# Transit User Mode Choice Behaviour in Response to TTC Rapid Transit Service Disruption

by

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## Abstract

Disruption of transit service is a common occurrence in many cities around the world, and these incidents may have serious impacts on the transit user's journey. The purpose of this study is to investigate transit user commuting mode choice in response to rapid transit service disruption in the City of Toronto. A joint Revealed Preference and Stated Preference survey is designed to gather information on the respondent's actual response to the most recent service disruption and also responses under a set of hypothetical service disruption scenarios. A transit trip planner tool is developed to generate alternative transit options to avoid the disrupted segment. Econometric models are presented, including a joint RP-SP model, showing that the following factors, in addition to travel time and cost, are significant at 95% confidence: frequency of subway trip, trip purpose, subway delay, shuttle bus delay, weather, age, and income. Policy implications are also discussed.

# Acknowledgments

It seems fitting that my thesis on how passengers cope with transit disruptions is full of challenges and obstacles, but the most important thing in the end is to find a way to overcome those challenges and reach your eventual destination.

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# List of Conference Papers

The following chapters include materials reproduced with modifications from conference papers I have previously presented.

Chapter 2

Lin, T., A. Shalaby, E. Miller. Transit User Behaviour in Response to Service Disruption: State of Knowledge. Presented at the $51^{st}$ Annual Conference of the Canadian Transportation Research Forum, Toronto, Ontario, Canada, 2016.

Chapter 3

Lin, T., A. Shalaby, E. Miller. Transit User Behaviour in Response to Subway Service Disruption. Presented at the 2016 Canadian Society for Civil Engineering London Annual Conference, London, Ontario, Canada, 2016.

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# Glossary

| | |
|---|---|
| API | Application programming interface |
| Biogeme | Software for estimating parameters for discrete choice models |
| GEV | Generalized extreme value |
| GTHA | Greater Toronto and Hamilton Area |
| IIA | Independence of irrelevant alternatives |
| LOS | Level of service |
| MNL | Multinomial logit model |
| MNP | Multinomial probit model |
| Ngene® | Software for generating stated preference experimental designs |
| NL | Nested logit |
| OD | Origin and destination |
| RP | Revealed Preference |
| RP-SP | Revealed Preference and Stated Preference |
| SP | Stated Preference |
| SUBWAIT | Subway User Behaviour When Affected by Incidents in Toronto survey |
| TTC | Toronto Transit Commission |
| TTS | Transportation Tomorrow Survey |

Chapter 1

# 1 Introduction

## 1.1 Problem Statement

Public transit service disruption is common across different transit modes at different times and days for all transit agencies. Due to the significantly higher occupancy compared to personal vehicles and a smaller transit network compared to the road network, the impacts are significant for the transit agencies and users. Different transit users have different ways of coping with the service interruption. Even the same passenger may respond differently to various types of incidents, depending on the cause and severity of disruption.

While any disruption usually affects network reliability adversely, the nature of the resulting reliability issues and their effect on user behaviour are distinct from those related to general reliability issues under normal transit services. Sikka and Hanley (2013) classified expected delays or travel time variability under "general reliability" and unexpected delays under "disruption". Similarly, Carrel, Halvorsen and Walker (2013) considered recurrent issues under "general reliability" and incident-related occurrences under "disruption". While there has been many studies on the effects of general reliability of both auto and transit on passenger behaviour and decision making, including meta-analyses synthesizing various reliability studies (Tseng et al., 2008; Carrion & Levinson, 2012), there is disproportionately much less attention dedicated to the subject area of transit user behaviour in response to service disruptions.

Disruptions to the road network have very different consequences from those occurring in the transit network, due to the much smaller size of the latter and its limited number of route alternatives, especially within the rapid transit network. Zhu and Levinson (2011) reviewed a wide range of studies on transit and road network disruptions, such as transit strikes, bridge closures, special events and earthquakes, and they summarized the behavioural changes of both auto and transit users. However, the causes of transit service disruption are typically different from those of the road network and the effects on traveller behaviour are likely to vary. Moreover, information on unexpected road disruptions is usually more readily available to drivers through TV or radio channels, while the information seeking behaviour and information availability for transit users are likely very different. Compared to the auto mode, transit service disruption is not examined as extensively despite the potential of severe delays they could cause to overcrowded rapid transit systems.

Many transit agencies have established practices to respond to service disruptions, and there exist many studies on service recovery and management measures, including a synthesis study by Pender et al. (2013) of 71 international transit agencies. However, the effects of these disruptions and response strategies on transit user behaviour is not well understood (Papangelis, et al., 2013). Similarly, performance indicators which are widely used in the transit industry are usually operator oriented and less passenger oriented (Barron et al., 2013), for example focusing on train delay instead of passenger delay. Furthermore, some disruption studies are sometimes event driven, conducted due to an occurrence of a major disruption that provided a great opportunity to study passenger behaviour in response to that particular disruption. While the findings can be informative, these studies have limited ability to draw more generalized conclusions. In most cases, transit user behaviour in the event of a disruption is not well understood, and as a result disruption management and recovery may not be optimal.

Of special significance are disruptions to rapid transit services which may have severe impacts on transit users' journeys and experiences. User behavioural responses can vary across different time periods such as an immediate decision-making, pre-planned intention or gradual adaptation. The immediate response happens when a disruption has just occurred and been communicated (with or without relevant information) to a passenger, and he/she has to make a make a decision quickly for a single trip; this situation can be subdivided into pre-trip and en-route scenarios. For example, a passenger encountering an en-route transit service disruption may decide to take the replacement shuttle buses (if applicable) or other buses, walk to the destination, take a taxi, or wait until the disruption is over, while finding out about the disruption before starting the trip opens up other options such as a departure time change without route change. The pre-planned response refers to planned disruptions which are announced beforehand, allowing for alternate arrangements of travel. For example, a passenger informed of a planned disruption to a particular subway route may decide to utilize the subway system on a different route, change the destination or cancel the trip during the ongoing closure and return to the original choice after the disruption (no long-term change). The gradual response occurs after multiple encounters of disruptions, leading to behavioural changes in both the short and long terms. After the disrupted trip(s), the passenger may decide to change the departure time, switch to a different route or mode, or make no changes for the next trip. In the long run, the passenger may decide to permanently switch away from this route or mode, change the destination, cancel the trip, or simply continue the same routine without changes. Table 1-1 outlines the options that are usually considered for different time periods.

**Table 1-1: Common Mode Alternatives at Different Stages**

| **Immediate action (Pre-trip and en-route)** | **Pre-planned intention (Short and long term)** | **Gradual adaptation (Short and long term)** |
|---|---|---|
| Wait until service restored (no change) | No change (long-term) | No change |
| Departure time change only (pre-trip) | Route change only | Route change only |
| Route change only | Transit mode shift | Transit mode shift |
| Transit mode shift | Mode shift | Mode shift |
| Mode shift | Destination change | Destination change |
| Trip cancellation | Trip cancellation | Trip cancellation |

The passenger experience and behaviours can also differ based on the various causes of disruptions. For unplanned disruptions, passengers have to make a decision very quickly among a limited number of options at a different emotional state. For example, passengers are likely less understanding and angrier for disruptions where the transit agency is at fault or responsible; on the other hand, malicious attacks such as bombings can affect passenger behaviours beyond the incident occurrence. Pre-planned disruptions can happen due to maintenance and upgrade or labour strike. Passengers are likely going to behave differently given that they can find out about the severity and consider viable alternatives beforehand. Additionally, there are many service-oriented and user-oriented factors that affect passengers such as the availability and media of information, duration of delay, weather, purpose of trip, comfort, and habit, to name a few. These considerations demonstrate that passenger behavioural responses and adaptations can be extremely complex, requiring a more thorough empirical investigation.

The main purpose of this research is to understand the mode choice behaviour of transit users in response to service disruptions in the immediate response situation (pre-trip and en-route), which is the most common situation faced by transit passengers. The study aims to develop a transit user mode choice model when encountering a service disruption and gain a better understanding of what factors influence the transit user's choice making behaviour.

## 1.2 Motivation

The population in the Greater Toronto and Hamilton Area (GTHA) has been rising on average by 2% annually and number of trips taken has also been increasing at the same pace (Data Management Group, 2012). The Toronto Transit Commission (TTC, local transit agency of the City of Toronto) ridership has been steadily rising at a rate of approximately 2.5% annually since 2009 and these trends are likely to continue in the near future (Toronto Transit Commission, 2016). In response to the growing ridership and demand, the TTC and Metrolinx (the regional transportation agency of Government of Ontario) have many ongoing and planned expansion projects, including many LRT, subway, and regional express rail projects across the region (Metrolinx, 2008). With the increased transit network and service, there is more exposure to delay and more passengers to be affected should a delay occurs. How the agencies manage the disruption response and recovery currently and for the expanding network is critical in the reliability and resiliency of the transit system.

While transit agencies may have strategies to reduce the likelihood of breakdowns such as preventative maintenance, malfunctioning of transit infrastructure or fleet cannot be avoided completely. In addition, external factors such as medical emergency, security, or weather are beyond the agency's control. On the other hand, planned disruptions are also not uncommon for maintenance and upgrade as well as the occasional labour strike. These disruptions and service closures likely have varying degree of impacts on the transit users. The impacts of disruptions, including the impacts on transit users, are of great interest to the transit agencies. The top priority for the agencies is to resume service as soon as possible and minimize length of closure in terms of time and distance. On the other hand, the top priority for passengers is to get to their destinations as fast as possible. The priorities do not necessarily align if the system cannot resume service immediately. Therefore, understanding the transit user behaviour can help improve the agency response that addresses both priorities.

Transit user behaviour during a disruption can be significantly different from the regular travel pattern depending on the circumstances, availability of choices, and the attractiveness of these choices. Therefore, it is important to consider transit user behaviour under conditions of service disruptions separately from their behaviour under normal conditions, in order to capture the actual decision making and trade-offs. Traditional household travel surveys do not capture travel patterns under disruption conditions; neither do customer satisfaction surveys conducted by transit agencies have details on incidents and how customers respond to service disruptions. Therefore, available survey data provide very limited information for this study and there is a clear need to collect more specific data to better understand the user behavior during service disruptions.

## 1.3 Objectives

The objectives of this research are as follows:

1. Design an individually customized joint reveal preference (RP) and stated preference (SP) survey to gain a better understanding on how different factors affect rapid transit users' mode choice behaviour in response to service disruption.

2. Develop a web-based survey tool to collect data on the respondent's mode choice in the last encounter of service disruption and in a set of hypothetical scenarios.

3. Develop a mode choice model to understand how disruptions affect transit users' commuting trips and how transit users get to their destinations, incorporating factors that are usually not considered in traditional travel survey data or mode choice models.

4. Discuss the policy implications based on the findings on transit user mode choice behaviour and make recommendations on how transit agencies can make use of this information in service response and recovery during a service disruption.

## 1.4 Methodology

A joint RP-SP survey was designed where the RP part gathers information on the respondent's actual response to the most recent service disruption while the SP part solicits the respondent's responses under a set of hypothetical but realistic service disruption scenarios using a customized disruption generator tool. The SP experimental design adopted the state-of-the-art efficient design to minimize the number of scenarios required while incorporating many important factors with different variations of each factor. A transit trip planner tool was developed to search for alternative transit options in the event of a service. Socio-demographic information was also collected in order to investigate its effect on choice behaviour.

A web-based survey was developed using Bootstrap, HTML, CSS, JavaScript, jQuery, PHP, MySQL, and cPanel. The transit trip planner tool was implemented using Google Directions API. Data collection was done online through an email invitation sent to randomly selected participants in a market research panel.

A mode choice model was developed to gain a better understanding on how transit users respond to service disruptions and what factors influence their decisions. In particular, factors associated with information availability and length of delay, which are key factors in the decision-making process but are difficult to capture, were further analyzed to facilitate a more comprehensive discussion and to reach a more generalized understanding of the effects of disruption. A joint RP-SP specification was developed to overcome the respective limitations in RP and SP data.

Policy implications based on the findings are discussed. With a better understanding of transit user behaviour, policies related to customer-oriented response and recovery strategies are discussed. The effect of information provision and media of information on transit user mode choice behaviour are also discussed.

## 1.5 Thesis Layout

There are six chapters in this thesis. The content of remaining chapters is outlined here. Chapter 2 presents an overview of the literature on transit service disruption, survey methodology, and econometric modelling. Chapter 3 provides the methodology of the Subway User Behaviour When Affected by Incidents in Toronto (SUBWAIT) survey. Chapter 4 presents the implementation of SUBWAIT survey and the descriptive statistics of the survey data. Chapter 5 presents the empirical work of the research and a discussion on policy implications. Chapter 6 highlights the research summary, research contributions and directions for future work.

# Chapter 2

# 2 Literature Review

## 2.1 Disruption Type and Frequencies

Given that different types of disruptions can result in different transit user behavioural responses and adaptations, it is important to understand what the root causes of disruptions are and classify the disruptions by type of cause. Nielsen classifies the causes of service disruptions into external and internal incidents where external events include weather, accidents, and network outages while internal events include fleet breakdown, crew shortage, and malfunctioning infrastructure (2011). Expanding on this classification, transit disruptions can generally be classified into the following four categories of causes: natural, human accidental, human intentional, and operating environment. These categories can each be subdivided, if applicable, into external causes and internal causes. External causes are instances where the transit agency has no control and the cause of incident is not related to the transit personnel or properties, while internal causes are those with some level of involvement or responsibility of the transit agency. Given that the geographic scope of this study is the City of Toronto with emphasis on rapid transit, the 2013 TTC subway incident report was reviewed to obtain the number of occurrence and duration of each type of disruption. The incidents with delays less than 10 minutes were considered minor incidents related to recurring reliability issues and thus were not included in the analysis while incidents with a 10-minute delay or longer, 627 recorded in 2013, were considered as major incidents (or simply referred to as incidents henceforth) or disruptions. Table 2-1 summarizes the types of disruptions by cause and the likely consequences with relation to transit service, while Table 2-2 provides the incident counts and average durations in the TTC rapid transit system in 2013.

All of the natural causes identified here are considered external and are weather related. Weather related incidents can result from hurricanes, thunderstorms, or blizzards and consequently flooding, power outage, and heavy snow. These natural disasters can result in a shutdown of the transit system due to damages, inoperable conditions or precautionary closures. Not surprisingly, natural causes of incidents, while rare, had the longest delays from the 2013 TTC incident report, accounting for 6 of the 8 lengthiest delays in 2013 and each lasting many hours. Furthermore, the report does not include extended closure from the July 8th storm and December 22nd storm that saw partial or full closure on all subway lines where full service was not resumed until the third day of each incident respectively (Toronto Transit Commission, 2013a; Toronto Transit Commission, 2013b). It should be noted, however, that 2013 was not a typical year and that having two major system wide weather disruptions is not a common occurrence.

Human related incidents include those occurring accidentally or intentionally. Accidental incidents include but are not limited to collisions and crashes. In the form of collisions, accidents can be external or internal depending on the involvement with other traffic or within the transit system, and they include crashes with other vehicles, the infrastructure, or other obstacles. In addition, external accidents also include passenger illnesses, passenger related issues that require assistance, or false alarms. Internal accidents on the other hand include fire incidents, operator errors, crew illnesses and crew availability issues. Accidents accounted for the majority of all 2013 subway incidents, at 56%. Approximately half of those were external, mostly due to passenger illness or injury, while the other half were internal, mostly due to fire related accidents at transit infrastructure. The average durations of delay for external and internal accidents, however, were the smallest, at 15 minutes and 19 minutes, respectively, as the incidents are usually local.

Human intentional incidents have varying degrees of consequences and can be subdivided into external and internal as well. External causes range from security issues and suicide attempts to malicious terrorist attacks. Internal causes include actions with a specific agenda, such as a pre-planned maintenance or upgrade of the infrastructure or rolling stock, as well as labour shortage in the form of a labour strike. There were no acts of terrorism in 2013 and external incidents were dominated by security issues, averaging 27 minutes of delay, 2nd longest behind weather, and accounting for 21.5% of total incidents. Pre-planned maintenance or upgrade were not included in the dataset but there were many occurrences during the weekends. There was also no labour strike of the TTC in 2013 with the last occurrence in 2008 (Toronto Transit Commission, 2008).

Operating environment disruptions can also be subdivided into external and internal causes. The external causes are network outage, such as power outage or communication outage, or external interruptions, such as the lone instance in 2013 due to wildlife. Network outages due to weather were classified under weather and as such there were no network outage incidents reported due to non-weather causes. The internal causes can be infrastructure, rolling stock or other breakdowns of the properties of the transit agency. Internal operating environment incidents contributed to 21.4% of all 2013 incidents with an average delay of 23 minutes.

**Table 2-1: Taxonomy of Disruption Causes and Consequences**

| | **External Causes<br>[length of suspension, damages to transit properties]** | **Internal Causes<br>[length of suspension, damages to transit properties]** |
|---|---|---|
| **Natural (Weather)** | Hurricanes, thunderstorms, flooding<br>Blizzards, heavy snow<br>Extreme temperature<br>[medium to long term, yes] | N/A |
| **Human Accidental (collisions, passenger and operator issues)** | Medical issues, passenger assistance required<br>False alarms<br>Collisions (external party involved)<br>[temporary to short term, (for collisions) yes] | Operator error<br>Crew illness or availability issues<br>Collisions<br>Fire, smoke, debris (fire hazard)<br>[temporary to short term, (for fire, error, and collisions) yes] |
| **Human Intentional (crime related, labour strike, maintenance)** | Security issues and terrorist attacks<br>Vandalism<br>Suicide attempt<br>Disorderly patron and assault<br>[temporary to medium term, yes] | Pre-announced or last-minute announcement of labour strike<br>Pre-announced maintenance or upgrade<br>[medium to long term, no] |
| **Operating Environment (outage, breakdown)** | Power outage<br>Communication (internet, signal) outage<br>[short to long term, usually no] | Breakdown of infrastructure or rolling stock<br>Unreliable or unsafe to operate<br>[temporary to medium term, yes] |

**Table 2-2: Summary of 2013 TTC Subway Incidents Statistics**

| | External Incidents | External Average Delay (minutes) | Internal Incidents | Internal Average Delay (minutes) |
|---|---|---|---|---|
| **Natural** | 7 | >600 | N/A | N/A |
| **Human Accidental** | 191 | 15 | 159 | 19 |
| **Human Intentional** | 135 | 27 | 0 | N/A |
| **Operating Environment** | 1 | 12 | 134 | 23 |
| **Total** | 334 | 32.3 | 293 | 21.0 |

## 2.2 Transit User Behaviour in Response to Service Disruptions

Studies on transit user response to rapid transit disruptions can be classified into four types (with number of studies reviewed in parentheses): general (5), multi-type (0), single type (1), and single event (8). General transit disruption studies are not concerned with incident types and look into service interruptions or suspensions, which were all conducted for en-route situations only. There are no multi-type disruption studies that investigate how different types of incidents affect user behaviour in a controlled environment. Single-type disruption studies have recurring disruptions so they are potentially applicable to similar incidents in the future with a focus on long-term behaviour. Studies focused on a specific event or incident tend to have larger impacts immediately after the incident and possibly in the long term. Due to their specificity, the findings may only be applicable to a particular type of disruption at a geographical area, or possibly only the incident itself if it is very unique. Given the limited number of studies in the literature, studies that implicitly considered transit user choice behaviour or include information that can infer such information are also included; only 8 of the 14 studies reviewed conducted disaggregate mode choice analysis, which is summarized in Table 2-3.

**Table 2-3: Summary of Disaggregate Transit Disruption Mode Choice Studies**

| Year | Author | Stage | Mode | Location | Disruption | Sample Size | Survey | Logit Model |
|---|---|---|---|---|---|---|---|---|
| 2014 | Bai | En-route | LRT | Calgary, Canada | General | 505 | SP | MNL |
| 2015 | Teng | En-route | Subway | Shanghai, China | General | 500, 300 | RP, SP | MNL |
| 2008 | Bachok | En-route | Commuter Rail | Kuala Lumpur, Malaysia | Derailment | 537 | SP | MNL |
| 2011 | Pnevmatikou | Pre-planned short-term | Subway | Athens, Greece | Pre-planned maintenance and upgrade | 1116 | RP | None |
| 2015 | Pnevmatikou | Pre-planned short-term | Subway | Athens, Greece | Pre-planned strike | 1944 | SP | MNL/ NL |
| 2009 | van Exel | Pre-planned short-term | Regional Rail | Netherlands | Pre-planned strike | 1263, 976 | SP, RP* | MNL |
| 2013 | Ministry of Transport | Gradual short- and long-term | Regional Rail | Wellington, New Zealand | Weather (Storm) | 1072 | RP | None |
| 2014 | Murray-Tuite | Gradual long-term | Subway | Washington DC, USA | Accident | 304 | RP | MNL |

*before and after study

The following five studies looked into general disruptions and the immediate response of passengers. Tsuchiya, Sugiyama, and Arisawa (2007) conducted a revealed preference (RP) survey that required extensive collection of reliable data during a month-long study period that saw 18 service disruptions of the regional rail systems in Japan. The study showed four possible route recommendations for users updated every minute: original route recommended, detour route recommended, no detour available (wait for service resumption), and not affected. The study, however, was focused on the traveller perception and accuracy of information provision without a thorough analysis of passengers' choice behaviour.

Fukasawa et al. (2012) conducted a stated preference (SP) survey of passenger behaviour in response to an en-route disruption in Japan to compare their departure time and level of service (local vs. express) choices between scenarios with and without information provision of the estimated travel time and crowding. The study found that there would be more instances of switching to other trains if information on alternative options was provided. Both studies in

Japan found that passengers prefer having some information about the delays even if it is not always accurate.

Bai and Kattan (2014) conducted an SP survey to study the effect of information provision on the passengers' en-route mode choice given LRT delays and found that a significant mode and transit mode shift would occur (over half) when information on the length of delay is not provided, compared to less than 25% with next train arrival information given and not too long (10 minutes). Given a headway of 3 minutes, the additional wait time that is as short as 7 minutes might induce behaviours in response to service reliability as opposed to extended delays or disruptions.

Teng and Liu (2015) used the responses from an RP survey to design the attribute levels for an SP survey for Shanghai Metro where service disruptions are rare and found that the majority of the respondents would consider the replacement shuttle bus while crowding is less important. The extensive metro system offers multiple competitive transit options such as alternative metro routes, shuttle and metro, and shuttle only (with the last option being taxi) that may not be applicable in smaller rapid transit systems.

Bachok (2008) investigated disruptions due to train derailment but it appeared that the study might be considering service suspension in general. The study considered different media of information and delay duration and found that those who have previously switched travel modes would likely to switch again (instead of waiting) but encountered challenges with findings of insignificant travel time and cost.

Only one study investigated a single type of incident (implicitly) without focusing on an event although there is little information on the transit user mode choice behaviour. The UK Department for Transport (2008) conducted a study on the experiences and perceptions of anti-social behaviour and crime. The study found that 3% of infrequent bus users or non-users did not use the bus more often due to concerns about crime and 2% of infrequent train users or non-users did not use the train more often due to the same reason. The study showed that security issues (most likely recurring) can change long-term behaviours due to psychological factors in addition to the impacts from disruptions.

The following four single-event studies reviewed pre-planned closures due to maintenance and upgrades as well as labour strikes. Mojica (2008) studied the station closure and service reduction (partial disruption) of Chicago's rail lines using smart card data and concluded that 79% of all riders continued to use rail with 8.4% for bus, 4% for non-transit and the rest unknown. There was no strong evidence of boarding time change, as a proxy for departure time change. The study found that long-term changes (post-disruption) are negligible using limited data collected 2 to 4 weeks after restoration of full service.

