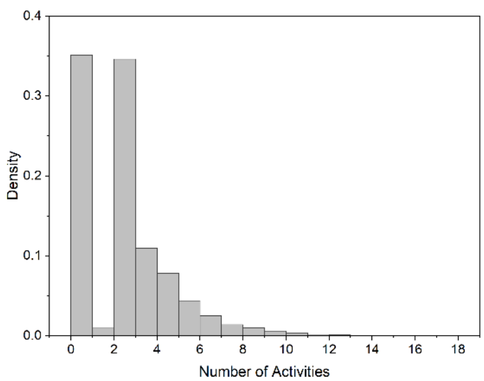
WFH =Yes

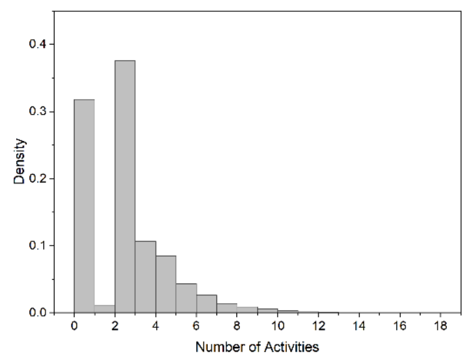
WFH =No



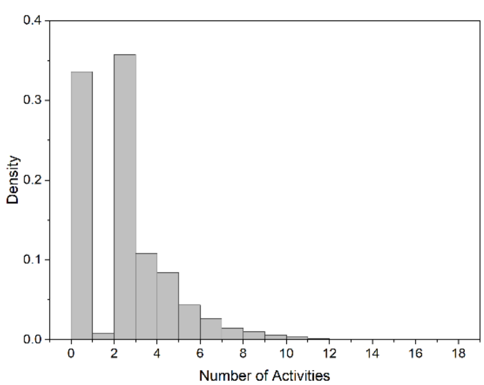


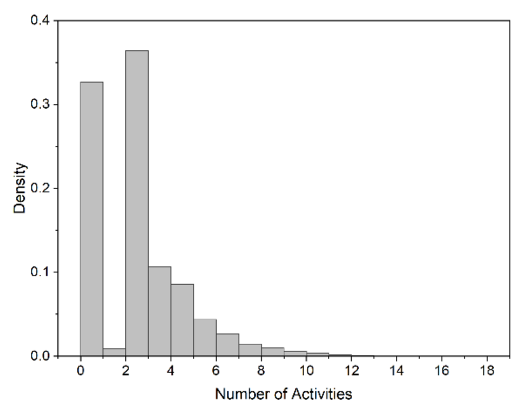
2021



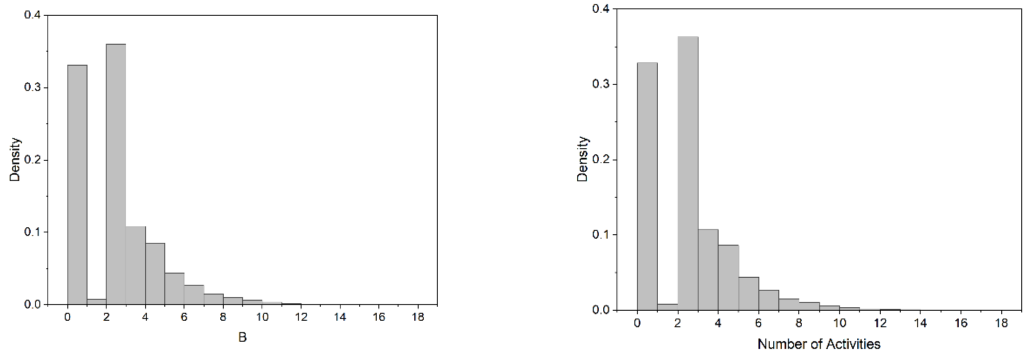


2022

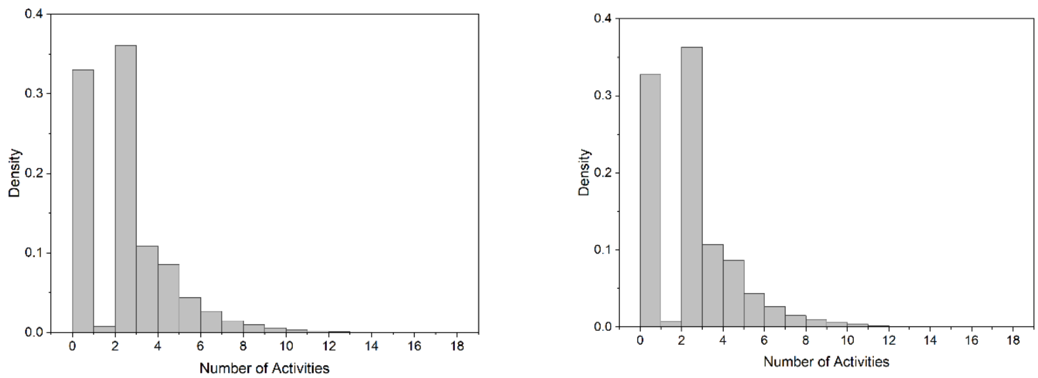




2023



2024



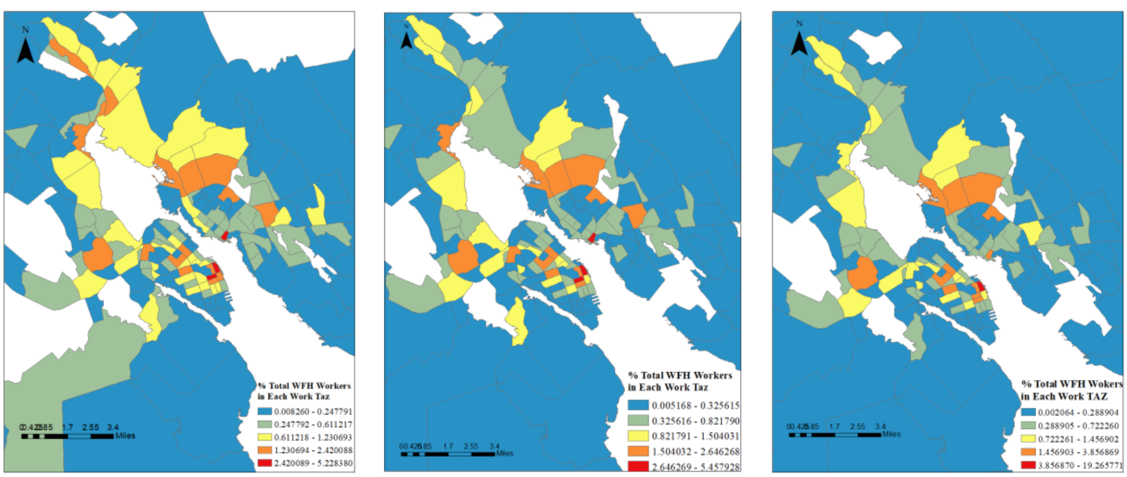
2025

Figure 7-4 Density Plot of Individuals' Number of Activities (WFH=yes and WFH =no)

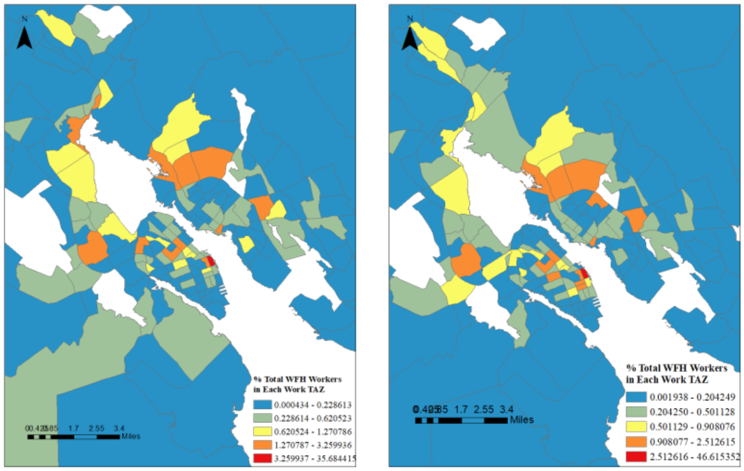
Year 2022 yields interesting results. People making zero trips per day is increased for the telecommuting cohort postulating that working from home may significantly increase people with zero number of trips made in the city. For telecommuting cohort, most of the people will be making zero trips whereas for non-telecommuting group, most of the individuals will be making two trips. Another interesting finding is that people making zero trips on average are significantly increased for both groups of people between years 2021 to 2022. This can be caused by the rapid adoption of technologies among communities that may allow for online shopping, virtual schools, food delivery and working from home (Sheonty and Anik, 2021). These opportunities may offer people to get their daily activities done from home without going to the places in person. Consequently, trip-making may notably decrease among these group of people. According to Figure 7-4, the trend of number of activities are mostly similar between 2022 and 2025 - only a slight decrease of zero trip-making people among telecommuting cohort. This phenomenon indicates that once people get accustomed to a new habit, they may not abruptly change their activity behavior in the following year.

7.4.3 WFH and Work Location

Figure 7-5 shows the percent of workplaces in each TAZ zones which will have employees working from home. Year 2021 results indicate these work places are distributed quite evenly among downtown and sub-urban areas. Some of the TAZs in the downtown Halifax will have around 2.5% to 5.25% of employees working from home. This trend continues in the following years – with this concentration of work TAZs with large number of people working from home gets narrower within the urban core.



2021 2022 2023



2024 2025

Figure 7-5 Percentage (%) of Total Work from Home (WFH) Workers in Each Work TAZ from 2021 to 2023

This finding is critical from urban planning perspectives. This trend gives planners a lot to think about the possible reconfiguration of urban centers.