Pnevmatikou & Karlaftis (2011) conducted an RP study on transit mode and route choice in response to a five-month pre-announced closure of an Athens Metro Line. The results showed that 58% of the respondents took the replacement bus service, 9% switched to modes involving auto and 13% chose to walk (only 15-20 minutes between closed stations). The results provided insights on passengers' choice behaviours for pre-planned and pre-announced closures and showed a low percentage of mode switch to auto in this study. The study, however, only recruited respondents who took the closed metro line after the re-opening and thus induced sampling bias by excluding those who no longer took the same line or transit mode or those who did not transition back to transit immediately.

Pnevmatikou, Karlaftis, & Kepaptsoglou (2015) then extended the study with an SP questionnaire during a series of planned strikes and found that the joint RP-SP estimation with nested logit model performed better than the RP-only or SP-only model. The study found income, trip purpose and work schedule flexibility to be significant but only considered three options (auto, bus, and taxi) for investigating short-term and long-term behavioural changes.

Van Exel and Rietveld conducted a synthesis study on passenger behaviour in the event of a crew shortage due to a labour strike (2001) and also conducted a case study on the pre-planned and pre-announced one-day rail strike in the Netherlands in 2004 (2009). It was found that 62% of the people who intended to travel did not take the trip and 24% chose to drive. The study also showed that almost half of those who intended to travel using auto mode also changed their behaviour in anticipation of major mode shifts due to the transit network disruption. The study did a before-and-after comparison among four available options (drive, other mode, travel on another day by train, cancel trip) and found that 86% of all respondents chose the same option as their intended choice beforehand; in addition, the number increased to 91% when the last two options (no travel on the day of disruption) were combined.

The following four single-event studies reviewed unplanned disruptions due to weather, an accident, and terrorist attacks. The New Zealand Ministry of Transport (2013) conducted a study following the June 2013 storm that resulted in a 6-day partial closure of one commuter rail line and found substantial short-term changes in rail mode share for the area served by this rail line from 51% to 22% (the latter using rail and shuttle bus). More than half of the commuters in the affected area chose an earlier departure time over the closure period (short-term) despite the comparable travel times before and during peak periods. The study also showed that 11% of riders changed their departure time or mode in the long term (a month after the incident), but the agency drew the conclusion that long-term changes were not observed as a result of the storm.

Murray-Tuite, Wernstedt, and Yin (2014) studied the behavioural changes due to a fatal rapid transit accident in Washington DC and observed that 17% of Metrorail users avoided the front or rear car of the train while 10% switched to a different transit mode or travel mode. The data collection started 5 months after the incident but it was unclear whether the observations referred to the short-term or long-term changes. The study noted the sampling bias due to the data collection method which omitted passengers who no longer took transit.

Lopez-Rousseau (2005) analyzed the travel patterns after the March 2004 Madrid train bombing using aggregate data and found that both train and car trips decreased after the incident. In contrast to the 9-11 attack in the U.S., the study noted that psychological (scale of incident), cultural (car dependency), social, and political (preparedness) differences led to different behaviours, suggesting that there is a limitation in the transferability of findings.

Rubin et al. (2007) examined the short to long term effects of the July 2005 London Underground bombing and found that 30% of passengers would travel less in an SP survey 2 weeks after the incident while only 19% confirmed their reduction of travel in an RP survey 7 months after. The study noted some limitations, namely that the RP respondents might not be representative of the SP respondents or the general population and that heightened perception of threats of terrorism could have led to behavioural changes prior to the incidents which could have been incorrectly captured in post-incident survey.

## 2.3 Available Travel Mode Options

Understanding the available and feasible choices in a service disruption is important for analyzing transit user's choice behaviour. Table 2-4 shows the available modes of the eight disaggregate mode choice studies. The auto option includes auto driving, auto passenger, carpooling, and taxi. All eight mode choice studies reviewed above include the auto option and four of those subdivide the private vehicle option into various choices such as auto drive, auto passenger, and taxi. Taxi is also used as a response strategy where Munich tram passengers are offered free rides for delays less than one hour (Zeng et al., 2012). Bus bridging (providing replacement bus service for rail disruption) is the most common response for agencies with 85% of surveyed agencies implementing it (Pender et al., 2013), but it was only considered in two studies based on the nature of these studies and availability from the transit agency. Re-routing within the transit network using other routes or transit modes is also an option that some transit agencies advertise to help passengers and divert some demand to other parts of the network; Van Exel's study on rail strike was the only one without the re-routing option. Waiting (until the disruption is over and following the same route to destination) is also an option for passengers, particularly for long-distance heavy rail services or incidents with short delays. Two of the three temporary disruption studies provided this option for the survey respondents. Bai and Kattan (2014) included productive waiting (doing something) and unproductive waiting as two different options and found that 40% of the waiting passengers did not engage in any activities (unproductive) while waiting. Active transportation modes such as biking and walking are only feasible for shorter distances for subway disruptions. Destination change and trip cancellation are also possible, but are more likely for the pre-planned disruptions and gradual adaptations. Van Exel's study (2009) is the only pre-planned disruption study with the trip cancellation option (and also a trip rescheduling option); the only unplanned extended disruption study also considered trip cancellation as an option (New Zealand Ministry of Transport, 2013). With the emergence of telecommuting and flexible work hours, it is possible that trip cancellation can become a feasible and considered alternative for unplanned disruption. It is important to recognize that the available and considered choices may change throughout the trip, for example, being close enough to walk to the destination or willing to take a taxi. It is also important to provide all the possible choices to survey respondents if appropriate to obtain more accurate data.

**Table 2-4: Summary of Available Modes in Transit Disruption Mode Choice Studies**

| Year | Author | Available Modes |
|---|---|---|
| 2014 | Bai | Driving or taxi, bus, walk access to same route, productive waiting, unproductive waiting, other |
| 2015 | Teng | Other subway, shuttle direct, shuttle indirect, other (taxi) |
| 2008 | Bachok | Wait, other buses, private vehicle |
| 2011 | Pnevmatikou | Auto driver, auto passenger, bus, other subway, tram, commuter rail, bike, walk, motorbike, taxi, other |
| 2015 | Pnevmatikou | Auto, bus, taxi |
| 2009 | van Exel | Auto driver, auto passenger, trip cancellation, bike |
| 2013 | Ministry of Transport | Auto driver, auto passenger, bus, shuttle bus, bike, walk, trip cancellation, departure time |
| 2014 | Murray-Tuite | Bus, auto, bike/walk, commuter rail and seat location change |

## 2.4 Influential Factors to Transit Users

Human behaviour and decision making is extremely complex. It is essential to have a good understanding of the factors that influence transit user behaviour in the choice making process. The factors that are usually considered in the literature include travel time and cost as well as socio-demographic variables such as age and income (see Table 2-5). Based on the literature, the following factors are also believed to have a potential effect on the mode choice of travellers in response to a disruption: cause of incident, stage of trip, trip purpose, anticipated delay information, uncertainty of delay duration, attitudes (desire to experiment, habit, grievance), subjective level-of-service attributes (comfort, cleanliness), flexibility, and weather. The extent to which the aforementioned variables are considered in the literature is discussed below. From a transit user's perspective, the following information needs were identified as important in a UK study: transparency of agency, length of delay, information provision for passengers before starting their journeys, information media (live announcement preferred), acknowledgement and announcement of short delays, information on alternative routes, display of information at station, timetable display if altered, overview of service changes on website, and style of information (Passenger Focus, 2011). For customers faced with incidents en-route, the three most important pieces of information are length of delay, route alternative and reason for delay.

On the other hand, customers informed of an incident before entering the transit system have the same set of priorities in a different order: length of delay, reason for delay, and route alternative.

**Table 2-5: Summary of Attributes in Transit Disruption Mode Choice Studies**

| Year | Author | LOS variables | Other variables |
|---|---|---|---|
| 2014 | Bai | delay length, IVTT | age, gender, auto ownership, license, weather, main mode, familiarity with system, familiarity with APIS, perceived accuracy |
| 2015 | Teng | cost, relative speed, crowding | age, gender, income, luggage, purpose |
| 2008 | Bachok | travel time, trip length, cost | age, gender, vehicle ownerships, household characteristics, trip purposes, previous choice, delay information on previous trips |
| 2011 | Pnevmatikou | travel time | departure time, trip purpose, auto availability |
| 2015 | Pnevmatikou | IVTT, cost, OVTT, number of transfers | age, gender, income, employment, flexible work hours, |
| 2009 | van Exel | trip distance | age, gender, purpose, fare type, opinion on strike, opinion on union, opinion on reputation damage of agency, opinion on info provision |
| 2013 | Ministry of Transport | N/A | N/A |
| 2014 | Murray-Tuite | travel time, cost | age, gender, income, children, education, frequency of usage, 1st and 2nd preferred mode, previous experience |

Based on the literature review on different causes of disruption, it is clear that transit users prefer to know what the cause of disruption is and this information can affect their choice behaviour. None of the studies in Section 2.2 examined how different types of disruption causes, in a controlled experiment, affect the transit user choice making. In fact, many transit disruption studies are event driven, conducted due to an occurrence of a major disruption that provided an opportunity to study passenger behaviour in response to that particular disruption. While the findings can be informative, these studies have limited ability to draw more generalized conclusions.

When riders are faced with an unplanned transit service disruption, finding out about the incident before or during the trip can make a significant difference. Kattan, de Barros, & Saleemi (2013) considered pre-trip and en-route stages for the auto mode and found significant differences, especially with the option of mode switching at the pre-trip stage (22%). For transit user behaviour, all of the studies reviewed in Section 2.2 are concerned with passengers facing a service disruption during their trips. For pre-planned scenarios, most studies focused on short-term behaviours (during the closure, regardless of how long the closure is). Only Mojica (2008) considered long-term (post-disruption) behaviours but the data were limited. The long-term behaviour can have more significant implications for the transit agencies than it appears because a 10% loss of ridership during a one-month closure results in a smaller reduction in total ridership count compared to a 1% loss for the year following the closure. For gradual adaptations, short-term and long-term periods are harder to distinguish and sometimes not explicitly stated in the studies. Generally, short-term is up to a few months after the incident(s) and long-term is beyond a few months and sometimes related to recurrent major disruptions. Most studies focus on behavioural changes after a particular major disruption, providing a good opportunity to conduct such study. The impacts of recurring events are very difficult to capture and requires information over a longer period of time across many disruptions.

The purpose of the trip has been considered in several studies in terms of its effect on the transit users' choice behaviour. Not surprisingly, business and commuting trips were more likely to be shifted to another mode than cancelled for pre-planned disruptions (Van Exel & Rietveld, 2009) and unreliable metro service during partial closure led to shifts to another transit mode for work trips (Pnevmatikou & Karlaftis, 2011). Two studies that investigated en-route behavioural responses to service disruption considered trip purpose (Bachok, 2008; Teng & Liu, 2015) but there was no strong evidence on the significance of trip purpose in the choice behaviour. More investigation is needed to reach a more meaningful conclusion.

Information regarding the disruption is important for the passengers, and it is well understood that such information may not always be available to them. For the cause of disruption, the agency might not know it right away before a preliminary investigation or diagnosis; sometimes, the agency may not want to reveal the actual cause (e.g. suicide) for fear of triggering similar actions and instead opt for a generic and less transparent reference (e.g. medical emergency). Even when the cause is identified and announced, it is unlikely that all riders are made fully aware of the incident. For the length of delay, the agency usually has a ballpark estimate of the duration but in most instances, it does not share it due to the uncertainty and the possibility of heightened frustration of customers if underestimated; even if shared, not all passengers would receive the information despite multiple channels of information provision. Therefore, it is important to consider scenarios where the information is not available. Among the studies reviewed, Bai and Kattan (2014) designed scenarios between a 10-minute delay and no information while Bachok (2008) considered three different media of information (audio, visual, and text) and three different lengths of delay (30, 45, and 60 minutes). However, both studies modelled the different levels of information separately so it does not reveal the individual effect of information availability and delay duration.

While it is known that uncertainty of the delay information provided (e.g. range of estimate for delay duration) can lead to a wide range of possible responses of the transit users, it has not been well studied other than the reliability aspects of travel, which are usually considered recurring and expected. Unexpected service disruptions lead to delays where the duration is often unknown to the passengers and sometimes even to the agency.

There are other factors that are more subjective and hard to capture that may influence transit user choice-making behaviour. In addition to the commonly used variables such as travel time and cost as well as the factors mentioned above, Goodwin (2008) lists the following considerations for choosing among different modes such as a desire to experiment, habit, grievance, comfort, cleanliness, and flexibility. Desire to experiment and habit are hard to capture but may be inferred from previous experiences and choices. Murray-Tuite et al. (2014) confirmed the hypothesis that travel inertia and mode inertia would decrease the tendency to switch away from the transit mode after a fatal incident. Grievance can be explained by resentment and negative emotion towards the incidents as a reason for mode shifting, such as less frequent transit trips due to security issues (Department for Transport, 2008). Teng and Liu (2015) found that crowding is not important in disruption scenarios while Fukasawa et al. (2012) had similar findings for comfort relative to the importance of speed. Pnevmatikou et al. (2015) found that flexible work hours had a negative correlation with mode switch to auto. Depending on the duration of the disruption, it could be beneficial to consider departure time change if the disruption is known to the transit user before the start of the trip. Most studies did not consider weather conditions with the exception of the consideration of temperature by Bai and Kattan (2014), which was found significant for switching to auto.

## 2.5 Current Practice of Discrete Choice Models

Discrete choice (or qualitative choice) situations are characterized by a decision maker choosing an alternative from a finite, mutually exclusive and exhaustive choice set (Train, 1986).

McFadden provides a good overview of the discrete choice modelling and applications (1973; 1984). The study of choice behaviour includes three components: the choices available to the decision makers, the observed attributes of the decision makers, and a model to describe individual choice and behaviour and distribution of behavioural patterns in the population (McFadden, 1973). A model is a tool to explain observed phenomena using available information and intuitive assumptions. A behavioural model requires understanding of the underlying behaviour and formulating a set of rules to describe this process. In discrete choice models, RUM (random utility maximization) is a decision making rule which assumes that an individual chooses the alternative that maximizes his or her utility with some randomness (or unobserved component); in mathematical representation, the utility function consists of a systematic (representative) component and an error (idiosyncratic) component (McFadden, 1973; Manski & McFadden, 1981). The systematic component is usually a linear function of explanatory variables and the error component is a random variable with an assumed distribution (Train, 1986), as shown in Equation 1:

$$U_m = V_m + \varepsilon_m = (\beta \cdot x)_m + \varepsilon_m,$$

where U is the utility of alternative m, V is the systematic utility component of alternative m, β is a vector of the coefficients (weights) of the explanatory variables, x is a vector of explanatory variables, and ε is the error term to capture the unobserved portion of utility. In the simplest form, the probability of choosing mode m is proportional to the exponential value of the utility for mode m, as shown in Equation 2:

$$P_m = \frac{e^{V_m}}{\sum_{m'}^{M} e^{V_{m'}}} ,$$

where P is the probability of choosing mode m, and M is the total number of mode alternatives available. This formulation is very convenient because the probability of each alternative is necessarily between 0 and 1 and the probabilities of all alternatives necessarily sum up to 1.

The most widely used mathematical models in discrete choice modelling are the logit models due to their simplicity of mathematical formulation and parameter estimation (Train, 1986). The binary logit (for 2 alternatives) and multinomial logit (MNL, for more than 2 alternatives) models are the simplest forms of the logit formulation and are based on the assumption that the error terms are identically and independently distributed (IID) type I extreme value, meaning that the variance of the error terms are the same for all alternatives and are uncorrelated. This leads to the independence of irrelevant alternatives (IIA) property where the introduction of a new alternative (or removal of an existing alternative) does not change the ratio of choice probability (or relative attractiveness) of the other alternatives. In other words, alternatives are assumed to be distinct and uncorrelated and exhibit proportional substitution patterns. Such assumption can be confirmed through hypothesis testing to see if MNL is appropriate.

GEV models can overcome the IIA restriction by allowing the partition of alternatives into subsets (nests) where alternatives across subsets are uncorrelated and those within are correlated (McFadden, 1986; Train, 2002). This means that the IIA property only holds within a subset and the ratio of choice probability between two alternatives in the same subset is independent of the alternatives in other subsets. The most widely used model in the GEV family is the Nested Logit (NL) model (Train, 1986). In the NL formulation, alternatives across subsets have zero covariance and alternatives within the same subset have the same covariance. The MNL is a special case of NL where all co-variances between alternatives are 0. While IIA does not hold in NL, it has a similar property where the alternatives are independent from irrelevant nests. Sometimes an alternative may be similar to different groups of alternatives, such as park and ride to both auto and transit. In this case, the alternative may be placed in more than one nest and this type of model is called a cross-nested logit model.

Both logit and GEV models cannot represent random taste variations and capture unobserved factors over time for repeated choices such as a panel data. To overcome these restrictions multinomial probit (MNP), and mixed logit (ML) have been developed (Train, 2002). MNP assumes that the unobserved factors follow a normal distribution, though this can sometimes be inappropriate. The MNP and ML do not have closed form expressions and require simulation for their estimation. This can be computationally intensive and limit their applications in the early stages of development. However, with the advancement in computation power and the ability to overcome various limitations, probit and mixed logit models have become more widely used.

## 2.6 Current Practice in RP-SP Survey Design

The two main types of travel surveys are revealed preference (RP) and stated preference (SP) surveys. Traditionally, RP surveys collect data from a sample of respondents on trips they have made in a previous time period (e.g. the previous day). The stated preference approach was conceived in the 1960's, with applications starting in 1970's in market research (Green & Srinivasan, 1978; Kroes & Sheldon, 1988). SP data capture the preferences and choices of respondents when presented with hypothetical scenarios of various travel options that may or may not be available in the real-world transportation system at the time of the survey.

The SP approach has recently gained more traction due to several disadvantages of RP data, including limited data variation, treatment of strong correlation of variables, limitations in evaluating hypothetical conditions, and objectiveness of variables (Kroes & Sheldon, 1988). Firstly, RP data are limited to observations only and can have insufficient number and variation of the variables within the collected data to conduct insightful analysis on the effects of the variables of interest. This can also lead to incorrect conclusion of insignificance of variables simply because there is not enough variation in the observed data (Train, 2002). Secondly, the variables considered may be strongly correlated, such as travel time and cost, and it is hard to capture the effect of each variable and the trade-off in between from RP. Thirdly, RP data are based on observations and thus cannot be used to evaluate hypothetical scenarios while SP data allow for investigation of hypothetical scenarios that do not exist yet (such as a new policy or mode of transportation). Fourthly, RP data usually include objective and quantifiable measures of variables, such as travel cost and time, and the evaluation of other qualitative variables, such as comfort and convenience, is difficult due to their subjectivity. SP, on the other hand, can incorporate these subjective variables by quantifying them (e.g. crowding level for comfort) to include more variables of interest. Due to the difficulty to collect observational (RP) data, SP data collection is usually less time consuming and cheaper (Louviere 2000 Stated Choice Models).

However, SP data also have its limitations. The main issue of SP is the inherent bias or inaccuracy of the collected data, as the respondents might not actually choose the option selected in the SP survey in real life. This issue can be more prominent in situations where it is difficult for respondents to understand the hypothetical scenarios, such as creating and describing scenarios that induce long-term transit user behavioural adaptation. SP data are also subject to other biases such as policy bias and justification bias (Kroes & Sheldon, 1988; Ben-Akiva & Morikawa, 1990).

In the context of transit user behaviour under conditions of service disruption, pre-trip and en-route behavioural investigations are hard to conduct using RP surveys due to the impracticality to observe certain types and scenarios of disruptions of interest and also due to the challenge in avoiding sampling bias. RP surveys tend to target transit users who continue to use the service without behavioural changes and thus the sampling frame excludes respondents who already switched transit route, transit mode, travel mode, or made other behavioural changes. On the other hand, transit service disruptions in SP scenarios can lead to the respondent not choosing the same alternative in real life, especially because the respondent might not be making the decision completely rationally in irregular and unfamiliar situations.

Due to the issues with RP and SP data mentioned above, studies have been done to compare the performance of RP and SP data. Ben-Akiva and Morikawa (1990) compared model estimations using RP only, SP only, and joint RP-SP formulations and found that the joint model had more accurate parameter estimates. The study demonstrated that combining RP and SP together can address the limitations of each type while utilizing the strengths of both. While the RP-SP approach has overcome the issues of RP and SP respectively and has become more widely used, it has not been adopted for mode choice studies on transit disruptions.

## 2.7 SP Experimental Design

Stated preference experimental design was proposed by Louviere and Hensher (1983) and Louviere and Woodworth (1983) in order to determine the individual effects of the factors on the observed choices, which is validated through the test of statistical significance. Significance of a variable depends on the sample size, which is a major constraint. Experimental design provides multiple scenarios to a single respondent with changing attributes to collect information on the trade-offs between these attributes; these scenarios can be arbitrarily constructed by the researcher. However, designs that can maximize information gain or minimize the number of respondents required (or number of responses per respondent) are much more effective.

The consideration of experimental design includes the following: labelling of alternatives, attribute levels, attribute range, balancing attribute level, and the number of choice tasks (ChoiceMetrics, 2014). If alternatives are specific, e.g. car vs. transit, they should be labelled in general to account for the inherent properties of the alternatives. The number of attribute levels should be minimized and kept at the same number (or with a common denominator) between different attributes to minimize the number of choices required. Two levels can be sufficient to capture linear effects. Balancing of attribute levels means all attribute levels are equally represented, which is usually desired and satisfied for attributes with only two or three levels, even if it leads to suboptimal design. Sometimes, it might not be possible depending on the number of choice tasks and the number of attribute levels required. The attribute range should also be balanced and realistic such that it is not too wide to be reasonable or too small to capture the effects and lead to higher errors. The number of choice tasks (scenarios) for each respondent is a trade-off between information gain and respondent fatigue. There is no single number that should not be exceeded as the complexity of choice tasks can vary greatly so some judgement is required.

There are two main types of SP experimental design: full factorial design, where all possible choice situations (all combinations of different attribute levels of all variables) are included, and fractional factorial design, where only a subset of the full factorial design is included (ChoiceMetrics, 2014). Full factorial design is usually not feasible due to the large number of choice situations and sometimes not reasonable in terms of certain combinations of attribute levels. There are three main types of fractional factorial design: random, orthogonal, and efficient. Random design selects choice situations randomly and can lead to biased results due to unbalanced attributes. Orthogonal design requires a balancing of attribute levels since it measures the independent effects of each variable. It has been widely used due to the widespread use of simple linear models in the past that is more suitable for orthogonal design and the lack of studies to evaluate different design methods (Bliemer & Rose, 2011). However, its properties do not align with the properties of the ensuing analysis, i.e. econometric models such as the logit model formulation.

Efficient design tries to minimize the standard errors for the parameter estimates. Without the parameter estimates, the standard errors cannot be computed and minimized. However, often times some prior knowledge is available through a test survey, pilot study, intuition and basic concepts in economics (Zwerina et al., 1996). The knowledge of a parameter sign, without any information on its magnitude, is still useful. Prior estimates allow generation of choice set with utility balance and more even attractiveness or probability of choice. A dominant alternative in a choice set provides no new information but the same can happen for no dominant alternative if there is an easy choice; however, there are strategies that increase the efficiency while at the same time avoid dominant alternatives.

The asymptotic standard errors are the square roots of the diagonal of the asymptotic variance-covariance (AVC) matrix, which is the negative of the inverse of the second derivative of the log-likelihood function (ChoiceMetrics, 2014). The standard errors are proportional to the reciprocal of the square root of the sample size, so increasing the sample size can lower the standard errors. However, the incremental improvement diminishes as the sample size increases; on the other hand, finding a design with a higher efficiency can substantially lower the standard errors.

Finding the best efficient design requires using a well-defined criterion for comparison. For simplicity, a measure of efficiency is defined to evaluate the experimental design as opposed to comparing the entire AVC matrix. Several measures have been proposed, such as D-error or A-error. The most common measure of efficiency is D-error, which takes the determinant of the AVC matrix. A design with the lowest D-error is called a D-optimal design but it is very difficult to find in practice. A design with sufficiently low D-error, called D-efficient design, is usually good enough (ChoiceMetrics, 2014; Zwerina et al., 1996). Rose and Bliemer proposed that a theoretical lower bound of sample size requirement can be derived from the t-ratio of each parameter (Bliemer & Rose, 2005). They suggested that some parameters might be harder to estimate and require a much larger sample size to achieve statistical significance; it is possible that the researcher is more interested to minimize the lower bound sample size requirement, which is referred to as the S-estimate.

Huber and Zwerina showed that design without orthogonality that minimizes asymptotic standard errors of parameter estimates can increase information gain or decrease sample size while maintaining the same information gain (1996). Efficient design, in theory, should perform better than orthogonal design or at worst perform equally well with orthogonal design if no prior information can be obtained. Recent studies have shown that the efficient design outperforms orthogonal design empirically (Bliemer & Rose, 2011; Rose et al., 2008). Therefore, efficient design presents an improvement over orthogonal design, and obtaining prior estimates to construct efficient design would be crucial to make the design efficient.

## 2.8 RP-SP Data in Mode Choice Models

The method for estimating joint RP-SP mode choice models can be found in Ben-Akiva & Morikawa (1990), Hensher and Bradley (1993) and Ben-Akiva et al. (1994). For simple logit models, explicit normalization or scaling is not necessary. However, it is important to note that the unobserved factors in RP and SP are likely different (Train, 2002). In RP data, there is almost always unobserved factors as the researcher is limited to the information available and observable; in SP scenarios, sometimes respondents are asked to make choices based on attributes provided and assume all else are the same. Even though they may still make decision based on attributes not known to the researcher, the extent to which it does is still probably different from that of RP. To account for this difference, a scale parameter is introduced to quantify the relative magnitude of the variances in RP and SP. Usually RP scale is set to 1 such that the SP scale is relative to RP scale because the RP data is assumed to be the correct data reflecting actual behaviour (Brownstone et al., 2000). SP scale parameter is usually smaller than 1 and it scales down the explanatory variables because of overstating the intention of switching (Ben-Akiva & Morikawa, 1990). Scale parameters can also be used to capture other differences, such as the respondent's fatigue over a series of SP scenarios in an experimental design (Bradley & Daly, 1994). With the repeated observations in SP and also the corresponding RP observation, advanced econometric models have been developed to capture the correlation among repeated observations by the same respondent through simulation techniques. Brownstone et al. (2000) demonstrated that mixed logit models for joint RP-SP data outperform MNL models.

# Chapter 3

# 3 Survey Methodology

## 3.1 Data Needs

Transit user behaviour during a transit service disruption can be significantly different from regular and repeating trips depending on the circumstances, availability of choices, and the level of service (LOS) of various choices, and whether the transit users are aware of these choices and their LOS attributes. The primary mode choice can become unavailable due to a service disruption while sometimes alternative choices may become available (such as the replacement shuttle bus service), feasible (such as walking to destination), or considered (such as taking a cab). The level of service attributes including travel time, travel time variation, information provision, comfort, and other factors can also vary greatly and be perceived differently. Therefore, it is important to consider transit user behaviour under conditions of service disruptions separately from their behaviour under normal conditions in order to properly capture the actual decision making and trade-offs. Traditional household travel surveys do not capture travel patterns under disruption conditions; customer satisfaction surveys conducted by travel agencies do not have details on incidents and how customers respond to service disruptions either. Therefore, available survey data provide very limited information for this study and there is a clear need to collect specific data to better understand the user behavior during service disruptions.

The Subway User Behaviour When Affected by Incidents in Toronto (SUBWAIT) survey was conducted to collect data on transit user behaviour in response to rapid transit service disruption. The survey methodology is discussed in the remainder of the chapter and the survey implementation is discussed in Chapter 4.

## 3.2 Survey Study Area

The survey study area is the City of Toronto, the largest city in Canada with the largest transit system in Canada as well. The study aims to investigate rapid transit trips within the city where at least one rapid transit segment is included. The TTC rapid transit network currently includes two major subway lines (Yonge-University-Spadina Line and Bloor-Danforth Line), a third short subway line (Sheppard Line), and an LRT (Scarborough RT). Figure 3-1 shows the rapid transit system map of Toronto with 3 subway lines and 1 LRT (blue) enclosed by the city boundary (black) on Google Maps.

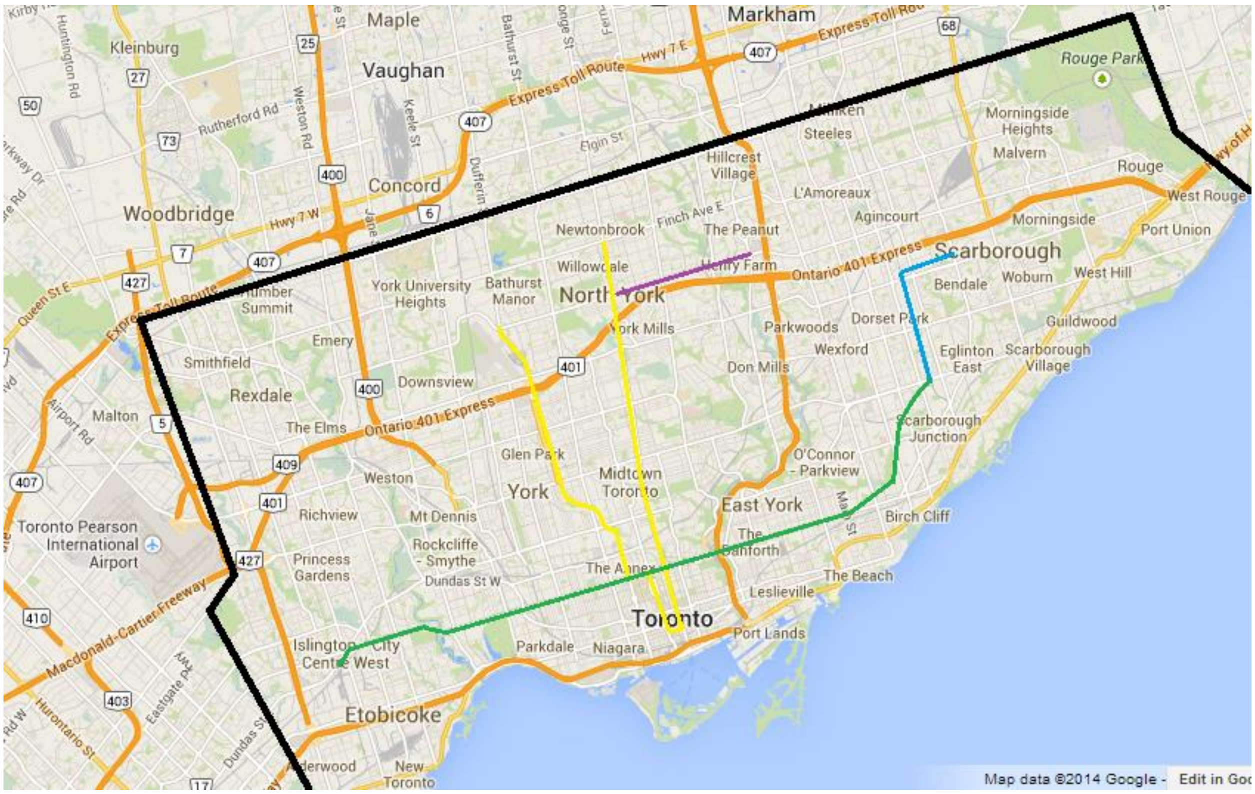


**Figure 3-1: Rapid Transit Map of City of Toronto**

This study focuses on rapid transit trips, as rapid transit is the mode subject to the highest potential impacts. Subway (Metro) services, in particular, have higher frequency than regional rail services. For this study, rapid transit trips include only rail transit with exclusive right-of-way operations (such as subway, LRT) and exclude rubber-tired transit or lower order right-of-way operations such as Bus Rapid Transit. This is due to the fundamental difference between rail rapid transit and other transit modes, where the isolation of the rail transit line makes the system unique in terms of disruption causes, recovery, alternative options for transit users, and the accessibility of those alternative options. For example, a bus that breaks down while in service can be removed more easily from a dedicated lane or general purpose lane compared to a train on a track, possibly underground. The number of stranded bus passengers is much lower than that of a subway train, and other buses along the route are not significantly impacted. On the other hand, a malfunctioning train can shut down part or all of the line indefinitely until removed and fixed.

## 3.3 Survey Sample Design

### 3.3.1 Target Population

The target population of the SUBWAIT survey is defined as 18-year-old or older users of TTC subway or Scarborough RT system for school-bound or work-bound trips that start and end in the City of Toronto. According to the Transportation Tomorrow Survey (TTS) conducted every 5 years on household travel of 5% of the population of the region, the total number of rapid transit commuters aged 18 or over within the City of Toronto is around 293,300.

### 3.3.2 Sample Unit and Method

This is a person travel survey targeting subway commuters as opposed to a household travel survey. Therefore, the sampling unit is a person. Random sampling was used to reduce selection bias.

### 3.3.3 Sample Size Estimation

The initial estimate of the sample size required given a margin of error of 0.05 and 95% confidence interval for simple random sampling, adjusted for population size, is 384 (Hasnine, A Comprehensive Study on the Effectiveness of Office-based TDM Policies, 2015). The sample size required for the survey also depends on the requirement for the D-efficient experimental design, which was found to be 610. Therefore, the higher requirement of 610 for D-efficient design determines the sample size requirement; however, only 384 is required to achieve statistical significance. The total number of invitations required would depend on the estimated contact rate, qualification rate, and completion rate.

## 3.4 Travel Mode Options

There are seven alternative mode options included in this study: auto (including taxi), waiting (and continue with subway on the same route), taking the shuttle bus, taking alternative TTC routes, biking, walking and cancelling the trip. There are three different transit options provided as a result of the transit service disruption. While cancelling trips are not considered in a typical travel survey, the effect of the disruption and the inclusion of pre-trip scenarios in this study make this option much more likely to be considered and chosen.

There are three restrictions on modal feasibility, affecting the number of alternatives available to a transit user. These include the availability of the cycling mode only for pre-trip disruptions with non-zero household bike ownership, availability of cycling only if the trip distance is less than 15 km, and availability of walking only if the distance is less than 5 km. The threshold distances for cycling and walking are higher than the usual ranges of acceptable distances with journeys possibly taking up to one hour to complete (Habib et al., 2012). This is due to the removal of the most desired alternative due to the disruption and several factors that make cycling and walking more attractive in this situation, including lowest variability of travel time, no wait time, and no availability or crowding issues. Taxi is included in the auto mode option, so possession of a driver’s license or a vehicle is not required for the auto alternative.

## 3.5 SP Experimental Design

The main advantage of SP data over RP data is the ability to capture choice behaviours in hypothetical scenarios that are otherwise difficult or impossible to obtain from RP data. The SP experiment includes different attributes and levels of potentially influential characteristics and factors, some of which are very difficult to capture in RP data, to study the effects of each attribute on the individual’s choice making. Given the importance of capturing all effects of the numerous attributes and the importance of minimizing the number of scenarios (and thus survey length) to avoid fatigue and inaccurate responses, D-efficient design will be used for the SP experiment. D-efficient design requires prior estimates of attribute parameters from similar studies or a pilot study. Since no comparable study can be found for the initial estimates of the parameters, a pilot survey was developed and conducted among the same target population as the full-scale survey.

Ngene, a software program for stated preference experimental design, was used to for the stated preference experiments for the pilot survey and the full survey (ChoiceMetrics, 2014). The utility equations were entered in the software for each alternative (mode choice) along with the attributes (variables) of interest and their levels (values). The number of scenarios was determined based on the lowest number that could generate a design in Ngene. Attribute balance in this SP experimental design was not possible because there are attributes with 4 and 5 levels in the specification (see Table 3-2). There was a total of seven SP scenarios for the pilot and the full survey.

A multinomial logit model was estimated using the pilot survey data to obtain parameter estimates from a small subset of the target population. These parameter estimates were used to re-design the SP experiments for the full-scale survey and therefore the pilot survey does not need to meet the sample size requirement or achieve statistical significance. A sample size of 50 was used for the pilot round. The pilot survey results and the re-design are discussed in Section 4.2 and 4.3.

## 3.6 Survey Instrument Design

### 3.6.1 Survey Data Model

The joint RP-SP survey consists of three main sections: RP, SP, and socio-economic information. In Section A, the RP component collects information on the individual’s last encounter of service disruption, the choice made during the disruption and the relevant information of the trip. In Section B, the SP component presents hypothetical scenarios of service disruptions by providing various attributes and levels of travel mode alternatives to the respondent to obtain his or her stated choices and the effects of individual variables on the choices made. In Section C, background and socio-economic information captures individual and household characteristics to analyze the demographics and its representativeness of the population. The survey data model is presented in Figure 3-2.

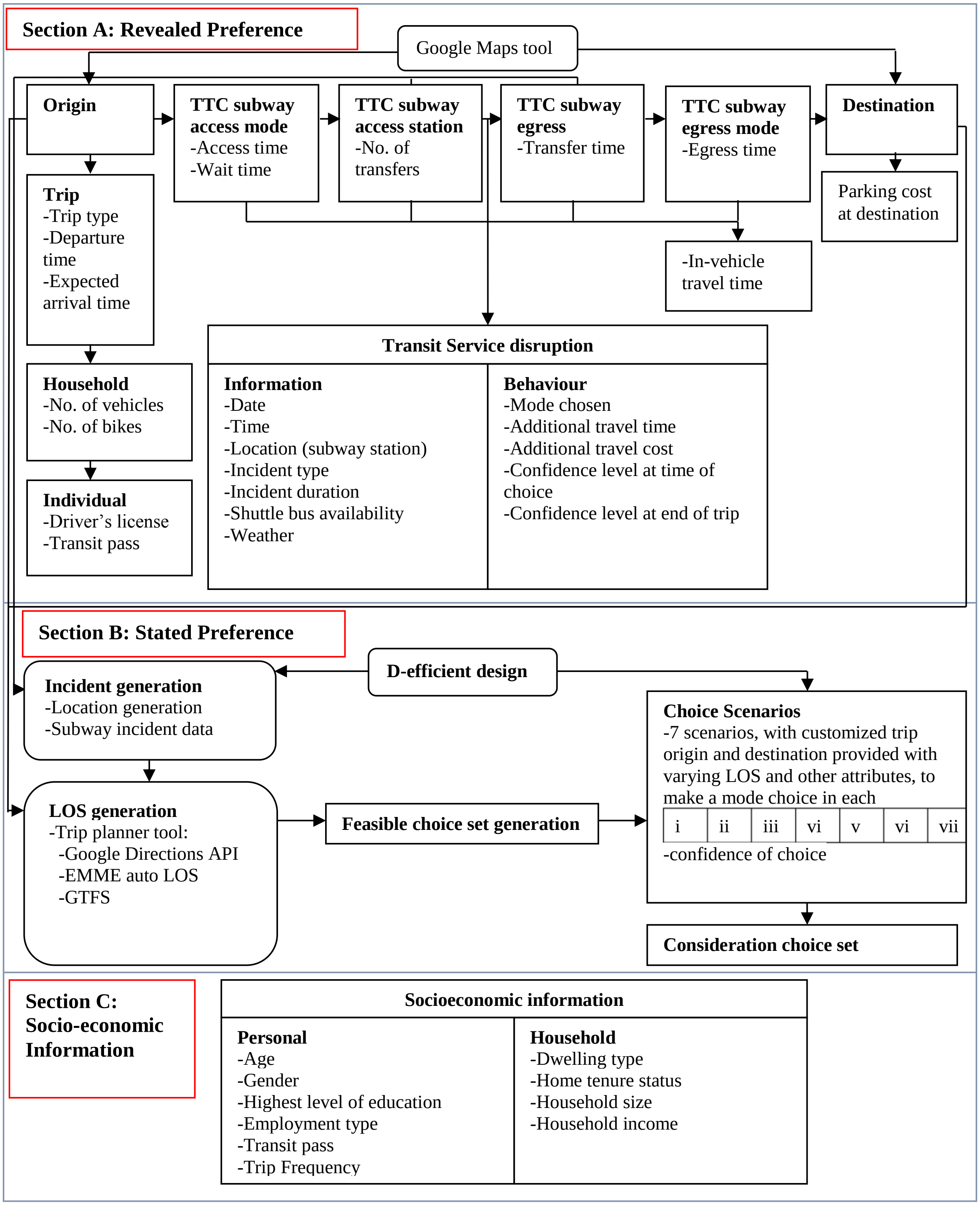


**Figure 3-2: Survey Data Model**

### 3.6.2 Trip Planner Tool

The survey provides hypothetical scenarios reflective of the respondent's usual commute by customizing the trip using the origin-destination (OD) pair of the respondent's commute. The attributes for these scenarios can be specified by either constructing a trip planner tool that can compute alternative routes online or looking up the level of service attributes for a particular OD zone pair from a pre-calculated attribute table. The trip planner is more accurate and reflective of the respondent's actual OD pair but requires extensive design and testing of the trip planning application as well as online computation of all the required trip attributes for each alternative. On the other hand, the lookup table allows computation of all required attributes offline at a zonal aggregate level for each mode without providing the route using a network assignment model. Based on the trade-offs between complexity, computation efficiency and accuracy, both methods were utilized. The auto travel time and cost were retrieved from the EMME network assignment model (a travel demand modelling system for transportation forecasting developed INRO) using 2011 trip data and 2012 network model. The taxi cost was calculated based on the published cab fare from the City of Toronto website (City of Toronto, 2016). The access, egress, in-vehicle time, transfer time, and number of transfers were calculated for all choices involving transit using the trip planner to enable generation of multiple routes. Cycling and walking distance is calculated offline using GPS coordinates.

Google Directions API (application programming interface) was used to construct the mode and route alternatives for the customized trip planner tool. While Google API can retrieve transit mode specific travel times (e.g. with subway or with surface transit), it cannot be instructed to remove or block a specific segment of the subway line to represent a transit service disruption scenario. This was found to be problematic because the best alternative route often times involves using the subway in the non-disrupted section. The trip planner tool was later modified such that the API would be used for surface transit only and the subway travel time and transfers were pre-calculated offline using GTFS (General Transit Feed Specification) data for each pair of subway stations to provide realistic and competitive options to get to the destination.

### 3.6.3 Section A: Revealed Preference

In Section A, the following information is collected regarding the respondent's last encounter of subway service disruption: origin and destination of the commuting trip, TTC subway access station, access mode, egress station, egress mode, number of subway/LRT transfers, date and time of last encounter of service disruption, location (subway station) of disruption, incident type, length of disruption (delay), purpose of trip, departure time, expected arrival time, parking cost at destination, weather condition, information provided pre-trip and en-route, availability of replacement bus service, chosen alternative, additional travel time, additional travel cost, possession of a driver's license, household bike and auto ownership. The Google Maps API was used for the respondents to enter the origin and destination of the trip so it can be geocoded based on a variety of inputs (address, postal code, name of place) and displayed on a map.

### 3.6.4 Section B: Stated Preference

The attributes to be included in the survey are various factors that can influence transit user behaviour. There are many variables of interest and relevance but only the 10 most important attributes were selected to be varied in the survey to limit the length of the survey. In order to minimize the total number of possible scenarios, all but two of the attributes have only two levels, which are deemed sufficient to distinguish among different circumstances. The only exceptions are the disruption type by cause where the top three incident categories were included. The list of disruption types is discussed in the following paragraph and the list of all other attributes and their levels is summarized in Table 3-1.

**Table 3-1: Summary of SP attributes and levels**

| Attribute name | First level | Second level | Third level | Fourth level |
|---|---|---|---|---|
| **Stage of trip** | Pre-trip disruption | En-route disruption | | |
| **Weather condition** | Comfortable | Not comfortable (heat, cold, snow, extreme temp) | | |
| **Incident type** | No information | Signal or train problem | Medical emergency | Fire investigation |
| **Delay information on subway** | Unavailable | Available | | |
| **Length of delay or wait time (subway) [1]** | 25 minutes | 50 minutes | | |
| **Accuracy of delay duration (subway) [1]** | Up to 10 minutes longer | Up to 30 minutes longer | | |
| **Wait time (delay) information on replacement shuttle** | Unavailable | Available | | |
| **Length of delay or wait time (shuttle) [2]** | 10 minutes | 20 minutes | | |
| **Accuracy of delay duration (shuttle) [2]** | Up to 5 minutes longer | Up to 20 minutes longer | | |
| **Auto cost [3]** | Pre-trip normal | En-route low (-25%) | En-route normal | |
| **Transit cost [4]** | $0 | $2.9 | | |

[1] dependent on “Delay information on subway”; [2] dependent on “Wait time information on shuttle”; [3] dependent on “Stage of trip”, low level for alternative ride hailing service; [4] entirely dependent on “Stage of trip” (fixed)

The following types of disruption will be considered in the survey: breakdowns of subway infrastructure or fleet (with signal and train problems being the most frequent), medical emergencies (caused by passenger illness, contact with train or other injuries), and fire investigations (mostly smoke or odour of smoke at track or on platform) (see Table 2-1). The other types of disruptions occur less frequently and have been excluded. There is also an additional level for the lack of information on the disruption type to represent situations when passengers are not informed of the type of incident.

A hypothetical disruption event needs to be created before the SP experiment can be constructed. A disruption generator tool was developed based on the respondent's commuting route, the frequency of service disruption at each station, and how disruptions propagate across the system. The location of disruption was selected from the list of subway stations that the respondent passes by to create realistic scenarios that the respondent can easily relate to or may have encountered before. The station selection was randomly generated based on the relative probability (frequency) of incident occurrence at each station in the 2013 incident report. This weighted probability helps account for the higher incident frequency at certain stations or segments, such as those near the terminal stations or yards as shown in Figure 3-3 on Google Maps. Once the location (subway station) of the disruption was determined, the segment of the subway line that would be closed was determined based on track cross-over location so that the "new" origin of the en-route disruption scenario could be presented (while the pre-trip origin remains the same) along with the level of service attributes for the respondent. This process was repeated for each SP scenario so the respondent would likely see a number of different disruption locations in the set of seven scenarios.