7.4.4 WFH and Mode Choice

Mode choice analysis of people preferring to work from home yield interesting results. Figure 7-6 indicates high dependency of telecommuting cohort on auto (58%) for 2021, surprisingly, it decreases to 31% within 2023. Mode share of bike, transit and walking substantially increases for these group of people in between 2021 to 2023. This indicates that for the next years, people who will be telecommuting may become highly encouraged to use sustainable forms of transport and leave their private vehicles at home. This finding postulate that the pandemic situation may encourage telecommuting people to bike and walk more while depending less on auto. This phenomenon can be caused by the fact that autos are mostly used for work trips and these people will be working from home – which may motivate them to explore other modes. However, from 2023, up to 2024, there may be a drastic increase in auto-dependency, auto mode share reaching to around 79%. Ridership of bike, transit as well as percentage walking trips may significantly decrease.

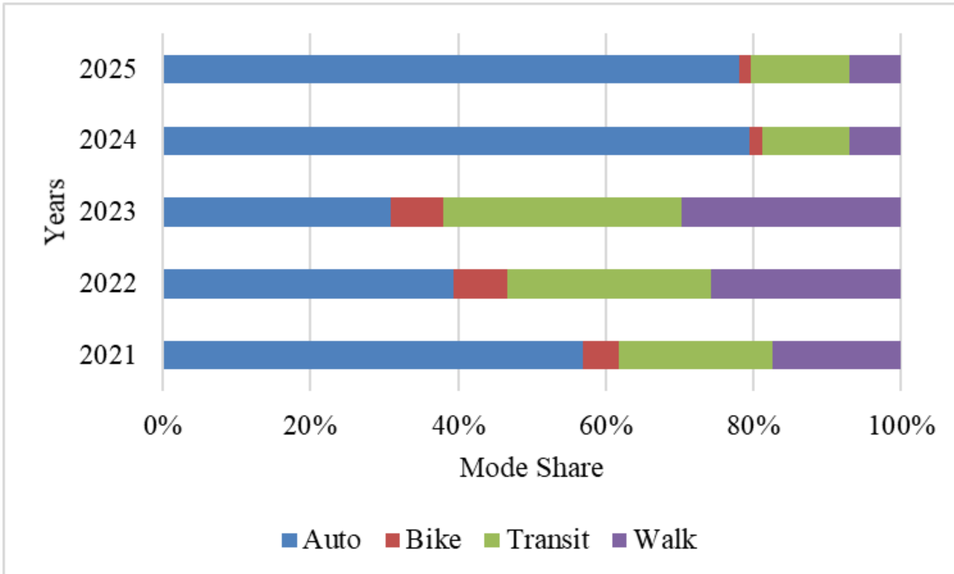


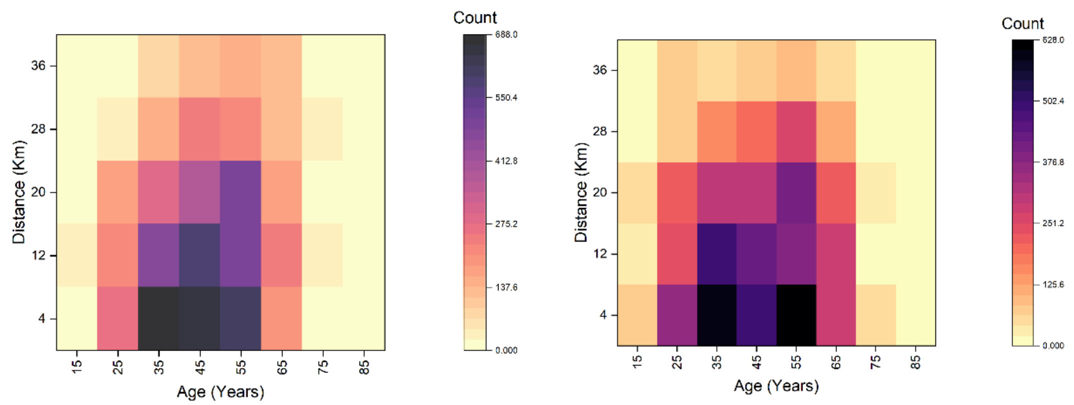
Figure 7-6 Mode Share of People Willing to Work from Home

According to Habib and Anik (2021b), COVID-19 pandemic can cause boom in car sales across countries within next 2-3 years. As the economy comes back to life and individual household income increases, the traumatic experience of using public transit - during the pandemic may drive people to buy private vehicles. According to Figure 7-6 the trend for mode share among people who wants to telecommute stays more or less same in between 2024 and 2025. This indicates that once people get settled with their household vehicle transactions, they may not suddenly change their travel mode choice and may behave consistently.