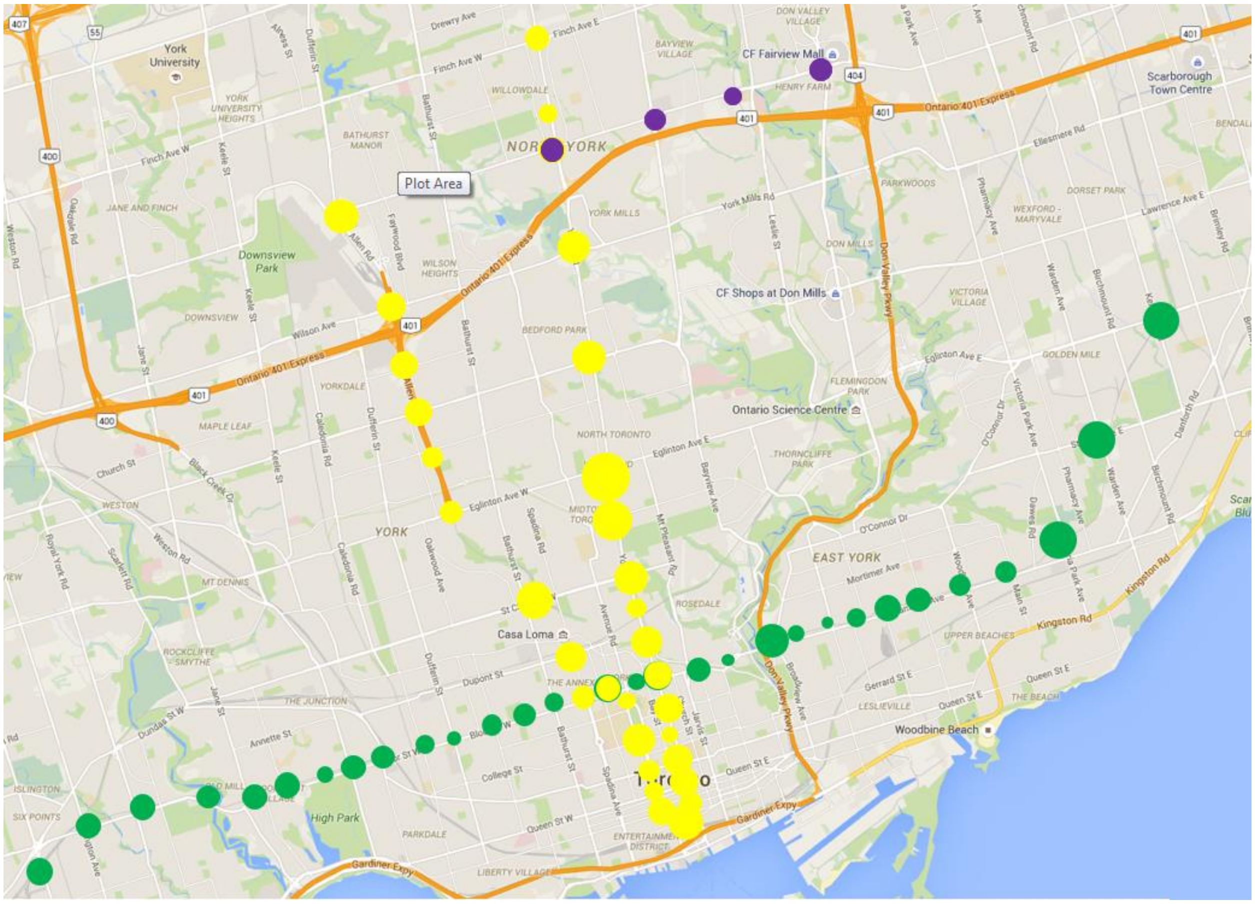


**Figure 3-3: Incident Frequency by Station in 2013 (10 minutes delay or longer)**

The SP scenarios were created by changing the attribute levels of different variables based on D-efficient design using the Ngene software (ChoiceMetrics, 2014). Each respondent was presented with seven scenarios with up to seven alternatives and asked to select a preferred mode choice for each of the scenarios as well as indicate a confidence level for each choice. Upon completion of the last scenario, the respondent was asked to identify the alternatives in the presented choice set he/she considered while making these choices because the respondent might not consider all possible alternatives provided in the choice set. The seven SP scenarios are summarized in Table 3-2.

**Table 3-2: SP Scenarios with Attribute Levels**

| Scenarios | Stage | Weather | Shuttle Delay | Type | Subway Delay |
|---|---|---|---|---|---|
| **1** | En-route | Not Comfortable | 10-30 | Signal/Train Breakdown | 25-55 |
| **2** | En-route | Comfortable | 20-40 | Fire Investigation | 25-35 |
| **3** | At home (pre-trip) | Comfortable | Unknown | Medical Emergency | Unknown |
| **4** | At home (pre-trip) | Comfortable | 20-25 | Unknown | Unknown |
| **5** | At home (pre-trip) | Comfortable | Unknown | Medical Emergency | 25-35 |
| **6** | En-route | Not Comfortable | 10-30 | Signal/Train Breakdown | 50-60 |
| **7** | En-route | Not Comfortable | 10-15 | Fire Investigation | 50-80 |

### 3.6.5 Section C: Socio-demographic Information

The socio-economic information includes those pertaining to the individual and his/her household. Household information includes dwelling type, home tenure status, household size, and household income. Individual information includes age, gender, highest level of education, employment type, student status, possession of a TTC monthly Metropass, and subway trip frequency.

Chapter 4

# 4 Survey Implementation and Data Collection

## 4.1 Data Collection

The date collection was done in September of 2016 for pilot the survey and in October to early December of 2016 for the full-scale survey with the help of a market research company. The average completion time for the survey was 12 minutes. The survey has been approved by the Research Ethics Board of the University of Toronto. Respondents were randomly selected from a panel of survey participants who previously agreed to be contacted. Invitations to the online survey were sent by email from the market research company. Feedback from the pilot survey was reviewed and improvements were made prior to the launch of the full-scale survey.

## 4.2 Pilot Survey Result

A multinomial logit model was estimated using Biogeme (Bierlaire, 2003). Despite a small sample size, the t-stats for some key variables such as travel time and cost were high. Table 4-1 shows the summary statistics for the pilot model.

**Table 4-1: Pilot Summary Statistics**

| Variables | Values |
|---|---|
| **Final log-likelihood** | -286.277 |
| **Null log-likelihood** | -338.86 |
| **Adjusted rho-square** | 0.093 |
| **Number of individuals** | 50 |

The parameter estimates are presented in Table 4-2 and with the corresponding utility equation shown in Table 4-3. The signs of the parameters match with general intuition. The following variables are categorical: stage of trip (at origin), weather, subway incident type (cause), and availability of information (subway info and shuttle info). The units for time, delay and delay range variables are in minutes while the cost variables are in Canadian dollars. The subway incident type (cause) parameters are in reference to an unknown subway incident.

**Table 4-2: Parameter Estimates for Pilot Survey Data**

| Name | Parameter | t-statistic |
|---|---|---|
| ASC_AUTO | 0 (fixed) | |
| ASC_BIKE | 0.616 | 0.72 |
| ASC_CANCEL | -2.14 | -2.47 |
| ASC_OTHERTTC | 0.687 | 1.5 |
| ASC_SHUTTLE | 0.518 | 0.99 |
| ASC_SUBWAY | -0.586 | -0.62 |
| ASC_WALK | 1.51 | 2.5 |
| B_AT_ORIGIN | 0.702 | 0.88 |
| B_BAD_WEATHER_ACTIVE | -1.55 | -2.13 |
| B_BAD_WEATHER_AUTO | 0.183 | 0.44 |
| B_BAD_WEATHER_CANCEL | -0.293 | -0.39 |
| B_CAUSE_FIRE | 0.875 | 1.16 |
| B_CAUSE_MEDICAL | 1.39 | 1.54 |
| B_CAUSE_SUBWAY | 1.74 | 1.85 |
| B_COST | -0.0276 | -2.1 |
| B_SHUTTLE_DELAY | -0.116 | -2.55 |
| B_SHUTTLE_DELAY_RANGE | -0.0158 | -0.56 |
| B_SHUTTLE_INFO | 1.11 | 1.42 |
| B_SUBWAY_DELAY | -0.0812 | -2.93 |
| B_SUBWAY_DELAY_RANGE | -0.033 | -0.95 |
| B_SUBWAY_INFO | 1.82 | 1.4 |
| B_TIME | -0.0323 | -3.82 |

**Table 4-3: Utility Equations for Pilot Design**

| Name | Specification |
|---|---|
| **SUBWAY** | ASC_SUBWAY * one + B_TIME * SUBWAY_TT + B_COST * SUBWAY_COST + B_SUBWAY_INFO * SUBWAY_INFO + B_SUBWAY_DELAY * SUBWAY_DELAY + B_SUBWAY_DELAY_RANGE * SUBWAY_DELAY_RANGE + B_CAUSE_SUBWAY * CAUSE_SUBWAY + B_CAUSE_MEDICAL * CAUSE_MEDICAL + B_CAUSE_FIRE * CAUSE_FIRE |
| **SHUTTLE** | ASC_SHUTTLE * one + B_TIME * SHUTTLE_TT + B_COST * SHUTTLE_COST + B_SHUTTLE_INFO * SHUTTLE_INFO + B_SHUTTLE_DELAY * SHUTTLE_DELAY + B_SHUTTLE_DELAY_RANGE * SHUTTLE_DELAY_RANGE |
| **OTHERTTC** | ASC_OTHERTTC * one + B_TIME * OTHERTTC_TT + B_COST * OTHERTTC_COST |
| **AUTO** | ASC_AUTO * one + B_TIME * AUTO_TT + B_COST * AUTO_COST + B_BAD_WEATHER_AUTO * BAD_WEATHER |
| **CANCEL** | ASC_CANCEL * one + B_TIME * CANCEL_TT + B_BAD_WEATHER_CANCEL * BAD_WEATHER + B_AT_ORIGIN * AT_ORIGIN |
| **BIKE** | ASC_BIKE * one + B_TIME * BIKE_TT + B_BAD_WEATHER_ACTIVE * BAD_WEATHER |
| **WALK** | ASC_WALK * one + B_TIME * WALK_TT + B_BAD_WEATHER_ACTIVE * BAD_WEATHER |

## 4.3 Re-design of SP Experiments

The estimated parameters in Table 4-2 provide an improvement over the initial (pre-pilot) estimate used to generate the pilot design and these estimates was used to generate the SP experimental design for the full survey. The updating of these parameters makes the final design more efficient due to the usage of reliable prior estimates. More information on efficient design and parameter updating can be found in Hasnine (2015) and ChoiceMetrics (2014).

## 4.4 Implementation for Full-Scale Survey

The full-scale survey was conducted in the fall of 2016 from October to early December. The full survey implementation statistics are summarized in Table 4-4. There was a total of 2,478 invitations sent with 2,288 accepted invitations, giving a contact rate of 92%. The high contact rate can be attributed to the long period of availability to fill out the survey and the reminders sent to the respondents to participate. Most of the participants who accepted the invitation qualified for the survey, with a total count of 2,052 and a qualification rate of 90%. The total number of complete responses is 556, giving a completion rate of 27%. The overall response rate for this study is 24%.

**Table 4-4: Full Survey Implementation Statistics**

<table>
<tr><td rowspan="2">Number of invitations sent</td><td rowspan="2">2,478</td><td colspan="4"></td></tr>
<tr><td rowspan="2">Contact rate</td><td rowspan="2">92%</td><td colspan="2" rowspan="2"></td></tr>
<tr><td rowspan="2">Number of invitations accepted</td><td rowspan="2">2,288</td></tr>
<tr><td rowspan="2">Qualification rate</td><td rowspan="2">90%</td><td rowspan="4">Response rate</td><td rowspan="4">24%</td></tr>
<tr><td rowspan="2">Number of qualified respondents</td><td rowspan="2">2,052</td></tr>
<tr><td rowspan="2">Completion rate</td><td rowspan="2">27%</td></tr>
<tr><td rowspan="2">Number of complete responses</td><td rowspan="2">556</td></tr>
<tr><td colspan="4"></td></tr>
</table>

## 4.5 Descriptive Data Statistics

As shown above, there are a total of 556 completed survey responses. However, the RP section has fewer responses for two reasons: (1) some respondents have not experienced a major disruption in the past year and (2) some respondents reported a disruption not on their commuting trip and thus we do not have enough information to model their choice behavior. It was also found that the RP data was difficult to process automatically without misinterpreting the data. Therefore, all RP trip records were reviewed manually by re-creating the scenario using the data available in order to ensure high accuracy of the data, especially when some of the information was missing or could not be recalled by the respondent. The final RP data set contains 414 records, including 324 work-bound or school-bound trips and 90 homebound (return) trips from work or school. It is also important to note that while the survey asked for the experience of a major subway disruption, some respondents reported a non-major disruption or a potential major disruption that resulted in minor delay in the end. These trip records were all kept in the final data set.

### 4.5.1 Revealed Preference Data

There are no comparable datasets to compare to the mode split of SUBWAIT survey and it is expected that the mode split would differ from a typical RP travel survey due to targeting of the subway users only and the unavailability of their most preferred mode during a service disruption. The RP data indicated that the majority of the respondents reported experiencing a subway delay within the last two weeks of completing the survey, while trip records of respondents reporting a disruption more than a year ago were not included. Figure 4-1 shows the RP mode split of SUBWAIT survey. Nearly two-thirds of the respondents chose to wait for the subway to resume services and continued on the same route to destination. As mentioned above, some of the choices were made in situations where the disruption was not necessarily a major disruption. Walking to the destination was the second most chosen option at 11%. As discussed in Section 3.4, walking is assumed to be considered when the total walking distance is less than 5 kilometres, (i.e. 60 minutes of walking time assuming an average walking speed of 5km/h); among those respondents, the percentage that chose walking is 24%. Taking the shuttle buses is the third most chosen option at 10%. Similar to walking, shuttle buses were not available or considered by the respondent for the majority of the incidents; among those 96 respondents that recalled shuttle buses being deployed, 42% took the shuttle bus. The other TTC option includes using all transit modes of the TTC to get to the destination: buses, streetcars, and subway lines or segments not affected by the disruption. There were only 2 records of trip cancellation upon encountering a service disruption. Of the 6 respondents that had biking as an option (based on the mode availability discussed in 3.4), none of them chose to bike to their destination.

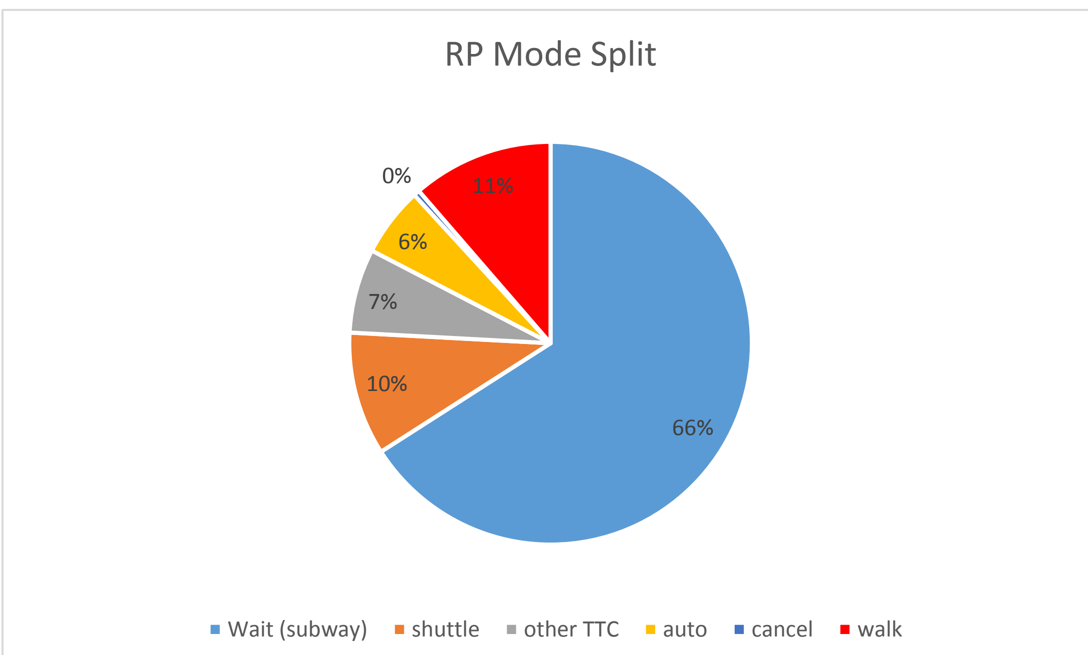


**Figure 4-1: RP Mode Split**

Figure 4-2 shows the mode share of walking to destination by the distance to the destination. There were no trip records where the distance was less than 500 m; this is not surprising as the trip makers would most likely be at least one subway station away from their destination to be affected by the disruption. For mode choice studies in the GTHA, walking is usually considered feasible if the distance is less than 3 km (Habib et al., 2012). However, in the event of a subway disruption where the subway option is not immediately available and other options may be affected by worse traffic in the road network, the trip makers may be willing to walk longer given that it is the most reliable mode of transportation and there is no wait time. This is evident in Figure 4-2 where 30% of trip makers chose to walk for distances between 3 km and 3.5 km. However, once the distance exceeds 4.5 km (which is approximately 54 minutes of walking time), the mode share of walk option drops to 0%. This trend in walking mode share confirmed the assumption in SP scenarios where walking is only available if the distance is less than 5 km.

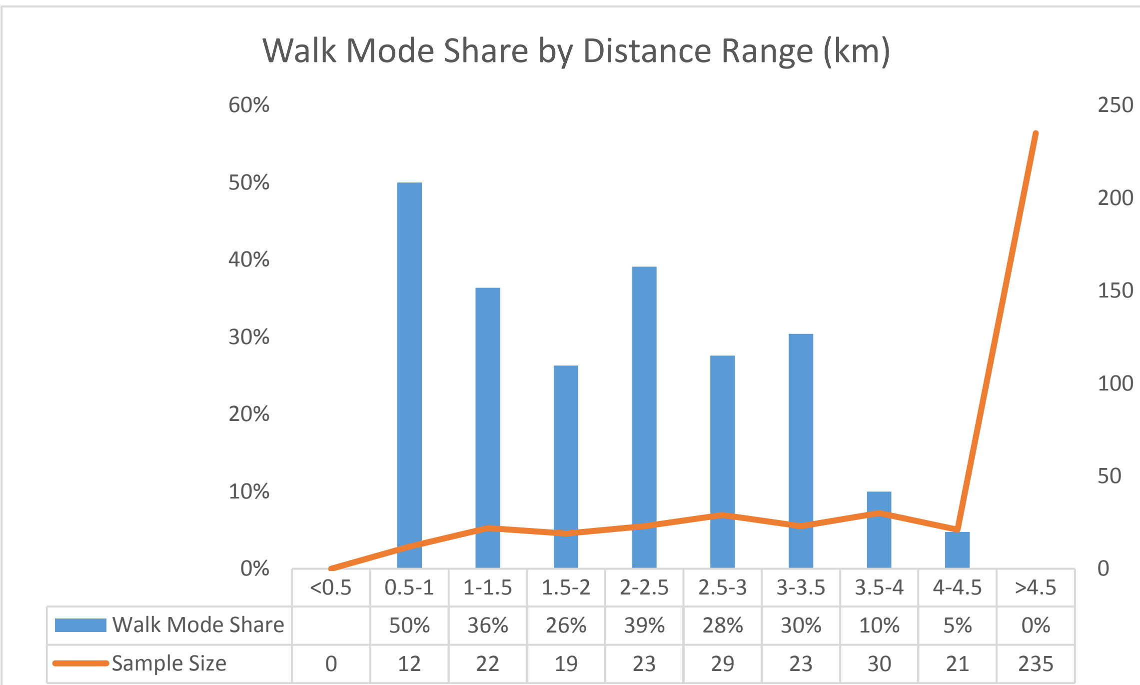


**Figure 4-2: Walk Mode Share by Distance Range**

### 4.5.2 Stated Preference Data

As discussed earlier, there are no comparable studies for comparison of mode splits. The mode splits for the SP data is shown in Figure 4-3. When there is a major disruption and travel time information on all options is given, the most chosen option in the hypothetical scenarios is using other TTC routes to get to the destination (39%). Taking the shuttle buses, assumed to be available in all SP scenarios, were the second most chosen option at 17% while driving or taking the taxi was a close third at 16%.

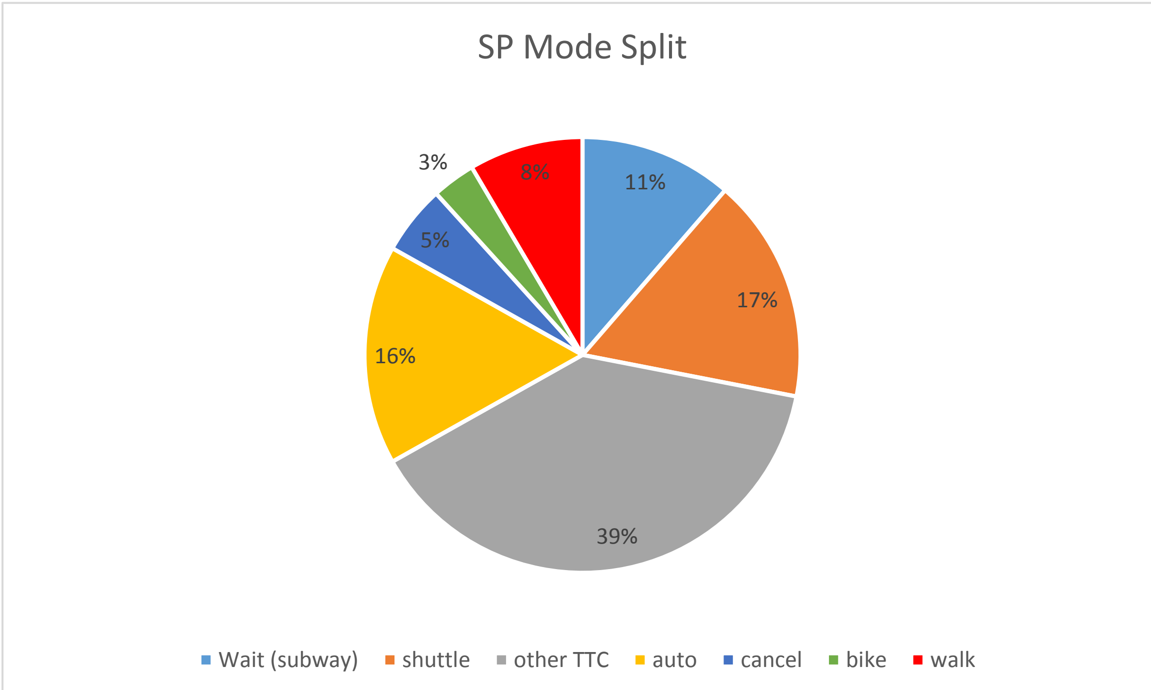


**Figure 4-3: SP Mode Split**

The mode splits by different categorical SP attributes are shown in Table 4-5. When informed of a major subway disruption before the start of the trip, a higher percentage of respondents wait for the subway to resume service (or hope that the service is resumed by the time they reach the subway station). When the weather is not comfortable (e.g. extreme temperature or heavy rain/snow), respondents are more likely to choose the auto option and less likely to use active modes. When subway delay information is given and respondents were told that there is a major disruption, a much lower percentage of respondents chose to wait for the subway. On the other hand, when the shuttle delay information is given, a higher percentage of respondents chose to take the shuttle bus.

**Table 4-5: SP Mode Split by SP Categorical Variables**

| Stage of trip | Wait | Shuttle | Other TTC | Auto | Cancel | Bike | Walk |
|---|---|---|---|---|---|---|---|
| Not at origin | 8% | 21% | 39% | 17% | 5% | 0% | 9% |
| At origin | 15% | 11% | 38% | 16% | 5% | 8% | 7% |
| **Weather** | | | | | | | |
| Good weather | 15% | 12% | 39% | 15% | 5% | 6% | 9% |
| Bad weather | 7% | 24% | 39% | 18% | 5% | 0% | 7% |
| **Subway delay info** | | | | | | | |
| No subway delay info | 19% | 9% | 36% | 15% | 6% | 7% | 7% |
| With subway delay info | 8% | 20% | 40% | 17% | 5% | 2% | 9% |
| **Shuttle delay info** | | | | | | | |
| No shuttle delay info | 14% | 13% | 37% | 16% | 5% | 7% | 7% |
| With shuttle delay info | 10% | 18% | 39% | 16% | 5% | 2% | 9% |
| **Overall** | 11% | 17% | 39% | 16% | 5% | 3% | 8% |

The mode splits by different length of delay variables are shown in Table 4-6. When a longer subway delay is provided, respondents are proportionally choosing the wait option less often; this is observed similarly for shuttle delay on choosing shuttle buses. When a longer subway delay variation or a higher uncertainty is provided, respondents are proportionally choosing the wait option less often, but not by a big margin. The shuttle delay variation does not show a big difference between the two levels of variability.