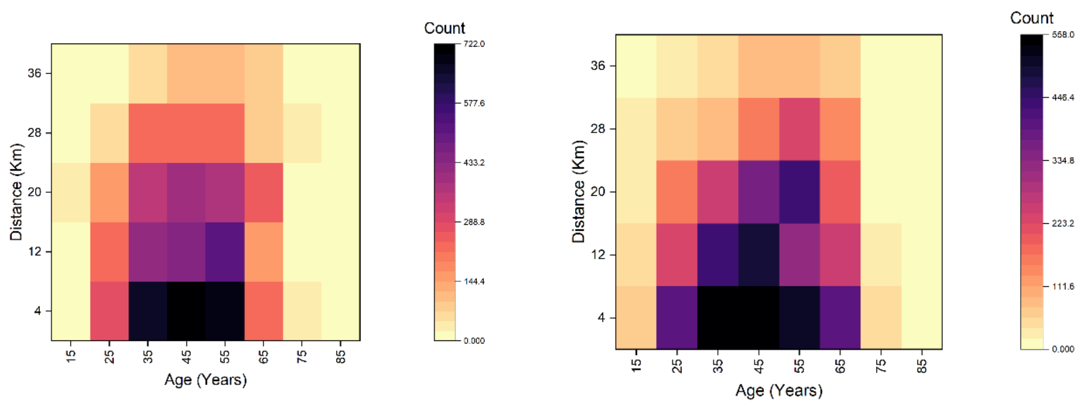
7.4.9 WFH and Travel Distance

According to Figure 7-7, most of the people are making trips within 0-24 Kilometres (KMs) throughout the years. This result is quite understandable considering the size of Halifax Regional Municipality (HRM). No significant difference is found between telecommuting and non-telecommuting cohort for year 2021 in terms of travel distance. For year 2022, average travel distance of age group 50-60 years of non-telecommuting people increases compared people working from home. For years 2023-2025 the trend for travel distance with respect to age across telecommuting and non-telecommuting groups stay quite similar.

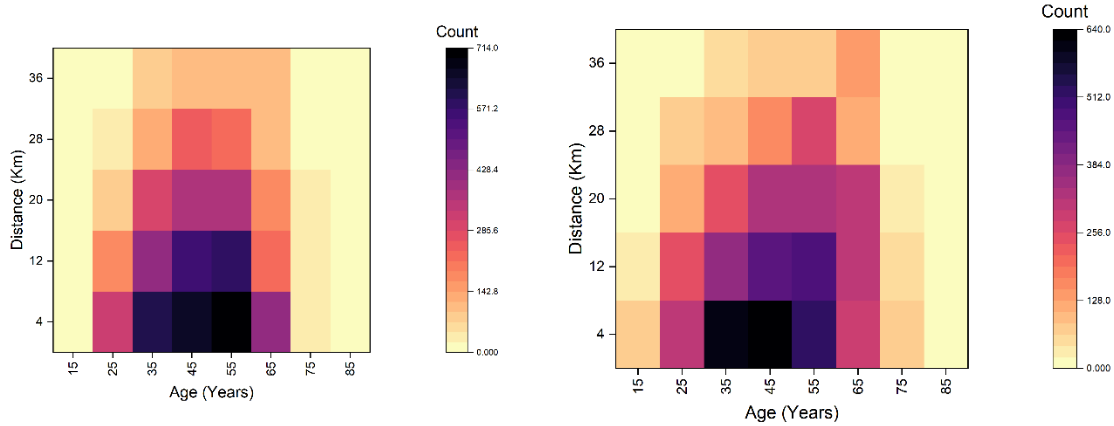
WFH =Yes WFH =No



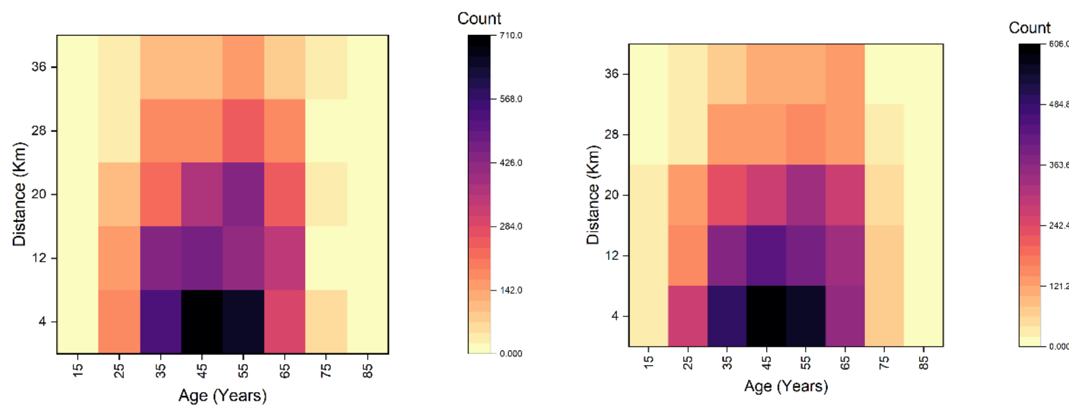
2021



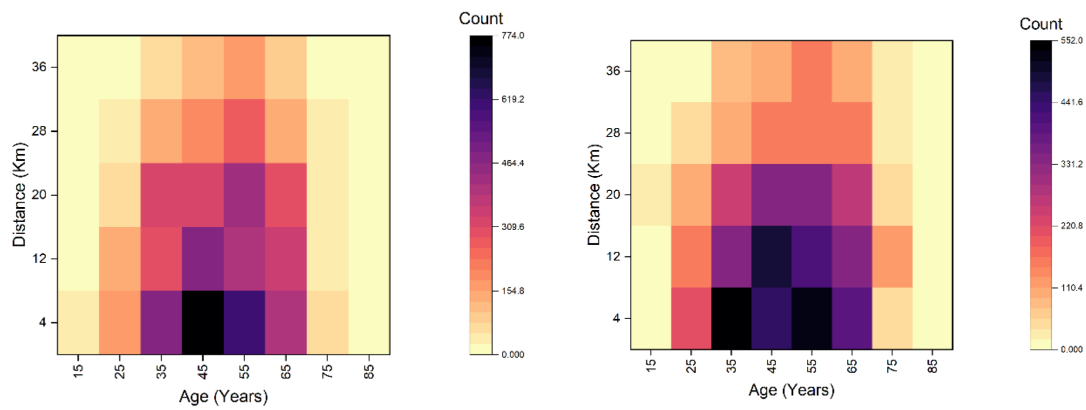
2022



2023



2024



2025

Figure 7-7 Travel Distance of Telecommuting vs Non-Telecommuting People with Respect to their Age (Years 2021-2025)

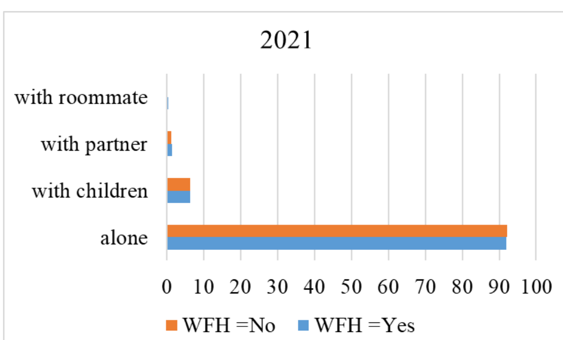
Average travel distance is found to be higher for telecommuting people than non-telecommuting people. Table 7-2 shows that average travel distance for both groups decreases up to year 2023, then increases abruptly in year 2024, and stays same for the next year.

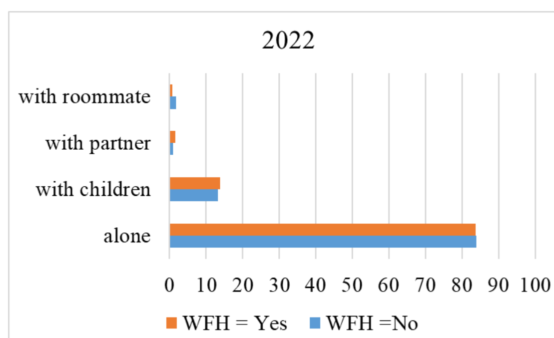
Table 7-2 Average Travel Distance (KMs) of Telecommuting and Non-Telecommuting People for Years 2021-2025

Year	WFH =Yes	WFH =No
2021	17	16
2022	16	15
2023	15	15
2024	19	18
2025	19	19

7.4.6 WFH and Shared Travel Decision

Figure 7-8 illustrates comparison between shared travel behavior of people 'working from home' and 'not working from home'. The analysis is shown for years 2021-2025.