**Table 4-6: SP Mode Split by SP Delay Variables**

| Subway Delay Length | Wait | Shuttle | Other TTC | Auto | Cancel | Bike | Walk |
|---|---|---|---|---|---|---|---|
| 25 minutes | 11% | 16% | 41% | 16% | 4% | 3% | 11% |
| 50 minutes | 4% | 26% | 39% | 18% | 6% | 0% | 6% |
| **Shuttle Delay Length** | | | | | | | |
| 10 minutes | 7% | 24% | 39% | 18% | 5% | 0% | 7% |
| 20 minutes | 16% | 10% | 40% | 14% | 5% | 4% | 12% |
| **Subway Delay Variation** | | | | | | | |
| Up to 10 minutes more | 9% | 17% | 40% | 16% | 5% | 3% | 10% |
| Up to 30 minutes more | 7% | 24% | 39% | 17% | 4% | 0% | 8% |
| **Shuttle Delay Variation** | | | | | | | |
| Up to 5 minutes more | 11% | 18% | 39% | 16% | 6% | 4% | 7% |
| Up to 20 minutes more | 10% | 19% | 40% | 17% | 5% | 0% | 10% |
| **Overall** | 11% | 17% | 39% | 16% | 5% | 3% | 8% |

One of the limitations of the SP data is that respondents might not necessarily make the same choices in real life. In the SP scenarios, a question was added after the scenario about the likelihood of making the same choice in real life to better understand the confidence or certainty of their choices. Figure 4-4 shows the distribution of the likelihood. Less than 4% of the choice scenarios would be unlikely or very unlikely chosen in real life.

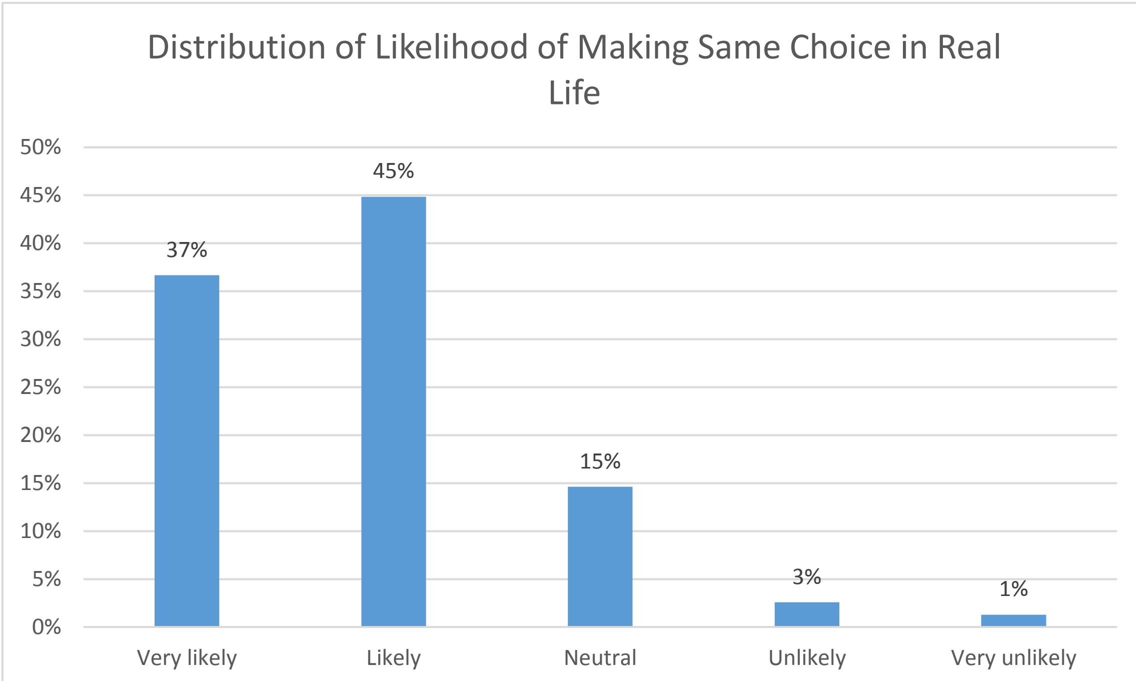


**Figure 4-4: Distribution of Likelihood of Making Same Choice in Real Life**

### 4.5.3 RP and SP Comparison

The RP and SP mode splits of this study are presented in Figure 4-5 where the inner ring represents the RP data and outer ring represents the SP data. The percentage of waiting is much higher in the RP data. The percentage of staying in the transit system (combining wait, shuttle and other TTC routes) is also higher in the RP data. The mode splits for biking and cancelling trips are also much higher in SP as these options are not necessarily available or considered in general in the revealed preference context.

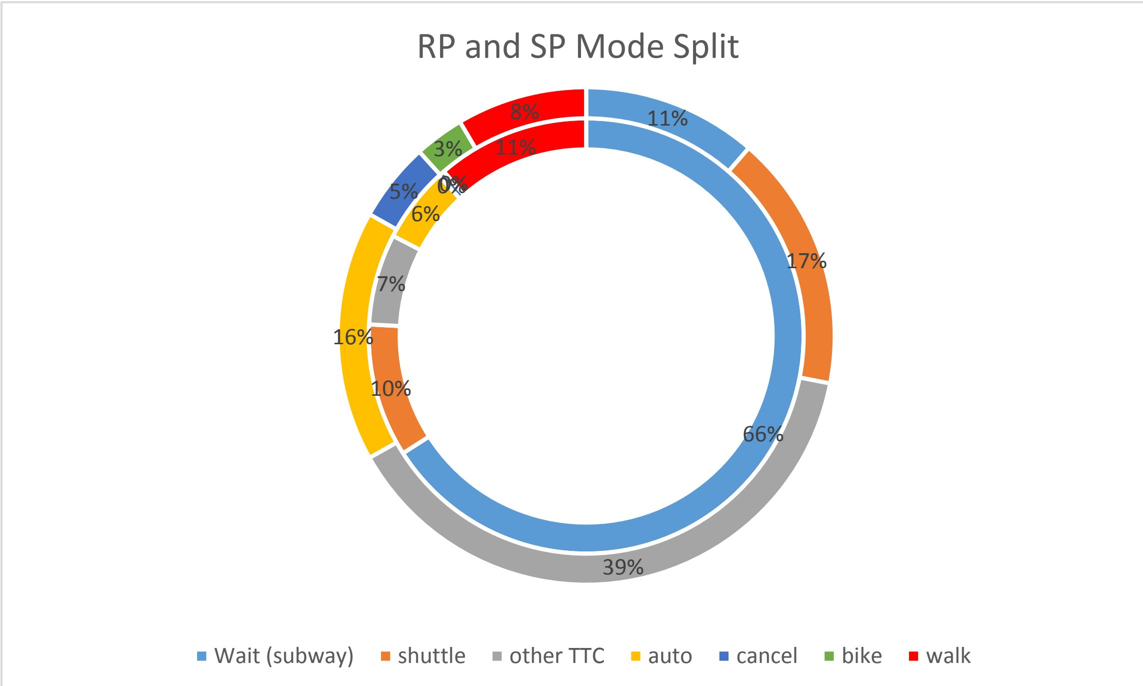


**Figure 4-5: RP and SP Mode Split**

## 4.5.4 Socio-demographic Information

The socio-demographic distribution of the 556 respondents in the SUBWAIT survey is compared against the 2011 Transportation Tomorrow Survey. The socio-demographic information pertaining to individuals are presented in Figure 4-6, Figure 4-7, Figure 4-8, and Figure 4-9. The SUBWAIT survey has a lower percentage of the population who are 24 years old or younger compared to that of the TTS and this is possibly due to the small sample size and the difficulty reaching young respondents.

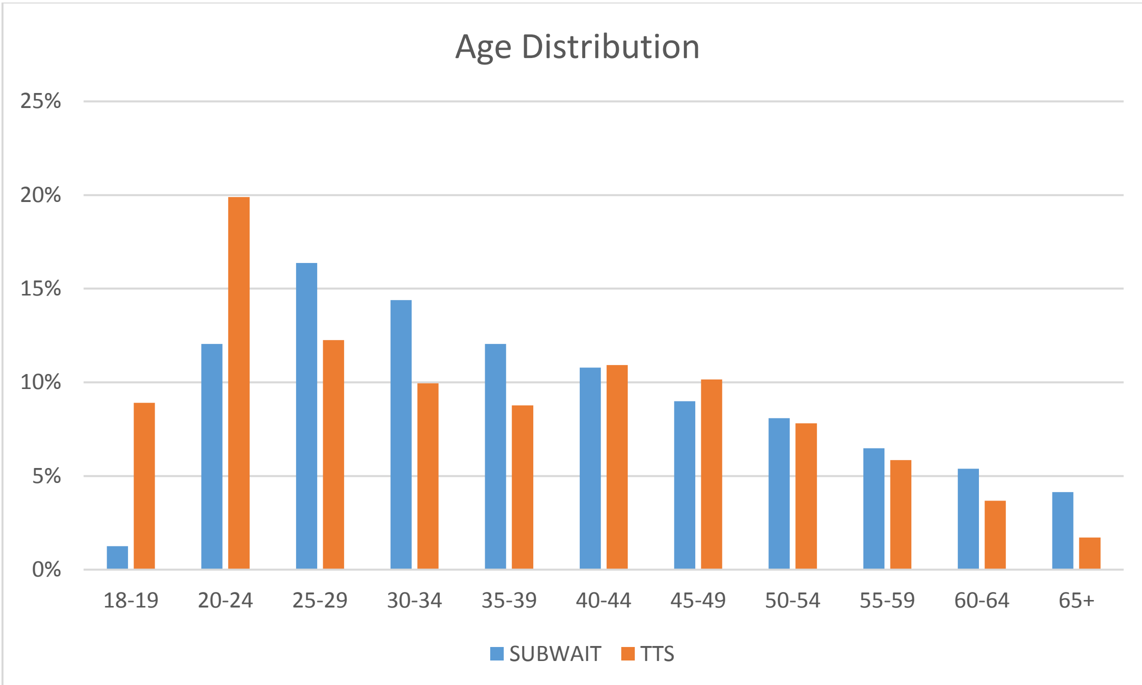


**Figure 4-6: Age Distribution**

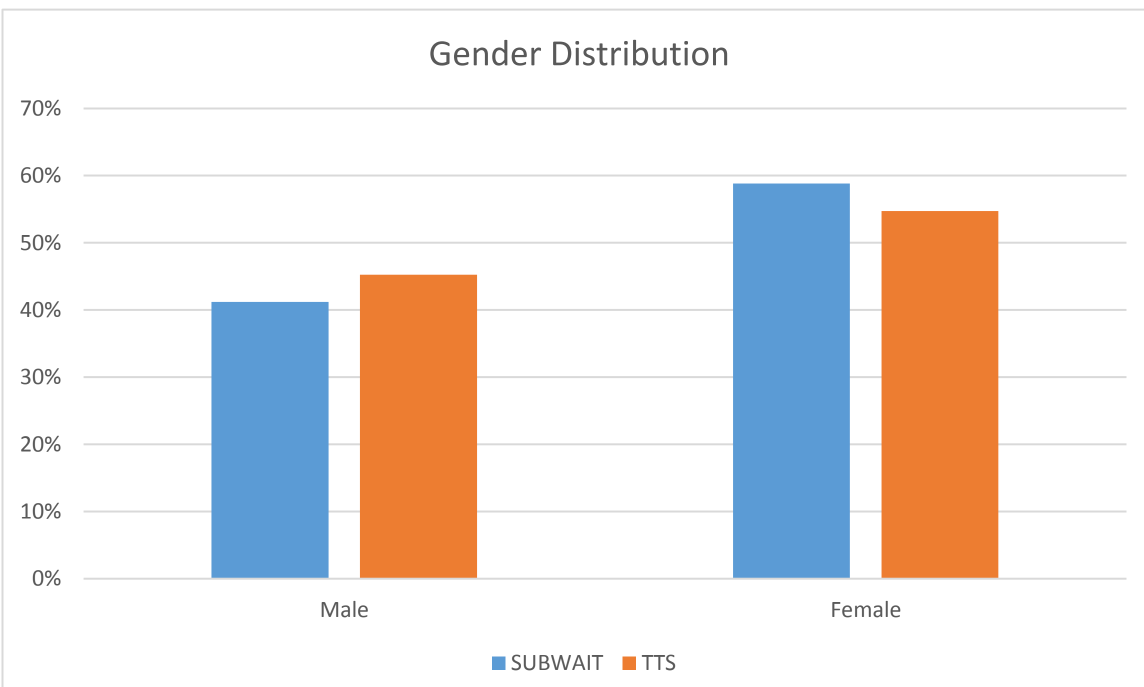


**Figure 4-7: Gender Distribution**

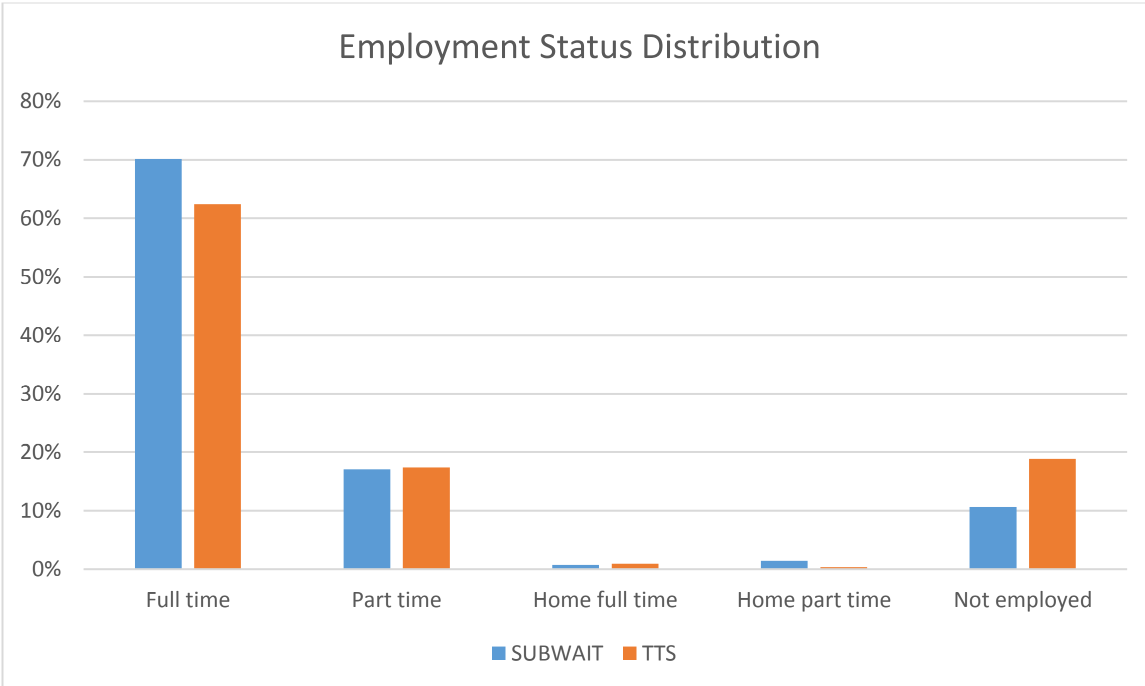


**Figure 4-8: Employment Status Distribution**

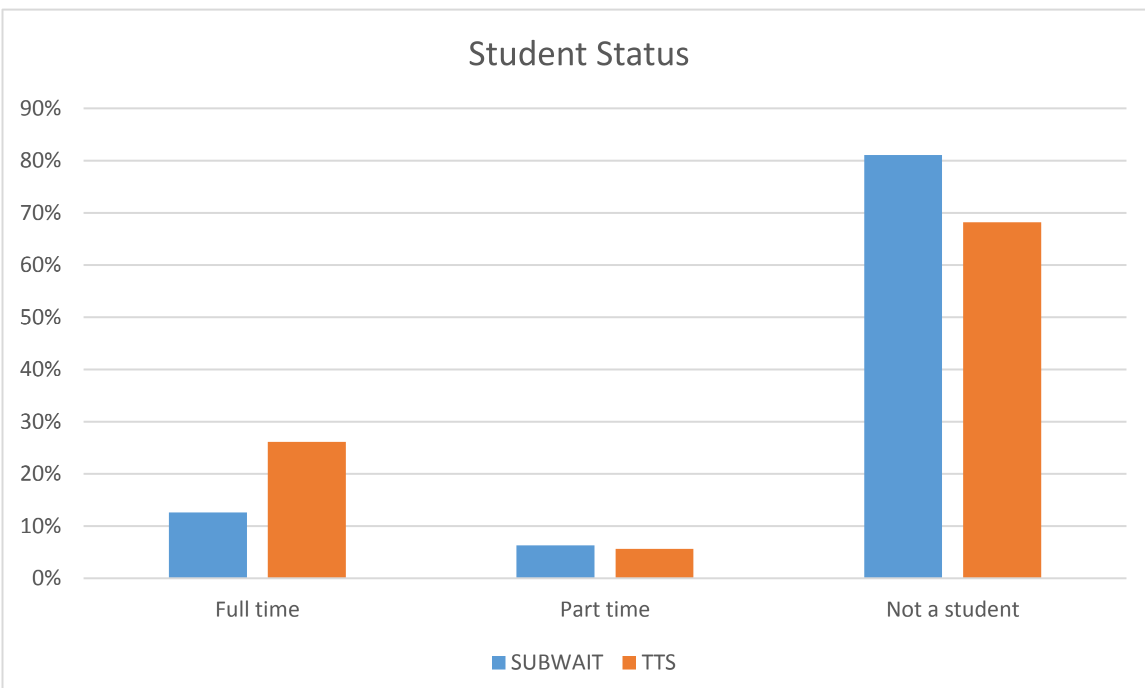


**Figure 4-9: Student Status Distribution**

The socio-demographic information pertaining to households are presented in Figure 4-10, Figure 4-11, and Figure 4-12. Households with 3 or more members are under-represented in the

SUBWAIT survey. Household income data is not available in the TTS. The income groups with the highest percentage are 40k to 60k and 60 to 80k; they combined for 37% of the sample.

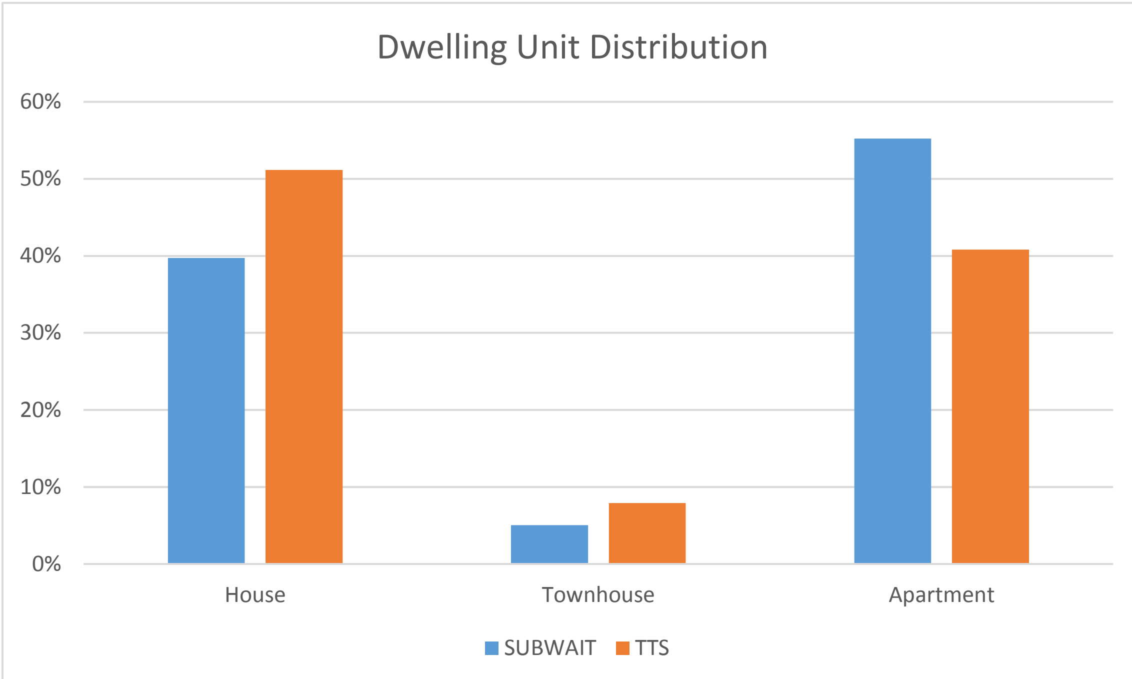


**Figure 4-10: Dwelling Unit Distribution**

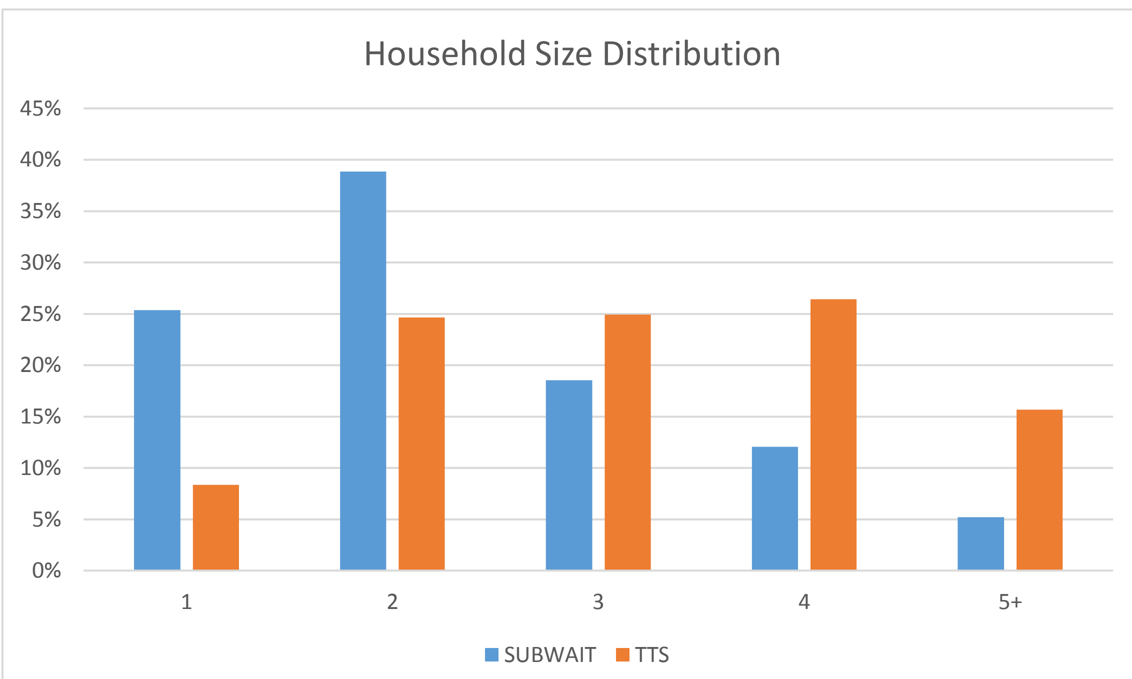


**Figure 4-11: Household Size Distribution**

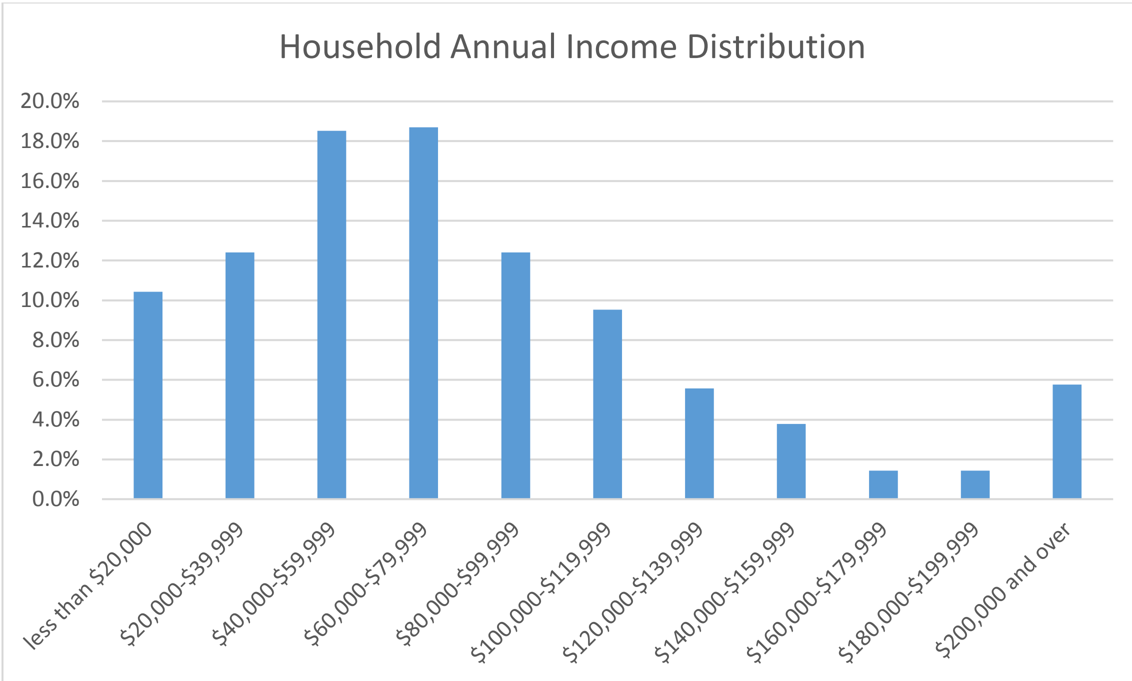


**Figure 4-12: Household Annual Income Distribution**

The distribution of mobility tools are shown in Figure 4-13, Figure 4-14, Figure 4-15, and Figure 4-16. There is a higher percentage of SUBWAIT respondents without a household vehicle and also a higher percentage without a TTC monthly Metropass, which allows unlimited trips in the transit system.