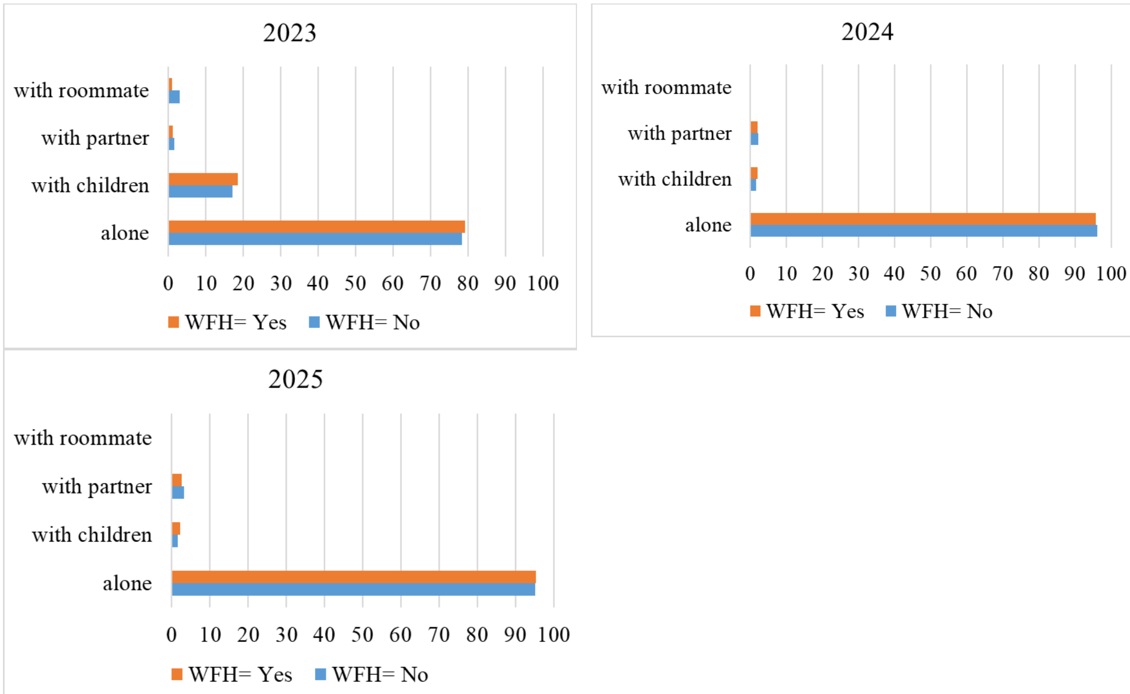


Figure 7-8 Shared Travel Behavior from 2021-2025 between People with Work from Home Preference/ No Work from Home Preference

According to the results, travelling alone is most popular (almost over 80% of all trips for each year) followed by travelling with children, with partner and with roommate. Non-telecommuting people are slightly more inclined to travel alone than telecommuting people. Travelling alone experiences a gradual decrease in between year 2021 and 2023 (from approximately 92% to 78%). In those years, trips where people are travelling with children increases (from approximately 5% to 15%). However, in year 2024, trips made alone increases again to more than 90%. During that year, travelling with children decreases. The trend remains constant in between 2024-2025. This finding is interesting and have a correlation with mode choice results. It is predicted that auto use will experience a steep decrease up to year 2023 and will crept upward in 2024 (Figure 7-6). Shared travel results show that 'alone' trips will decrease up to 2023 and will increase in the next year. Combining these two outcomes, it can be presumed that more auto-dependency will accelerate more trips made alone.

7.5 Discussion

This chapter attempted to analyze people's work from home decision and associated travel behavior for the individuals in Halifax, Canada. Comparative analysis is conducted between telecommuting and non-telecommuting cohort for the years 2021-2025 which shed lights on the contemporary question: 'how work from home due to COVID-19 may change peoples' mobility behavior as well as accelerate transformation of transport and land-use systems'. Outcome of this study has critical policy implications.

Results indicate that people having workplaces in downtown Halifax will be more inclined to work from home than people having workplaces in suburban areas. If employers can get their job done by their employees working from home, they may consider giving up office spaces in downtown areas and reduce their investment in commercial office spaces. Given that most of the employees can work from home, it is not prudent to spend millions as rent for office spaces in downtown metro areas. This effect of freeing up spaces of downtown areas can be compounded by retailers shifting to online and leaving in-person shops in central business districts. This insight is important for policy makers as transformation of these retail spaces may trigger reconfiguration of urban centers, also this phenomenon will have significant impacts on urban dynamism, such as, traffic demand, land-use systems, infrastructures, housing and retail spaces. This will offer opportunities for land-use planners and decision makers to reconsider policies and plan accordingly to make future urban spaces more inclusive, sustainable and green.

Mode share results show that auto-dependence of people working from home will decrease gradually up to year 2023 (58% to 31%). It is a good sign in terms of sustainable travel habits that in those years mode share of walking and biking gets almost doubled, while public transport trips increase by 20-25%. Research of Marsden et al. (2021) also indicate that people working from home are mostly bike and transit users. If working from home becomes mainstream, bike, walk and transit trips may increase. However, starting from 2024 the mode share results shift to pre-pandemic levels, with auto being the most popular mode (78%). Besides, the shared travel decision results indicate a decrease in 'alone' trips up to year 2023 and abrupt increase in year 2024. Both these results postulate that increase in car trips also trigger an increase in trips made 'alone'. These outcomes indicate a return to auto-oriented society once the pandemic settles down and virus threat is reduced. To continue building on the improvements made during the pandemic in terms of sustainable travel, apt planning is required by the governments to keep people attracted to walking, cycling, and at the same time make sure public transport is safe enough to use.

Simulation results also show that people telecommuting on average travels more distance than people not-telecommuting for years 2021-2025. This outcome is analogous to existing pre-pandemic researches investigating ‘work from home’ decision and travel habits (Mokhtarian, 2004; Moeckel, 2017). The reason behind this behavior can be the fact that many teleworker uses the commute time saved through telework to do other trips, such as driving a longer distance to the preferred grocery store or making additional leisure trips (Zahavi, 1982; Zahavi, 1979). This chapter tried to determine the income levels of people ‘working from home’ and found that high-income households (around $80,000 per year) are more inclined to telework. A survey conducted by Liu (2021) shows that, most of USA’s highest-income workers (62%) are able to work from home – everybody else: not so much. This highlights the matter of equity when it comes to large-scale digitalization of work in the post-COVID time. People whose jobs cannot be done remotely or who do not have access to high-speed internet should share the benefits telecommuting people may get by working from their houses. The day-to-day workers are mostly reliant on public transport and often come home in unsafe and overcrowded conditions. Governments should consider taking more expansive actions, such as internet infrastructure, more housing construction in existing neighborhoods and particularly near transit stops, and better public transport routes between residential and economic centers, ensuring location and availability of services for everyone especially people who must commute to work and access services in person.

7.6 Conclusion

This chapter is the culmination of the thesis where learnings from other chapters are merged together to develop an integrated modelling framework. This chapter couples Bayesian models and IUM to develop an integrated urban modelling framework (IUMF) that can be utilized to perform comprehensive analysis of individuals' travel behavior during and after a pandemic. The goal is to have a clearer understanding of how urban environment may change under the effects of the crisis. To illustrate the application of the developed framework, this chapter investigates how 'work from home' (telecommuting) decision may affect peoples' mobility behavior and subsequent short-term travel decisions, such as, mode choice, shared travel decisions, activity participation, average travel distance. Furthermore, it simulates work location choice of people who have a positive preference towards working from home. All these behavioral aspects are simulated from year 2021 to 2025 for Halifax Regional Municipality (HRM), Canada considering the effects of the COVID-19 pandemic. Outcomes of this longitudinal analysis of telecommuting and non-telecommuting cohorts' travel behavior offer critical insights on how adapting 'work from home' may change the dynamics of urban areas. For instance, results show that most of the workplaces in downtown Halifax may have their employees working from home, and this trend gradually increases throughout the next five years. Telecommuting cohorts' auto mode share is found to decrease substantially in the next two years, whereas walking and biking trips are found to increase. However, dependency on auto rapidly increases in year 2024 and stays almost same in year 2025. Trips made alone decreases up to year 2023 and then increases in the following year. Average travel distance of telecommuting people is found to be higher than non-telecommuting people. For both the groups, people making zero trips on average are found to significantly increase in between years 2021 and 2022. Interaction between income variable and 'work from home' decision shows that high-income individuals are mostly inclined to telecommute (peak of density plot found near 80,000$) than low and medium-income households.

'Work from home' is one of the emanating behaviors from the COVID-19 pandemic that experts think may last long and affect urban mobility dynamics significantly. The effects of this emerging behavior on urban transport and land-use environment are still quite unknown and needs to be examined. Research works exploring this particular topic is rare. This chapter focuses on this phenomenon and attempts to assess how adopting 'work from home' may change individuals' travel behavior. As future scope of this study, effects of other emerging behaviors from the pandemic, such as, vehicle purchase intention, migration decision, technological adoption can be explored with the aid of the developed tools.

Chapter 8

Conclusion

8.1 Summary

If we look back in history, the aftermath of sudden disruptive events, such as, disease outbreaks, natural disasters, large scale traffic crashes have always been critical for mobility of people and goods in cities. Most of those events have triggered reconfiguration and transformation of urban transport environment. Such events provide the governments the opportunity to rethink and update mobility plans in order to make transport systems more resilient, equitable and sustainable. The recent COVID-19 pandemic is considered as one of the major disruptive events in the human history, that have changed the concept of how we perceive travel. The effects of the crisis on our daily activity participation, travel habits, economy, retail and e-commerce, land-use systems have been unprecedented. This thesis advances travel behavior research by developing urban frameworks to assess COVID-19 pandemic's short-term, medium-term and long-term impacts on transport and land-use systems through analyzing changes in individuals' mobility behaviour. The short-term impacts (first six months of the crisis) are identified by examining public discourse data in Twitter. Data mining methods such as, text mining, and topic modelling are adopted as methods to carry out the analysis. The results offer useful information on general public's real-time concerns, opinions, and experiences regarding the major transport modes, such as public transport, private car, bicycling during the pandemic lockdown period. In addition, challenges and opportunities of 'economy reopening' following the lockdown are also identified. To go more deeper to understand emerging travel habits from the pandemic, and to incorporate uncertainty in behavioral models this thesis then develops Bayesian networks. For this it conducts a questionnaire survey in Halifax, Canada to get data on peoples' post-pandemic travel attitudes and preferences, mode choice, vehicle fleet information and socio-demographic condition. Bayesian Belief Networks (BBNs) are applied on the data to analyze the factors associated with individuals' preference for working from home, residential relocation to live near workplace and vehicle purchase intention. Results showed that 'working from home' became popular among the working individuals and people may work from home even after the pandemic. Results also indicate that very few percentages of people may relocate their households to live near workplace or purchase new vehicles in the post-COVID time. After that, through pandemic scenario simulation using a long-term decision simulator (LDS), this thesis predicts long-term mobility choices of households in Halifax, Canada for each year up to year 2030. These long-term decisions include residential location choice, vehicle ownership level, vehicle transaction decision and type choice, transit pass ownership. Results show that though some behaviors adopted during the pandemic may last long but the overall result suggest a return to pre-COVID auto-oriented society. The pandemic may accelerate urban sprawling, and auto-dependency may increase substantially with time. Next, BBNs are coupled to extend an integrated urban modelling framework that can be utilized to simulate transformation of land-use and transport systems of cities under the effects of a pandemic/disease outbreak. For illustration purposes, travel behavior of people with positive or negative preference for working from home are simulated up to year 2025. Significant differences are found in mobility choices and behavior between these two cohorts. Based on its results, this thesis finally presents policy discussions with an aim to show pathways to achieve safe, affordable, resilient, and sustainable transport and land-use system.