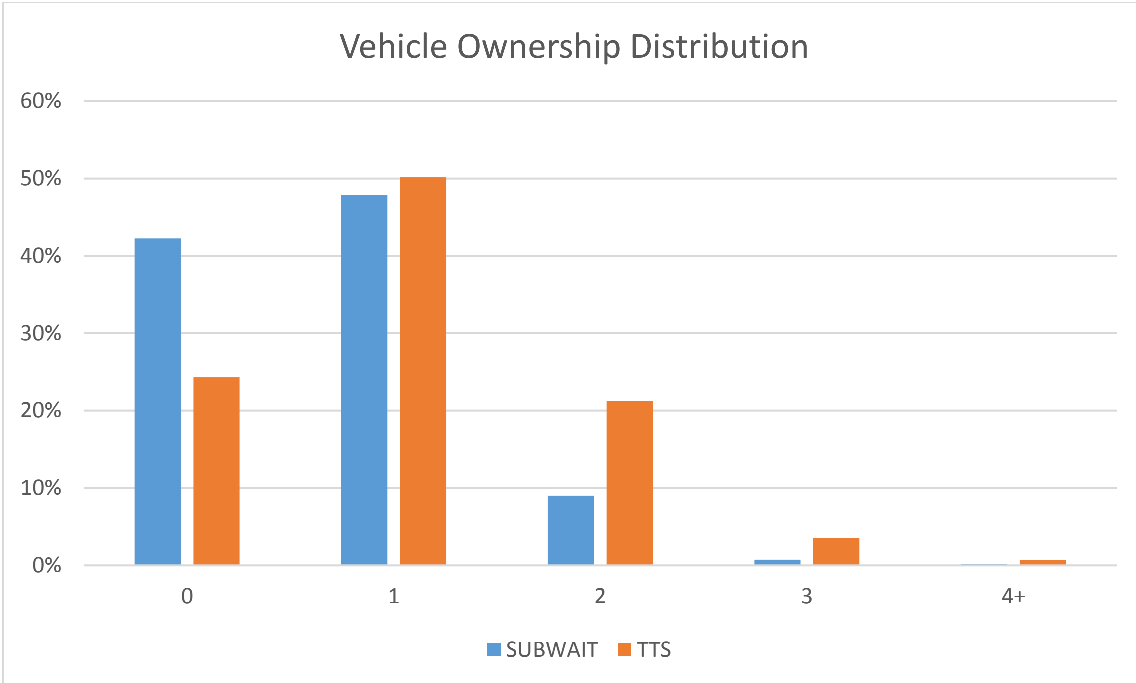


**Figure 4-13: Vehicle Ownership Distribution**

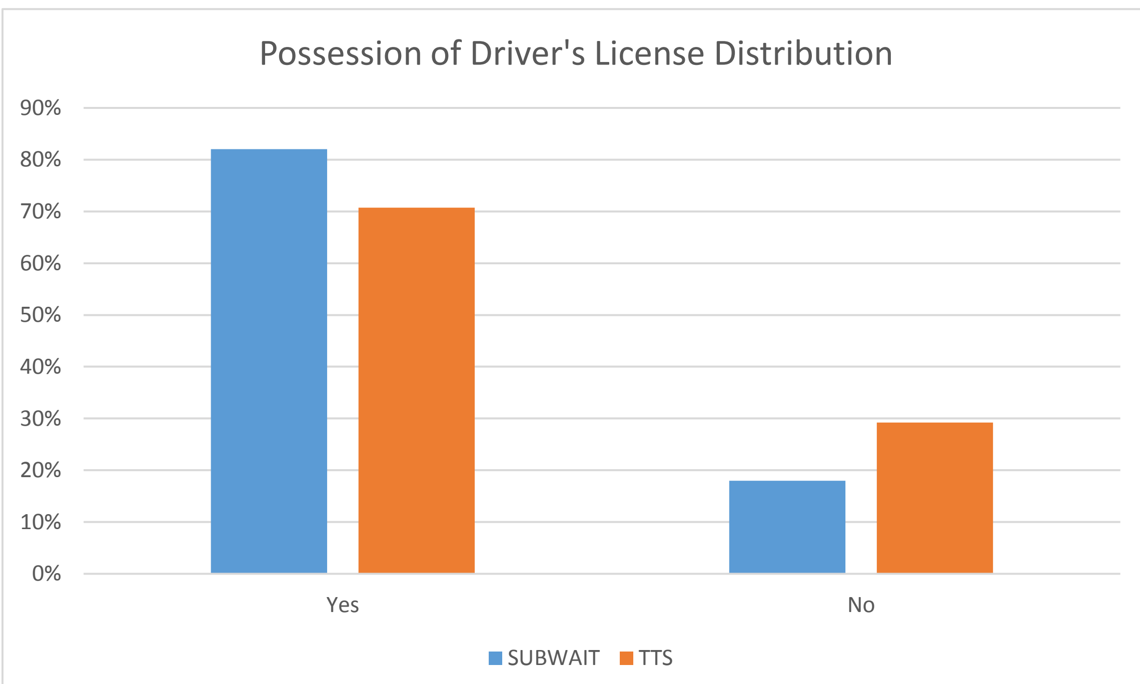


**Figure 4-14: Possession of Driver's License Distribution**

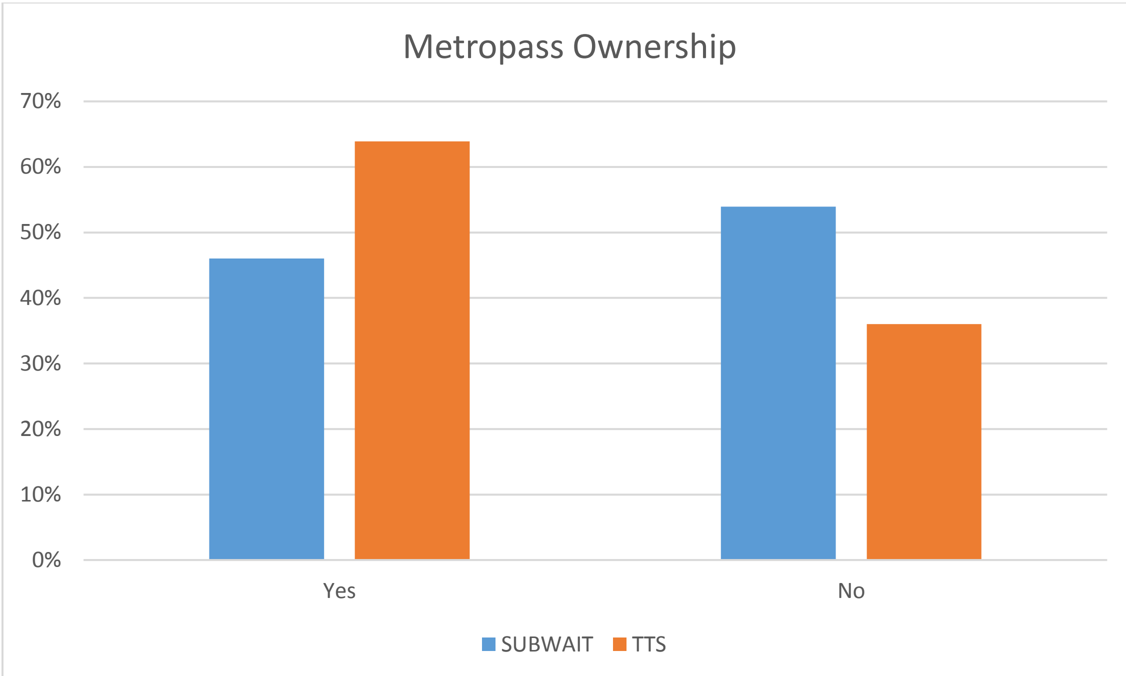


**Figure 4-15: Metropass Ownership Distribution**

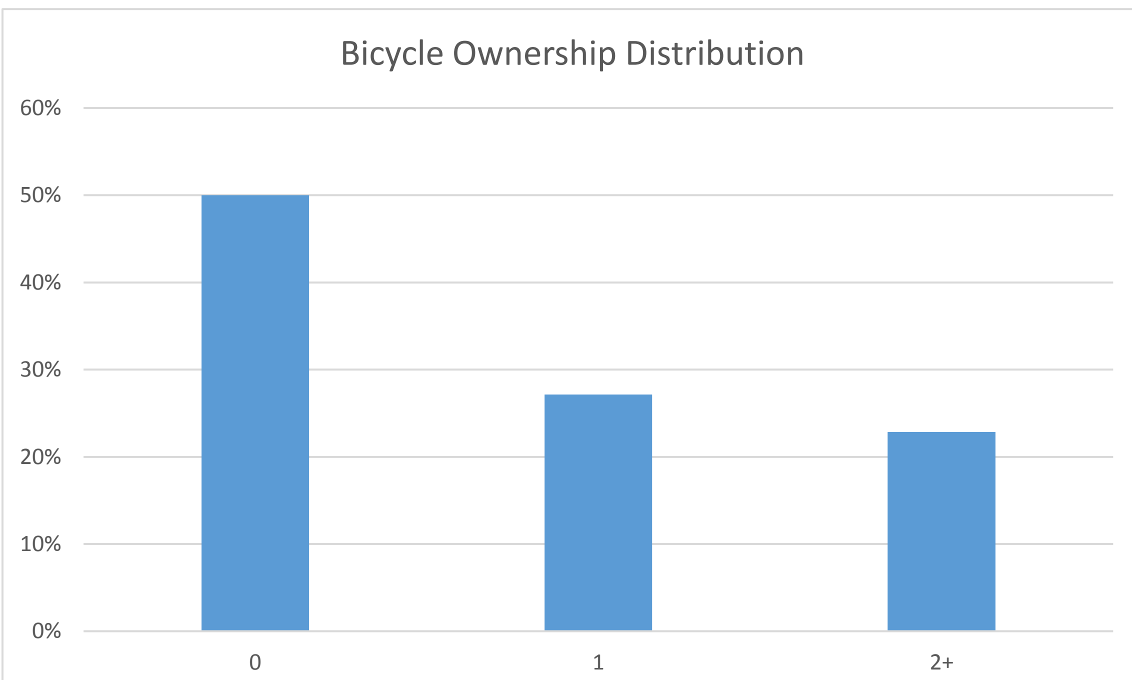


**Figure 4-16: Bicycle Ownership Distribution**

Chapter 5

# 5 Mode Choice Modelling of TTC Subway Users

## 5.1 Survey Data

### 5.1.1 Generating Level-of-Service Attributes for RP

The level-of-service (LOS) attributes, i.e. travel time and cost, for all modes considered in the RP situation are generated in the same manner as the SP scenarios (see 3.6.2). The total auto driving cost also includes the parking cost reported by the respondent.

### 5.1.2 Data preparation

There are three datasets prepared for empirical investigations: RP-only, SP-only, and joint RP-SP datasets. The RP-only dataset contains 414 trip records and data related to the RP trip. The SP-only dataset contains 556 individuals with 7 scenarios each for a total of 3892 observations. The joint RP-SP dataset combines the two datasets for a total of 556 individuals and 4306 trip records.

## 5.2 Econometric Model Formulation

An overview of discrete choice modelling was presented in Section 2.5. Multinomial logit models (MNL) are widely used in mode choice models and were used here to estimate the three empirical models: RP MNL, SP MNL and joint RP-SP MNL models. The joint RP-SP model requires a scale parameter to capture the difference in unobserved variances between RP and SP (Hasnine et al., 2016). All models were estimated using Biogeme (Bierlaire, 2003).

## 5.3 Empirical MNL Models

### 5.3.1 RP MNL Model

The RP MNL model was estimated with 414 observations. Only six respondents had biking as a feasible option and all of them indicated in the corresponding SP scenarios that they would not consider biking. Therefore, biking was removed from the choice set. The definitions of the variables used in the model specification are summarized in Table 5-1. All potential explanatory variables, including LOS variables, delay-related variables, and socio-economic variables, were tested for significance and the final model includes a combination of significant variables and variables that provide important insight to the mode choice behaviour.

Table 5-2 shows the final empirical model. The adjusted rho-square is 0.489 against the null model, meaning that log-likelihood of the final model is around 49% less in magnitude compared to the null model (without any parameters). Travel time (in minutes) has a negative coefficient at 95% confidence as expected. The travel cost (in Canadian dollars) was found to have a negative impact but not significant at 95% confidence. This is possibly due to the small sample size and also the fact that cost may not be the most significant factor in the events of subway service disruption that can potentially lead to emergency situations. The variables pertaining to the subway option, including long delay, subway info, and train announcement are also significant at 95%. The effect of subway delay and information provision can be interpreted using the alternative specific constant of subway and the subway-related parameters. Without other estimated parameters present, the ASC of subway represent the relative utility of taking subway (compared to other modes) when there is a subway delay and no information on the delay is provided. Therefore, the ASC of subway shown in the model includes two components: the true ASC of subway and an unknown but most likely negative value associated with the disutility an unknown subway delay. This means the true ASC of subway without a delay is likely higher than the 3.78 shown in the model; the high ASC is not surprising because the survey targeted subway users who have identified subway as the top choice in their mode choice decision. If delay information is provided (subway info = 1) and the delay is not too long (long subway delay = 0), passengers are more likely to wait for the subway. However, if the information is provided (subway info = 1) and the delay is going to be long (long subway delay = 1), passengers are less likely to wait compared to the above scenario and compared to the scenario when no information is provided. This matches with the general understanding of how passengers respond to subway disruption. The limitation here is that the exact length of delay is usually unknown to the trip maker and completely unknown to the researcher, so only a categorical variable (long subway delay) was used based on limited information. There are two main reasons why the respondents were not asked to report the exact length of delay: (1) the likelihood of them knowing and remember this information is low; (2) more importantly, the respondents may report post-incident information (based on how long they had to wait if they chose to wait) that was not available when the mode choice decision was made, which would lead to incorrect parameter estimates. Nevertheless, in the SP data, where a length of delay is provided to the trip maker, quantitative approaches to the length of delay can be further investigated.

The subjective value of travel time was found to be $84/hr. This is much higher than that of a typical mode choice study from a traditional household travel survey. There are several reasons why the value is expected to be much higher in this context. Firstly, the taxi fare is much higher than the cost of driving, which is no longer possible when encountering a service disruption en-route to your destination. Secondly, in the event of a service disruption, the expected arrival time can be severely affected and the travel cost might become much less important for these commuting trips than the desired arrival time. Thirdly, the cheaper option of Uber that respondents considered or chose could not be fully captured and properly accounted for in the model as this information was not available. The model assumed that the full taxi fare was paid for by the respondent when in reality, the respondent might have taken an Uber ride, thus overstating the true value of time (VOT) of the trip makers.

**Table 5-1: RP Variable Description**

| RP Variable Name | Description |
|---|---|
| **Good Income** | 1 if annual household income is greater than $40,000;<br>0 otherwise |
| **Long Subway Delay** | 1 if shuttle buses were dispatched;<br>0 otherwise |
| **Subway Info** | 1 if respondent indicated that the length of subway delay was provided;<br>0 otherwise |
| **Train Announcement** | 1 if respondent was informed of the disruption via announcement onboard the TTC subway train;<br>0 otherwise |

**Table 5-2: RP-only MNL Model**

| Variables | Value | | |
|---|---|---|---|
| **Final log-likelihood** | -313.595 | | |
| **Null log-likelihood** | -636.618 | | |
| **Adjusted rho-square** | 0.489 | | |
| **Number of individuals** | 414 | | |
| **Variables** | **Modes** | **Parameter** | **t-statistic** |
| **Alternative Specific Constant** | Auto | 0 (fixed) | |
| **Alternative Specific Constant** | Cancel | -1.63 | -1.45 |
| **Alternative Specific Constant** | Other TTC | 1.93 | 2.19 |
| **Alternative Specific Constant** | Shuttle | 3.22 | 3.56 |
| **Alternative Specific Constant** | Subway | 3.78 | 4.44 |
| **Alternative Specific Constant** | Walk | 3.75 | 4.24 |
| **Good Income** | Auto | 1.25 | 1.64 |
| **Long Subway Delay** | Auto | 0.739 | 1.48 |
| **Long Subway Delay** | Subway | -2.09 | -5.59 |
| **Subway Info** | Subway | 0.992 | 2.42 |
| **Train Announcement** | Subway | 0.726 | 2.61 |
| **Travel Time** | All | -0.0371 | -3.78 |
| **Travel Cost** | All | -0.0264 | -1.43 |

### 5.3.2 SP MNL Model

The SP MNL model was estimated with 556 individuals with 7 observations each for a total of 3892 observations. The definitions of the variables used in the model specification are summarized in Table 5-3. All potential explanatory variables, including LOS variables, all variables in the SP experimental design, and socio-demographic variables were tested for significance and the final model includes a combination of significant variables and variables that provide important insight to the mode choice behaviour.

Table 5-4 shows the final empirical model. The adjusted rho-square is 0.178, which is lower than that of the RP-only model; this is usually observed when comparing RP-only and SP-only models because the former type usually has a more dominant alternative. The model accounts for repeated observations by the same individual by dividing the t-stats by the square root of 7 (the number of the repeated observations of each individual) as an approximation (Louviere & Woodworth, 1983). This allows for a correction to reflect the actual sample size (556) instead of the number of observations (3892). Travel time and travel cost both have negative coefficients at

95% confidence as expected. The subway delay and shuttle delay, which are the waiting time in minutes for the service to resume or to become available respectively, also have negative coefficients at 95% confidence as expected. The parameter value for subway and shuttle delay are also higher in magnitude than that of travel time, showing that the wait time is perceived more negatively than travel time. The shuttle info has a positive coefficient, though not significant at 95% confidence. The subway info parameter, which is the availability of information on the length of delay, was found to have a small and insignificant value and was not included in the final model. This can suggest that in lengthy delays, which is the focus of the study, the information provided to differentiate a long delay from a very long delay is not very critical anymore in terms of mode choice. These results are consistent with the general understanding of transit user responses to subway and shuttle delays. In addition to travel time and travel cost, all seven modes include at least one other significant parameter that helps explain the choice behaviour.

The VOT was found to be $44/hr. This is also much higher than that of a typical mode choice study from a traditional household travel survey but lower than that of the RP-only model. The higher VOT compared to a typical mode choice model can be attributed to the high cab/Uber fare compared to driving and possibly relative higher value of time in disruption or emergency situations. The pricing of a cheaper ride hailing option (e.g. Uber) compared to the cab fare, was included as a variable in the SP experimental design but as an unlabeled alternative where respondents were not explicitly told if the fare displayed is a regular cab fare or a discounted cab fare.

**Table 5-3: SP Variable Description**

| Variable | Description |
|---|---|
| **Bad Weather** | 1 if the weather is bad (extreme temperature, heavy rain, heavy snow);<br>0 otherwise |
| **Frequent User** | 1 if the individual uses the TTC subway 9 times or more per week;<br>0 otherwise |
| **High Income** | 1 if annual household income is greater than $120,000;<br>0 otherwise |
| **Optional Trip** | 1 if the individual indicates that the RP trip is not essential<br>0 otherwise |
| **Shuttle Delay** | The waiting time until boarding a shuttle bus in minutes |
| **Shuttle Info** | 1 if Shuttle Delay is available;<br>0 otherwise |
| **Subway Delay** | The waiting time until the subway resumes service in minutes |
| **Young** | 1 if the individual's age is under 40;<br>0 otherwise |

**Table 5-4: SP-only MNL Model**

| Variables | Value | | |
|---|---|---|---|
| **Final Log-Likelihood** | -5442.194 | | |
| **Null Log-Likelihood** | -6642.915 | | |
| **Adjusted Rho-square** | 0.178 | | |
| **Number of Observation** | 3892 | | |
| **Variables** | **Modes** | **Parameter** | **t-statistic** |
| **Alternative Specific Constant** | Auto | 0 (fixed) | |
| **Alternative Specific Constant** | Bike | -0.416 | -0.77 |
| **Alternative Specific Constant** | Cancel | -2.61 | -7.10 |
| **Alternative Specific Constant** | Other TTC | 1.58 | 5.65 |
| **Alternative Specific Constant** | Shuttle | 0.77 | 2.31 |
| **Alternative Specific Constant** | Subway | 0.841 | 3.03 |
| **Alternative Specific Constant** | Walk | 2.11 | 5.98 |
| **Bad Weather** | Bike, Walk | -0.777 | -2.14 |
| **Bad Weather** | Auto | 1.02 | 3.45 |
| **Bad Weather** | Cancel | 1.08 | 2.50 |
| **Frequent User** | Other TTC | 0.402 | 2.20 |
| **High Income** | Auto | 0.53 | 1.89 |
| **Optional Trip** | Cancel | 1.31 | 2.32 |
| **Shuttle Delay** | Shuttle | -0.0735 | -2.29 |
| **Shuttle Info** | Shuttle | 0.831 | 1.62 |
| **Subway Delay** | Subway | -0.0403 | -4.81 |
| **Young** | Bike | 1.18 | 1.97 |
| **Travel Cost** | All | -0.0542 | -4.85 |
| **Travel Time** | All | -0.0396 | -7.54 |

### 5.3.3 Joint RP-SP MNL Model

The joint RP-SP MNL dataset combines the data in the RP-only dataset and the SP-only dataset. This includes a single RP observation with seven repeated SP observations for a total of 556 individuals and 4306 observations. Since some RP records were removed, only 414 have the complete RP and SP observations while the other 142 have SP observations only. Similar to the RP-only model, biking in the RP portion of the joint RP-SP model was also removed from the choice set. The definitions of the variables used in the model specification can be found in Table 5-1 and Table 5-3. All potential explanatory variables, were tested for significance and the final model includes a combination of significant variables and a few variables that provide important insight to the mode choice behaviour.