8.2 Major Contributions

This thesis has several contributions in the fields of transport and land-use system research. The key contributions are outlined below:

1. This thesis captures public discourses utilizing data mining techniques which offer valuable insights regarding COVID-19 pandemic's effects on transport modes and likely changes in travel behavior.

2. It advances Bayesian Belief network based modelling approach to assess post-pandemic travel behaviour utilizing a questionnaire survey.

3. It explores long-term impacts, specifically, residential mobility and location choice, vehicle ownership and type choice and transit pass ownership by utilizing an existing transport, land-use and energy model.

4. One of the most significant methodological contributions is that this thesis advances integrated urban modelling framework (IUMF) by coupling longer-term decision processes within an agent-based microsimulation modeling system.

8.3 Limitations and Future Scope

This thesis is a first step of investigating a rapidly evolving pandemic situation with advanced method, tools and modelling framework. Though this study contributes significantly to the growing body of research investigating disruptions of COVID-19 on transport and land-use environment, it has some limitations. The Twitter data used in the study are not inclusive of the people not using Twitter. In future, data fusion methods can be utilized to combine social media data and survey questionnaire data to make the data more representative for transport user groups. It is difficult to determine travel behavior directly from social media data, as peoples' actual activities may not reflect how they are stating their experiences or concerns in the public discourses. However, the insights from social media data analysis can offer the policy makers an idea about peoples' perception about transport modes and services during sudden disruptive events. Such outcomes may assist in making informed decisions in transport policy making . Another limitation of this study is the assumptions in the scenario simulation. Mobility behavior emerging from the scenarios may or may not reflect actual behavior of individual households and are subjected to events happening in future timeline. Future scope of this thesis is to conduct experimental studies to validate the prediction results of the simulation model. This thesis took Halifax, Canada as study area and the results may not totally replicate to other cities with different geographic and population characteristics. The urban systems model developed in this thesis may require some modifications and calibrations before applying it to different context. Future research may involve investigating the interrelationships between mobility factors by adding more decisive variables related to the pandemic such as vaccination, herd immunity or infection rate. As previously mentioned, developments of the COVID-19 immunization process may continue to have effects on urban mobility. Tools and techniques are needed to be developed to monitor the situation and plan proactively. Future extensions of the developed tools can be adding modelling components related to smart phone use, technology adoption, growth of e-commerce and their influence on mobility behavior. Furthermore, coupling of epidemiological models with activity-based travel demand models within IUFP may develop the capacity to examine connections between travel-related decisions and virus spread. Future researches may consider developing a housing price submodule within the long-term decision simulator of IUFP in order to make the residential location choice submodule more robust and dynamic.

The thesis could not validate the simulation results of the pandemic simulator due to data unavailability. Future research may consider utilizing a COVID-19 pandemic time travel survey data of Halifax, Canada to validate the micro-simulation results of IUFP. The developed tools in the thesis have multiple components which can be affected by multiple domains of changes. Therefore, it may get difficult to detect and identify the reasons for fluctuations in certain outcome variables. Further strengthening of coupling strategies and feedback mechanisms can be implemented to overcome this issue. This thesis develops the platform upon which future researches regarding 'impacts on mobility due to sudden disruptive events' can be hinged upon. In future, a comprehensive scenario forecasting tool can be built that will assist to examine not only the impacts of disease outbreaks but also the effects of any mobility disruptive events, such as, hurricane, earthquakes, connected and autonomous vehicles on transport and land-use systems. Such tool will offer researchers, practitioners and governments to forecast how these events may transform urban travel behavior, land-use dynamics, predict possible impacts on climate change, determine influence on social and economic prosperity.

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