Table 5-4 shows the final empirical model. The adjusted rho-square is 0.205, which is higher than the SP-only model. The model accounts for up to eight repeated observations by the same individual by dividing the t-stats by the square root of 8 as an approximation (Louviere & Woodworth, 1983). The parameters were estimated jointly with the same coefficient (before accounting for the scale parameter) if data is available in both RP and SP records and separately otherwise. The ASC's were estimated separately to account for the difference in mode share between the RP and SP datasets. Travel time and travel cost both have negative coefficients at 95% confidence as expected. The subway delay and shuttle delay, which are the waiting time for the service to resume or to become available respectively and only available in SP data, also have negative coefficients at 95% confidence as expected. The parameter value for subway and shuttle delay are also higher in magnitude than that of travel time, showing that the wait time is perceived more negatively than travel time. The subway delay info is not available in the RP data so a categorical variable (long subway delay) was used instead as a proxy for the severity of delay. The shuttle info has a positive coefficient, though not significant at 95% confidence. The subway info parameters, indicating the availability of information on the length of delay, were not identical in the RP and SP context and therefore were estimated separately. The RP data includes a range of incidents from minor to major disruptions, so it captures the effect of information when the severity of disruption is unknown. The SP data only includes major disruptions, so it would capture the effects between major disruptions. The SP subway info parameter, found to have a small and insignificant value, was not included in the final model. The subway info parameter suggests that when the severity of disruption is unknown, there is some value in knowing whether it is a minor or major disruption; on the other hand, if the disruption is known to be a major disruption, there is less value in distinguishing between a severe and very severe delay. These results are consistent with the general understanding of passenger responses to subway and shuttle delays.

The VOT was found to be $45/hr. This is also much higher than that of a typical mode choice study from a traditional household travel survey. The higher VOT compared to a typical mode choice model can be attributed to the high cab/Uber fare compared to driving and relative higher value of time in disruption or emergency situations.

When joining the RP and SP datasets, scale parameters were estimated to capture the differences between the two datasets. The SP scale parameter was fixed at 1 and the RP scale parameter was estimated to be 0.81. The null hypothesis states that the of the RP scale parameter is equal to 1; hence the t-stat is negative. The RP scale parameter is not significant at 95% confidence, possibly due to the small sample size of the survey. The smaller RP scale means that the variance in RP data is higher (though not significant at 95% confidence), which is different from most joint RP-SP models. This is likely due to the unique nature of the SUBWAIT survey RP dataset where information, specifically delay information, was very limited to the trip maker. Therefore, it is difficult to make the most rational decision in a highly uncertain situation and thus difficult to model the behaviour in such situation. This was also evident when 142 trip records were excluded because the response did not add up to form a coherent scenario and the respondent's situation could not be recreated with enough certainty.

**Table 5-5: Joint RP-SP MNL Model**

| Variables | Value | | | | |
|---|---|---|---|---|---|
| **Final Log-Likelihood** | -5760.172 | | | | |
| **Null Log-Likelihood** | -7279.533 | | | | |
| **Adjusted Rho-square** | 0.205 | | | | |
| **Number of Observation** | 4306 | | | | |
| **Variables** | **Modes** | **Parameter** | **t-statistic** | **Parameter** | **t-statistic** |
| | | RP | | SP | |
| **Alternative Specific Constant** | Auto | 0 (fixed) | | 0 (fixed) | |
| **Alternative Specific Constant** | Bike | 0 (fixed) | | -0.405 | -0.70 |
| **Alternative Specific Constant** | Cancel | -4.03 | -1.26 | -2.62 | -6.67 |
| **Alternative Specific Constant** | Other TTC | 0.206 | 0.20 | 1.6 | 5.39 |
| **Alternative Specific Constant** | Shuttle | 1.92 | 1.25 | 0.786 | 2.21 |
| **Alternative Specific Constant** | Subway | 3.25 | 1.41 | 0.853 | 2.88 |
| **Alternative Specific Constant** | Walk | 2.74 | 1.72 | 2.11 | 5.61 |
| **Bad Weather** | Bike | 0 (fixed) | | -0.721 | -1.88 |
| **Bad Weather** | Walk | -0.721 | -1.88 | -0.721 | -1.88 |
| **Bad Weather** | Auto | 1.03 | 3.31 | 1.03 | 3.31 |
| **Bad Weather** | Cancel | 1.11 | 2.40 | 1.11 | 2.40 |
| **Frequent User** | Other TTC | 0.407 | 2.10 | 0.407 | 2.10 |
| **High Income** | Auto | 0.529 | 1.79 | 0.529 | 1.79 |
| **Long Subway Delay** | Subway | -2.89 | -1.30 | 0 (fixed) | |
| **Optional Trip** | Cancel | 1.34 | 2.23 | 1.34 | 2.23 |
| **Shuttle Delay** | Shuttle | 0 (fixed) | | -0.0744 | -2.17 |
| **Shuttle Info** | Shuttle | 0 (fixed) | | 0.847 | 1.55 |
| **Subway Delay** | Subway | 0 (fixed) | | -0.0402 | -4.48 |
| **Subway Info** | Subway | 1.09 | 0.70 | 0 (fixed) | |
| **Young** | Bike | 1.18 | 1.84 | 1.18 | 1.84 |
| **Travel Cost** | All | -0.0535 | -4.55 | -0.0535 | -4.55 |
| **Travel Time** | All | -0.0399 | -7.17 | -0.0399 | -7.17 |
| **Scale** | | 0.813 | -0.99 | 1 (fixed) | |

## 5.4 Comparison of Models and Discussions

The joint RP-SP model combines the strength of SP (testing of variables unavailable in RP) with the strength in RP (representing actual behaviour). The joint model also has a higher rho square compared to the SP-only model. While the scale parameter in the joint RP-SP model was not found to be significant at 95% confidence, it still provides important insights that would otherwise be difficult to capture in the RP-only or SP-only model. The SP scenarios presented various types of major disruptions to the respondents, ranging from 25-35 minutes of delay to 50-80 minutes of delay. The RP part was intended for major disruptions only as well. However, due to a variety of factors, including the difficulty of recalling the last major disruption and perhaps respondents having a different interpretation of a major disruption, some medium and minor delays were also reported, providing a range of different delay durations that are different from the SP counterpart. With a wider range of length of delay in the RP data, the value of subway info could be captured, whereas the SP subway info was found to be small and insignificant for capturing the difference between a long delay and very long delay. However, the SP data were able to capture the value of shuttle info, as severe disruptions do not necessarily imply severe shuttle delays. Wai time (delay) from 10-15 minutes to 20-40 minutes were used for shuttle. The shorter delays were included to account for some passengers arriving at the disruption location when the shuttle buses are already en-route or on-scene. The ASC for subway in all the models is a combination of the true ASC of subway and the disutility of knowing a disruption occurrence. The ASC of subway for SP was found to be smaller than that of RP and this is likely due to the higher disutility of knowing a major disruption compared to that of knowing a disruption with no information.

It is very difficult to properly capture the effect of delay (certain or uncertain) on mode choice behaviour. However, the modelling exercises provide an overall direction on how to better understand it. At the beginning when a delay is detected by the passengers (e.g. subway not moving accompanied by an undecipherable announcement) or communicated to the passengers (through various channels), the ASC represents the relative preference of waiting for the subway compared to the other modes without considering LOS attributes and other factors. If the delay information is disclosed to the passengers, the passengers perceive the availability of information positively (positive subway info parameter estimate) but at the same time perceive the length of delay negatively (negative subway delay parameter estimate). If the length of delay is short, the positive utility of information availability would outweigh the negative utility of delay, and the passengers are more likely to wait. On the other hand, long delays would offset the positive utility of information provision and make passengers less likely to wait. Furthermore, there exists a breakeven point when the perceived disutility of an unknown incident matches that of a known length of delay, which can be calculated by equating the net utility to be 0. This value, the ratio of subway info to subway delay, represents the perceived expected wait time or delay of an incident when no information is provided. Since the subway info estimate was not found to be significant at 95%, the value found in this study may not be accurate. However, with a larger sample size and further investigation, the perceived average delay of an unknown incident can be derived with higher confidence. The perceived average delay of shuttle buses can also be derived similarly. It is also important to note that this perceived average delay with unknown information can vary greatly between individuals and thus have a very high variance. Finally, it is important to note that if certain types of minor delays are recurrent and already expected by passengers, such as slower travel speed, crew change, or delays due to crowding, they would not be perceived as unplanned disruptions and would not influence their choice behaviour the same way unplanned disruptions do.

In all three models, it was found that the delay (wait) time of subway and shuttle was perceived more negatively than the overall uninterrupted travel time. The weight factor of shuttle delay, defined as the ratio of delay parameter to travel time parameter, was unknown in the RP-only model and 1.86 for in the SP-only and the joint model. This suggests that passengers perceive one minute of waiting on shuttle buses to be about the same as 1.86 minutes of uninterrupted travel time, due to other factors such as anger, anxiety, or impatience associated with the disutility. The weight factor of subway delay was only slightly over 1, suggesting that waiting for subway is not perceived as negatively as waiting for the shuttle buses, and almost the same as travel time. There are different ways this can be interpreted but more investigation is needed to draw conclusions. Firstly, passengers can perceive subway wait time as productive wait time, especially with Wi-Fi available at many TTC subway stations. Secondly, this can be an indication that subway delays no longer come as a complete surprise. The RP data indicated that the majority of the respondents reported experiencing a subway delay within the last two weeks of completing the survey, so the expected trip time and perception of overall trip time might not be the same as the uninterrupted trip time.

The value of time was very high in the RP-only model ($84/hr) compared to the SP-only model ($44/hr) or the joint model ($45/hr). This is possibly due to the difficulty in capturing the consideration of private automobile option, specifically between the regular cab fare and cheaper options such as Uber. As a result, the RP analysis was conducted based on the assumption that regular cab fare was paid for by the respondent if selecting that option. In the SP scenarios, alternative taxi options that are cheaper were built into the SP experimental design and thus they were able to capture the cost and VOT better.

## 5.5 Practical Implications

Gaining a full understanding of the transit user mode choice behaviour under conditions of service disruptions is extremely difficult. However, this study can provide many insights on key factors affecting the transit user behaviour that can assist the transit agencies in making more informed decisions when responding to and recovering from service disruptions as well as communicating with the customers.

When there is a service disruption, the single most important piece of information to the passengers is usually the length of delay. While there are instances where the transit agency does not have a reliable estimate of the delay due to the nature of the problem, this information, even if highly uncertain, would assist the passengers in their decision making if shared. As shown in the joint RP-SP model, providing some information on delay duration is still better than providing no information.

There is a significant difference in the mode share of other TTC routes between the RP and SP data, which shows that passengers are willing to seek alternatives that helps them get to their destinations if the alternative transit route information is available to them. However, they might not be familiar with TTC network beyond their regular trips. Providing information on alternative routes can significant reduce the issues of overcrowding at station platforms, on the subway trains or on shuttle buses, and reduce anxiety. While other routes may be impacted more by the service disruption if more passengers are diverted, it helps reduce the total number of shuttle buses needed. As a result, fewer buses in service would need to be pulled out of service and this leads to higher capacity in other TTC routes to help with the extra passenger loads while saving or eliminating the deadheading time. This information can be made available for the whole network prior to disruptions, such as the information on the Philadelphia transit agency website (Southeastern Pennsylvania Transportation Authority, n.d.), provided specifically to each disruption and location through public announcement (when the incident is announced), and sent out to individuals based on their pre-selected routes or stations (when alerts are sent out).

The incident type was found to be insignificant and therefore not included in the final models. This suggests that when information on the length of delay is available, the cause of the incident is not as important. However, it is important to distinguish the need and desire for incident information and whether this information will influence mode choice behaviour. The analysis suggests that the latter is not significant at 95% confidence while the former is not investigated explicitly.

As discussed in Section 2.4, the three most important pieces of information for customers faced with service disruptions, according to a UK study, are length of delay, route alternative and reason for delay (Passenger Focus, 2011). Based on the SUBWAIT survey findings, length of delay was found to have a negative impact on choosing the delayed mode. Frequent users of the TTC subway system are more likely to choose alternative routes as they are probably more familiar with the transit system. While the passengers usually want to know the type of incident, it does not necessarily change their mode choice behaviour.

The weather condition was found to have an influence the passenger’s mode choice, shifting them towards auto and trip cancellation as well as shifting them away from biking and walking. While this finding is not surprising, policies can be put in place to help manage the service disruption. In clement weather conditions, for example, partnering with Toronto Bike Share can encourage active modes of transportation as an alternative without being constrained by the lack of access to bikes when away from home. In inclement weather conditions, the higher auto mode share and its impact on the road traffic and thus shuttle buses and other surface transit routes should be cautioned when managing service disruptions.

The media of information provision was collected in the RP data and it was found that 49% of respondents were informed of a service disruption at a subway station and 40% were informed on the train. It was also found that passengers learning of a disruption via train announcement are more likely to wait for the subway to resume services. This suggests that the channel of communication can influence mode choice behaviour and should be taken into consideration when managing the disruptions and crowding.

Providing information in a timely manner and to passengers not yet in the subway system can also help avoid the overcrowding issue in the subway network. Although not found to be significant, a higher percentage of passengers chose to cancel their trip if they have not started their trip. Being informed of a disruption when at home can also lead to additional options such as biking (if the trip maker has a bike) or departure time change.

Whether there is a service disruption or not, travel time is always a major factor in mode choice. While there is little room to improve the travel time on the subway and the surface routes, and practically impossible in the event of a service disruption, there is an opportunity to minimize the travel time through more creative operations of shuttle buses. For example, when a series of subway stations is closed due to a service disruption, running non-stop shuttle buses bridging the closed segments can reduce the travel time on shuttle buses. Running express or non-stop shuttle buses to another subway line can also be effective to divert passengers to the other parts of the transit network with the highest capacity while providing competitive options. In particular, this can be effective for bridging the northern portion of Yonge Subway Line to the northern portion of University-Spadina Subway Line where no express buses are available between the two sections of the subway line. This idea of a hybrid choice (shuttle bus and other TTC route) can also be considered for other modes to help the passengers find the most optimal route to destination, such as walking and continue onto the uninterrupted subway segment.

Transit agencies can also consider facilitating alternative options beyond the TTC network. This includes utilizing the services on regional transit, specifically the rail corridors of the GO Transit network or Union Pearson Express. The auto option can relieve crowding in the transit system but cause further traffic congestion, so it is important to know the priorities of service disruption response. Active modes should be encouraged and the availability of bike share, especially with close proximity to subway stations, can help with diversion of passenger loads at overcrowded stations.

# Chapter 6

# 6 Conclusions

## 6.1 Research Summary

In this study, the Subway User Behaviour When Affected by Incidents in Toronto (SUBWAIT) survey, a joint RP-SP survey, was designed, developed, and deployed online to collect data on the transit user behaviour when affected by service disruptions, incorporating key factors that may influence the mode choice behaviour. Three mode choice models, RP-only, SP-only, and joint RP-SP, were presented and compared. Policy implications were discussed based on the findings to highlight how transit agencies can make use of this information in service response and recovery during a service disruption.

## 6.2 Research Contributions

This dissertation has several major contributions. Firstly, a web-based joint RP-SP survey was designed with state-of-the-art efficient design, a transit trip planner tool to find alternatives avoiding the disruption, and individually customized survey with realistic disruption scenarios based on TTC incident reports and respondent's subway route. Secondly, it provides a deeper understanding of how transit users (in the immediate-term) respond to service disruptions by incorporating many factors while keeping the survey length reasonable (around 12 minutes). The factors incorporated in the experimental design includes the stage of the trip (at origin or en-route), weather condition, type of incident, location of incident, availability of information on subway and shuttle buses, length of delay for subway and shuttle buses, and uncertainty or range of delay for subway and shuttle buses. In particular, the stage of trip, type of incident, availability of information on delay duration, delay duration and associated uncertainty of delay duration were not explicitly considered in prior literature. With the literature lacking RP surveys, and therefore joint RP-SP surveys, on transit user behaviour during service disruptions, the joint RP-SP survey was a significant improvement that provided useful insights on transit user behaviour that were otherwise difficult to capture in RP-only or SP-only studies. This study also allows for a broader understanding of transit use behaviour without limiting the findings to a past incident or specific situations, and therefore provides more generalized conclusion that can be useful for the transit agencies. Thirdly, this study attempts to quantify the value of information on delay, the length of delay, the variance/uncertainty of delay for both subway and its replacement mode (shuttle bus) and how it compares to the travel time of the journey. Due to the complex nature of imperfect information and how it influences the decision making of transit users, the study provides insights in a quantitative way on how to compare among various disruption situations, such as a disruption with no information, a major disruption with no additional information, a disruption with an expected length of delay, and a disruption with an highly variable length of delay.

## 6.3 Directions for Future Research

Given the limited literature in this topic, there are many areas of future research, including expansion of scope, advanced econometric modelling, and applications. This survey focuses on situations where the respondent is informed of a disruption during a trip or just before a trip; however, if advance notice is provided, departure time change can be incorporated into decision making of trip makers with a joint departure time and mode choice model. Given that the majority of the respondents reported to have encountered a service disruption within the last two weeks, it is reasonable to hypothesize that passenger behaviour in response to disruptions can also change over time if encountering them frequently. It would be interesting to see if there are any short-term or long-term changes to their behaviour over time, specifically major changes such as commuting mode choice. Given that TTC has more weekends with a pre-planned subway service closure than those without any closure, it would be of great interest to see how trip makers' behaviour change given that they have the opportunity to plan ahead and explore alternatives. On the modelling side, the analysis in this study only considered the fact that individuals had repeated observations but did not consider the correlation between observations made by the same individual. A more advanced modelling technique, such as the mixed logit model, would be able to capture this relationship and provide more accurate results. The study also did not consider the confidence of choice in the SP scenarios and it can be incorporated in more advanced models. Finally, this study aims to fill a gap of transit user mode choice in a multimodal simulation framework designed to model the effect of a transit service disruption on the entire transportation network. By providing information on how the transit users choose to get to their destination, this simulation tool can better model the crowd flows at a local level such as a station platform or at a network wide level.

# References


Bachok, S. (2008). Estimating, calibrating, and validating demand for feeder services during incident detections. *30th Conference of Australian Institutes of Transport Research (CAITR).* Perth, Australia. Retrieved February 16, 2016, from http://eng.monash.edu.au/civil/assets/document/research/centres/its/caitr-home/prevcaitrproceedings/caitr2008/bachok-caitr2008.pdf

Bai, Y., & Kattan, L. (2014). Modeling Riders' Behavioral Responses to Real-Time Information at Light Rail Transit Stations. *Travel Behavior 2014, Journal of the Transportation Research Board, 1*, 82-92. Retrieved February 24, 2015, from Transportation Research Board: http://trb.metapress.com/content/r8886n45p2126u01/fulltext.pdf

Barron, A., Melo, P. C., Cohen, J., & Anderson, R. (2013). Passenger-Focused Management Approach to Measurement of Train Delay Impacts. *Transit 2013, Journal of the Transportation Research Board, 2*, 46-53. Retrieved January 6, 2015, from Transportation Research Board: http://trb.metapress.com/content/c40m3574120048hv/fulltext.pdf

Ben-Akiva, M., & Morikawa, T. (1990, November). Estimation of Switching Models from Revealed Preferences and Stated Intentions. *Transportation Research Part A: General, 24A*(6), 485-495. Retrieved May 15, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/0191260790900377

Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., & Rao, V. (1994, October). Combining revealed and stated preferences data. *Marketing Letters, 5*(4), 335-349. Retrieved May 7, 2016, from https://www.jstor.org/stable/pdf/40216355.pdf

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. *Proceedings of the 3rd Swiss Transportation Research Conference.* Ascona, Switzerland.

Bliemer, M. C., & Rose, J. M. (2005, April). *Efficiency and Sample Size Requirements for Stated Choice Studies.* Retrieved April 7, 2016, from The University of Sydney: http://ws.econ.usyd.edu.au/itls/wp-archive/itls_wp_05-08.pdf

Bliemer, M. C., & Rose, J. M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A, 45*(1), 63-79. Retrieved May 19, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0965856410001394

Bradley, M., & Daly, A. (1994, May). Use of the Logit Scaling Approach to Test for Rank-order and Fatigue Effects in Stated Preference Data. *Transportation, 21*(2), 167-184. Retrieved May 19, 2016, from http://link.springer.com/article/10.1007/BF01098791

Brownstone, D., Bunch, D. S., & Train, K. (2000, June). Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-fuel Vehicles. *Transportation Research Part B: Methodological, 34*(5), 315-338. Retrieved May 7, 2106, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0191261599000314

Carrel, A., Halvorsen, A., & Walker, J. L. (2013). Perception of and Behavioral Adaptation to Unreliability in Public Transportation. *Transit 2013, Journal of the Transportation*

*Research Board, 2,* 153-162. Retrieved January 6, 2015, from Transportation Research Board: http://trb.metapress.com/content/c40m3574120048hv/fulltext.pdf

Carrion, C., & Levinson, D. (2012, May). Value of Travel Time Reliability: A Review of Current Evidence. *Transportation Research Part A: Policy and Practice, 46*(4), 720-741. Retrieved February 11, 2015, from University of Minnesota: http://nexus.umn.edu/papers/VORReview.pdf

ChoiceMetrics. (2014, July 15). *Ngene 1.1.2 User Manual & Reference Guide.* Retrieved May 14, 2015, from ChoiceMetrics: https://dl.dropboxusercontent.com/u/9406880/NgeneManual112.pdf

City of Toronto. (2016). *Taxis - Taxicabs - Vehicle for Hire - Accessible Taxis - Fares - City of Toronto*. Retrieved 2015, from City of Toronto: http://www.toronto.ca/311/knowledgebase/39/101000038339.html

Data Management Group. (2012). *Transportation Tomorrow Survey*. Retrieved 2015, from Data Management Group: http://dmg.utoronto.ca/transportation-tomorrow-survey

Department for Transport. (2008). *Experiences and perceptions of anti-social behaviour and crime on public transport.* Department for Transport, Transport Statistics. The National Archives. Retrieved February 15, 2016, from http://library.college.police.uk/docs/dft/anti-social-crime-on-public-transport-2008.pdf

Fukasawa, N., Yamauchi, K., Murakoshi, A., Fujinami, K., & Tatsui, D. (2012, August 30). Provision of Forecast Train Information and Consequential Impact on Decision Making for Train-Choice. *Quarterly Report of Railway Technical Research Institute, 53*(3), 141-147. Retrieved February 18, 2015, from Japen Science and Technology Information Aggregator, Electronic: https://www.jstage.jst.go.jp/article/rtriqr/53/3/53_141/_pdf

Goodwin, P. (2008). *Policy Incentives to Change Behaviour in Passenger Transport.* University of the West of England, Bristol, The Centre for Transport & Society. International Transport Forum. Retrieved March 24, 2015, from http://www.internationaltransportforum.org/Topics/Workshops/WS2Goodwin.pdf

Green, P. E., & Srinivasan, V. (1978, September). Conjoint Analysis in Consumer Research: Issues and Outlook. *Journal of Consumer Research, 5*(2), 103-123. Retrieved May 8, 2015, from JSTOR: http://www.jstor.org/stable/2489001

Habib, K., Swait, J., & Salem, S. (2012). Investigating Structural Changes in Commuting Mode Choice Preferences with Repeated Cross-Sectional Travel Survey Data: The Contexts of Greater Toronto and Hamilton (GTHA) Area. *13th International Conference on Travel Behaviour Research.* Toronto. Retrieved 2016, from http://dmg.utoronto.ca/pdf/reports/research/StructuralChangesInModeChoice_Habib.pdf

Hasnine, M. (2015). *A Comprehensive Study on the Effectiveness of Office-based TDM Policies.* Retrieved 2015, from University of Toronto TSpace Repository: https://tspace.library.utoronto.ca/bitstream/1807/69640/1/Hasnine_Md_Sami_201506_MAS_thesis.pdf

Hasnine, M., Weiss, A., & Habib, K. (2016). Development of an Employer-based TDM Strategy Evaluation Tool with an Advanced Discrete Choice Model in its Core. *Transportation Research Record: Journal of the Transportation Research Board, 2542*, 65-74. Retrieved 2016, from https://www.researchgate.net/profile/Khandker_Nurul_Habib2/publication/293487401_Development_of_Employer-Based_TDM_Strategy_Evaluation_Tool_with_Advanced_Discrete_Choice_Model_in_Its_Core/links/56b8fbce08ae3b658a88bb99.pdf?origin=publication_list

Hensher, D. A., & Bradley, M. (1993, April). Using Stated Response Choice Data to Enrich Revealed Preference Discrete Choice Models. *Marketing Letters, 4*(2), 139-151. Retrieved May 5, 2016, from http://www.jstor.org/stable/pdf/40216294.pdf?_=1462498674229

Huber, J., & Zwerina, K. (1996, August). The Importance of Utility Balance in Efficient Choice Designs. *Journal of Marketing Research, XXXIII*, 307-317. Retrieved April 7, 2016, from https://faculty.fuqua.duke.edu/~jch8/bio/Papers/Huber%20Zwerina%201996%20Marketing%20Research.pdf

Kattan, L., de Barros, A. G., & Saleemi, H. (2013, November). Travel behavior changes and responses to advanced traveler information in prolonged and large-scale network disruptions: A case study of west LRT line construction in the city of Calgary. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*, 90-102. Retrieved February 25, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S1369847813000697

Kroes, E. P., & Sheldon, R. J. (1988, January). Stated Preference Methods. *Journal of Transport Economics and Policy, 22*(1), 11-25. Retrieved May 8, 2015, from University of Bath: http://www.bath.ac.uk/e-journals/jtep/pdf/Volume_XX11_No_1_11-25.pdf

López-Rousseau, A. (2005, June). Avoiding the Death Risk of Avoiding a Dread Risk. *Psychological Science, 16*(6), 426-428. Retrieved February 22, 2016, from http://journals2.scholarsportal.info.myaccess.library.utoronto.ca/pdf/09567976/v16i0006/426_atdroaadr.xml

Louviere, J. J., & Hensher, D. A. (1983, December). Using Discrete Choice Models with Experimental Design Data to Forecast Consumer Demand for a Unique Cultural Event. *Journal of Consumer Research, Inc., 10*(3), 348-361. Retrieved May 6, 2015, from http://www.jstor.org/stable/2488807

Louviere, J. J., & Woodworth, G. (1983, November). Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research, 20*(4), 350-367. doi:http://www.jstor.org/stable/3151440

Lu, Q.-C., Zhang, J., Peng, Z.-R., & Rahman, A. S. (2014, December). Inter-city Travel Behaviour Adaptation to Extreme Weather Events. *Journal of Transport Geography, 41*, 148-153. Retrieved December 19, 2014, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0966692314001781

Manski, C. F., & McFadden, D. (1981). *Structural Analysis of Discrete Data and Econometric Applications.* Cambridge: MIT Press. Retrieved June 30, 2015, from http://eml.berkeley.edu/~mcfadden/discrete.html

McFadden, D. (1973). *Conditional Logit Analysis of Qualitative Choice Behavior,.* New York: Academic Press. Retrieved June 23, 2015, from http://eml.berkeley.edu/reprints/mcfadden/zarembka.pdf

McFadden, D. (1984). Econometric Analysis of Qualitative Response Models. *Handbook of Econometrics, 2*, 1396-1456. Retrieved June 23, 2015, from http://down.cenet.org.cn/upfile/28/20052222719169.pdf

McFadden, D. (1986). *The Choice Theory Approach to Market Research.* Retrieved July 2, 2015, from JSTOR: http://www.jstor.org/stable/184004

Metrolinx. (2008, November). *The Big Move.* Retrieved 2015, from Metrolinx: http://www.metrolinx.com/thebigmove/Docs/big_move/TheBigMove_020109.pdf

Mojica, C. H. (2008). *Examining changes in transit passenger travel behavior through a Smart Card activity analysis.* Massachusetts Institute of Technology, Department of Urban Studies and Planning and Department of Civil and Environmental Engineering. DSpace@MIT. Retrieved March 9, 2015, from https://dspace.mit.edu/handle/1721.1/44364

Murray-Tuite, P., Wernstedt, K., & Yin, W. (2014, May). Behavioral Shifts After a Fatal Rapid Transit Accident. *Transportation Research Part F: Traffic Psychology and Behaviour, 24,* 218-230. Retrieved February 24, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S1369847814000527

New Zealand Ministry of Transport. (2013, November). *The Transport Impacts of the 20 June 2013 Storm.* Retrieved January 5, 2015, from New Zealand Ministry of Transport: http://www.transport.govt.nz/assets/Uploads/News/Documents/Transport-impacts-in-Wellington-storm-June-2013.pdf

Nielsen, L. K. (2011). *Rolling Stock Rescheduling in Passenger Railways.* Retrieved February 11, 2015, from RePub, Erasmus University Repository: http://repub.eur.nl/pub/22444/EPS2011224LIS9789058922670.pdf

Papangelis, K., Velaga, N., Sripada, S., Beecroft, M., Nelson, J. D., Anable, J., & Farrington, J. F. (2013, January). *Supporting Rural Public Transport Users During Disruption: The Role of Real Time Information.* Retrieved December 19, 2014, from University of Aberdeen: http://aura.abdn.ac.uk/bitstream/2164/3256/1/Konstantinos_et_al_UTSG_Paper_2013.pdf

Passenger Focus. (2011). *Information: Rail passengers' needs during unplanned disruption.* Passenger Focus. Retrieved February 11, 2015, from http://www.passengerfocus.org.uk/media/dca7e0b50f3ad90e6475953c74997ea3c4b0fa59/pf_unplanned_disruption_report__final.pdf

Pender, B., Currie, G., Delbosc, A., & Shiwatoki, N. (2013). Disruption Recovery in Passenger Railways International Survey. *Transit 2013, Journal of the Transportation Research Board, 4*, 22-32. Retrieved February 11, 2015, from Transportation Research Board: http://trb.metapress.com/content/a346702986221433/fulltext.pdf

Pnevmatikou, A. M., Karlaftis, M. G., & Kepaptsoglou, K. (2015, September 28). Metro service disruptions: how do people choose to travel? *Transportation, 42,* 933-949. Retrieved February 9, 2016, from SpringerLink: http://link.springer.com/article/10.1007%2Fs11116-015-9656-4#/page-1

Pnevmatikou, A., & Karlaftis, M. (2011). *Demand Changes From Metro Line Closures.* Retrieved January 30, 2015, from Association for European Transport: http://abstracts.aetransport.org/paper/download/id/3603

Rose, J. M., Bliemer, M. C., Hensher, D. A., & Collins, A. T. (2008, May). Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B: Methodological*, *42*(4), 395-406. Retrieved May 20, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0191261507000811

Rubin, G. J., Brewin, C. R., Greenberg, N., Hughes, J. H., Simpson, J., & Wessely, S. (2007, March). Enduring consequences of terrorism: 7-month follow-up survey of reactions to the bombings in London on 7 July 2005. *The British Journal of Psychiatry, 190*(4), 350-356. Retrieved February 13, 2016, from http://bjp.rcpsych.org/content/bjprcpsych/190/4/350.full.pdf

Sikka, N., & Hanley, P. (2013, September). What Do Commuters Think Travel Time Reliability Is Worth? *Transportation*, *40*(5), 903-919. Retrieved February 10, 2015, from SpringerLink: link.springer.com/content/pdf/10.1007/s11116-012-9448-z.pdf

Southeastern Pennsylvania Transportation Authority. (n.d.). *SEPTA Alternative Service*. Retrieved 2016, from Southeastern Pennsylvania Transportation Authority: http://www.septa.org/stations/rail/stations.shtml

Teng, J., & Liu, W.-R. (2015, March). Development of a Behavior-Based Passenger Flow Assignment Model for Urban Rail Transit in Section Interruption Circumstance. *Urban Rail Transit, 1*(1), 35-46. Retrieved July 14, 2015, from SpringerLink: http://link.springer.com/article/10.1007%2Fs40864-015-0002-0

Toronto Transit Commission. (2008, April 26). *TTC Settlement Rejected by Union*. Retrieved June 12, 2015, from Toronto Transit Commission: https://www.ttc.ca/News/2008/April/TTC_Settlement_Rejected_by_Union.jsp

Toronto Transit Commission. (2013a, July). *News for July 2013*. Retrieved June 12, 2015, from Toronto Transit Commission: https://ttc.ca/News/2013/July/index.jsp

Toronto Transit Commission. (2013b, December). *News for December 2013*. Retrieved June 12, 2015, from Toronto Transit Commission: https://ttc.ca/News/2013/December/index.jsp

Toronto Transit Commission. (2016, January 15). *TTC Ridership - Ridership Numbers and Revenues Summary*. Retrieved April 20, 2016, from City of Toronto Open Data: http://opendata.toronto.ca/city.manager/performance.management/PM_TTC.xls

Train, K. (1986). *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand.* Cambridge: MIT Press. Retrieved June 30, 2015, from http://eml.berkeley.edu/books/choice.html

Train, K. (2002). *Discrete Choice Methods with Simulation.* Cambridge: Cambridge University Press. Retrieved July 2, 2015, from http://eml.berkeley.edu/books/train1201.pdf

Tseng, Y.-Y., Rietveld, P., & Verhoef, E. (2008). *A Meta-analysis of Valuation of Travel Time Reliability.* Retrieved February 11, 2015, from Transport Planning Research Colloquium Netherlands: http://www.cvs-congres.nl/cvspdfdocs/cvs05_105.pdf

Tsuchiya, R., Sugiyama, Y., & Arisawa, R. (2007, December). A Route Choice Support System for Use During Disrupted Train Operation. *Japanese Railway Engineering, 47*(2). Retrieved February 25, 2015, from Intelligent Transportation Society of America: ftp://ftp.itsa.org/WC08_Presentations/Interactive%20Session%20Papers/IS03/IS03-10249.pdf

Van Exel, N. J., & Rietveld, P. (2001, October). Public Transport Strikes and Traveller Behaviour. *Transport Policy, 8*(4), 237-246. Retrieved December 17, 2014, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0967070X01000221

Van Exel, N., & Rietveld, P. (2009, June). When Strike Comes to Town … Anticipated and Actual Behavioural Reactions to a One-day, Pre-announced, Complete Rail Strike in the Netherlands. *Transportation Research Part A: Policy and Practice, 43*(5), 526-535. Retrieved March 25, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S0965856409000160

Zeng, A. Z., Durach, C. F., & Fang, Y. (2012, May). Collaboration decisions on disruption recovery service in urban public tram systems. *Transportation Research Part E: Logistics and Transportation Review, 48*(3), 578-590. Retrieved February 11, 2015, from ScienceDirect: http://www.sciencedirect.com/science/article/pii/S1366554511001414

Zhu, S., & Levinson, D. (2011, August 30). *Disruptions to Transportation Networks: A Review.* Retrieved March 23, 2015, from SpringerLink: http://link.springer.com/chapter/10.1007%2F978-1-4614-0947-2_2

Zwerina, K., Huber, J., & Kuhfeld, W. F. (1996, September). *A General Method for Constructing Efficient Choice Designs.* Retrieved May 19, 2015, from CiteSeerX: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.31.9438&rep=rep1&type=pdf

# Appendix A: SUBWAIT Survey

| | | |
|---|---|---|
| Do you take the TTC subway and/or Scarborough RT for your daily commute (work or school trips)? | Yes | No |
| Do you start and end your commuting trip within the City of Toronto (including Etobicoke, North York, and Scarborough)? | Yes | No |
| Are you at least 18 years old? | Yes | No |

## Transit User Behaviour in Response to Service Disruption of TTC Subway System

Dear Survey Respondent,

You have been randomly selected to participate in a research study conducted by the Department of Civil Engineering at the University of Toronto. This study aims to achieve a better understanding of transit user's travel mode preferences (such as shuttle bus, waiting, alternative transit options, cab, biking and walking) when faced with a service disruption of the TTC subway or Scarborough RT.

The survey is divided into three sections: **Section A** will gather information on your last commuting trip affected by a transit service disruption; **Section B** will ask about your mode choices in hypothetical disruption scenarios where the service attributes of alternative travel modes are specified; **Section C** will collect socioeconomic and demographic characteristics.

We kindly ask you to participate in this web survey so that your opinion is represented in our study. This **anonymous** survey is designed to be as short as possible and will take approximately **10 to 15 minutes** to complete. Please answer every question in each section in order to proceed to subsequent sections. You may choose not to complete the survey at any time without any penalty. Keep in mind, however, that the responses submitted in previous sections are not retrievable, and therefore will still be anonymously included in the final survey data set. Please note that there is no related risk involved with your participation in this study. All collected information will be stored securely and processed with the utmost confidentiality, and it will be used for academic purposes only. Your cooperation is highly appreciated.

Should you have any questions about the study, please feel free to e-mail us at info@nexus-utoronto.ca. For any questions regarding your rights as a respondent in this survey, you are free to contact the office of Research Ethics, University of Toronto, McMurrich Building, 2nd floor, 12 Queen's Park Crescent West Toronto, ON M5S 1S8, Tel: (416) 946-3273, Fax: (416) 946-5763, Email: ethics.review@utoronto.ca.

**Consent of Participant**

By pressing the "Start Survey" button, you will indicate to us that you agree, of your own freewill, to voluntarily participate in this study after carefully reading and fully understanding the information presented on this page.

Start Survey

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*Questions about the survey? Contact us at info@nexus-utoronto.ca*

Which of the following best describes your most recent **subway** commuting trip to work or school?

Home to school

Please enter the start location (origin) of your trip (full address or full postal code with space) and **verify** the location using the "Show on map" button

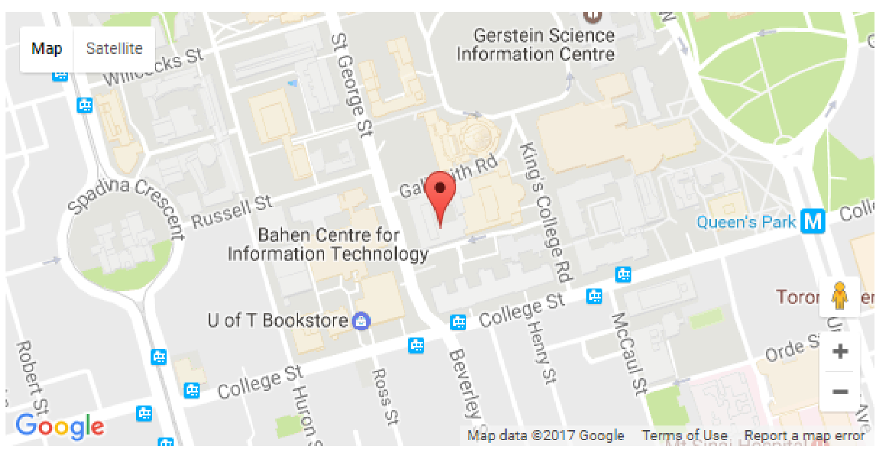
M9A 0B1

Show on Map


Please enter the end location (destination) of your trip (full address or full postal code with space) and **verify** the location using the "Show on map" button

M5S 1A4

Show on Map



| | |
|---|---|
| How would you classify the urgency of the trip? | Essential but not urgent (e.g. without a parti |
| What was your desired arrival time at the destination? | 09:00 AM |
| When did you start your trip from the point of origin? | 08:20 AM |
| When did you arrive at the point of destination? | 08:55 AM |
| How many household vehicles do you have for personal use? | 0 |
| How many household bicycles do you have? | 1 |
| Do you have a driver's license? | Yes |
| How did you get from your origin to the subway or Scarborough RT system? (access mode) | Walk only |

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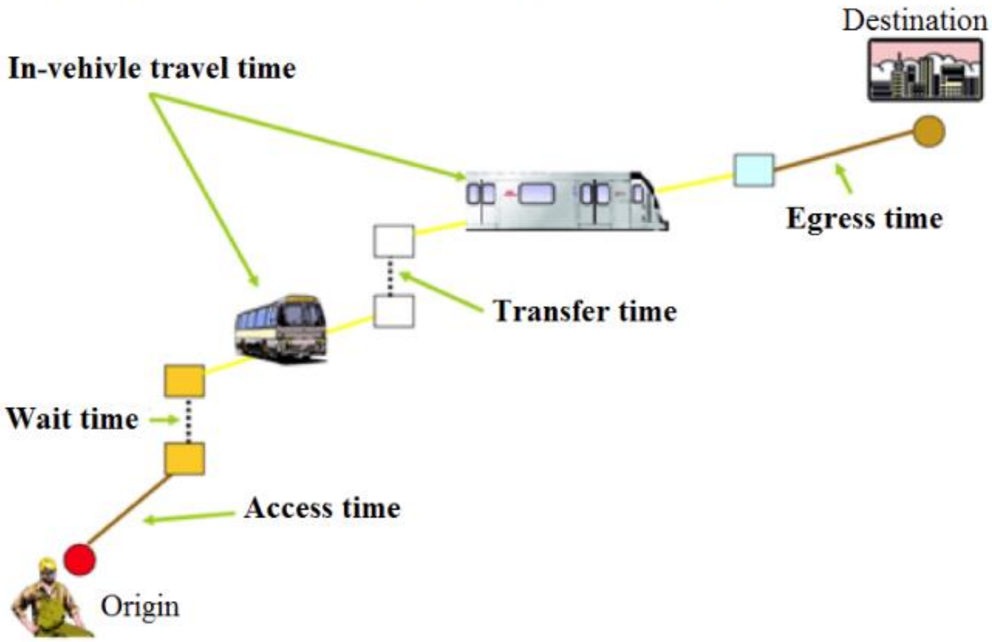
*Problem with the "Save and Next Page" button? Check for warning messages in pop-up windows*

# Page 2 / 15

You may find this figure helpful in understanding the stages of a transit trip.




How long (in minutes) did it take you to get to your first subway or Scarborough RT station by walk, bike or car? (access time)

5

How many times did you **transfer between a subway line and another subway line** and between a subway line and Scarborough RT? (Note: Boarding the subway train only once counts as 0 transfer; boarding the subway train twice (e.g. Line 2 and Line 1) counts as 1 transfer.)

1

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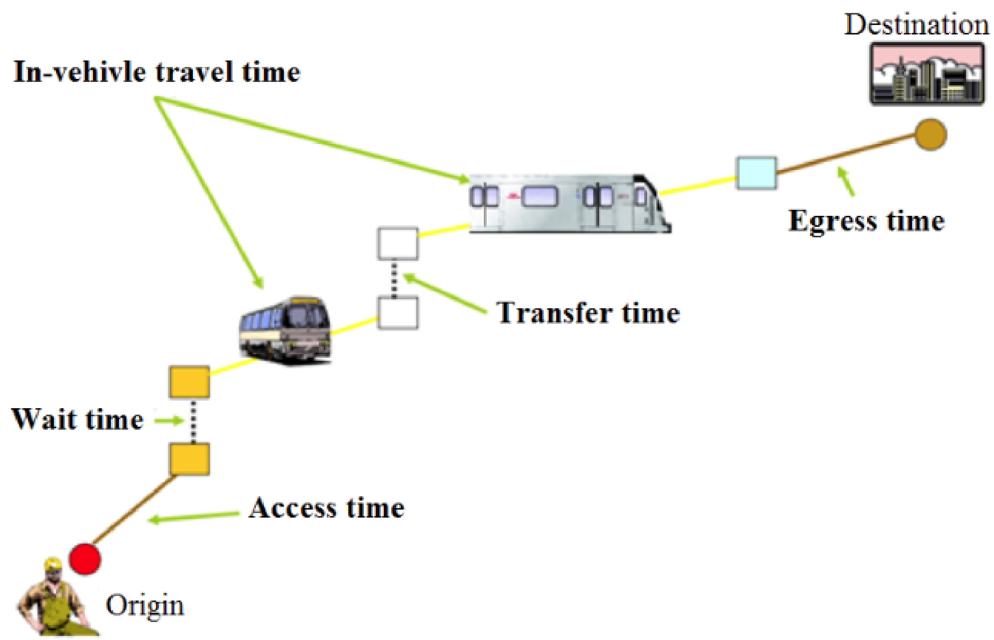
# Page 3 / 15

You may find this figure helpful in understanding the stages of a transit trip.




| | |
|---|---|
| What was the first subway or RT line you took? | Line 2: Bloor-Danforth |
| What was your boarding station (the station you got on)? | Kipling |
| What was your alighting station (the station you got off)? | St George |
| What was the second subway or RT line you took? | Line 1: Yonge-University-Spadina |
| What was your alighting station? | Queen's Park |
| What is your egress mode from the last subway or RT station to your trip destination? | Walk only |

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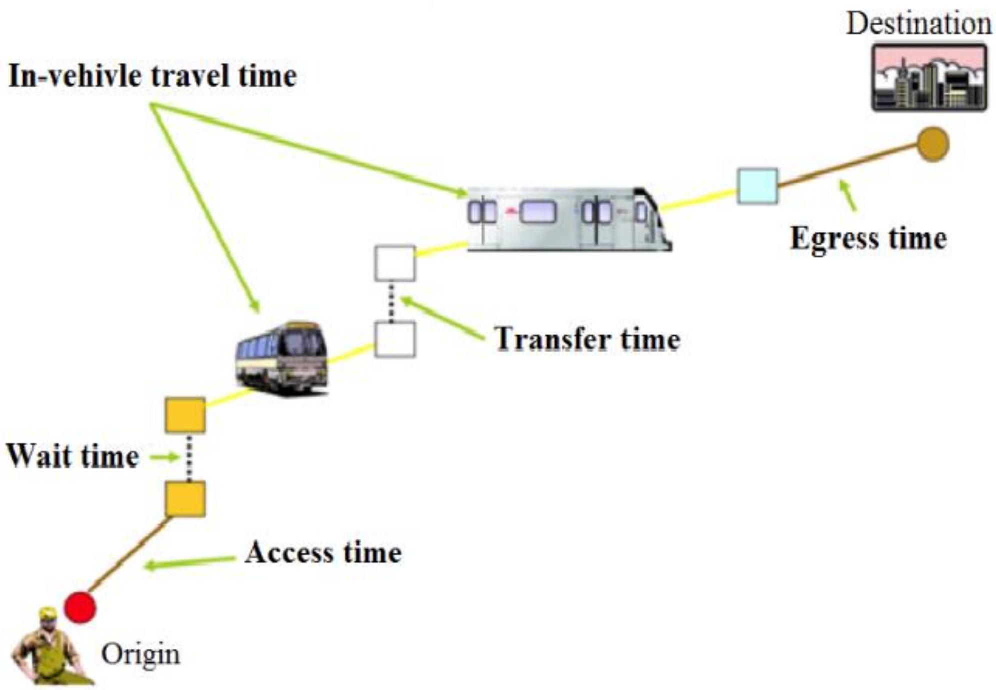
# Page 4 / 15

You may find this figure helpful in understanding the stages of a transit trip.




| | |
|---|---|
| How long did it take to go from the last subway or Scarborough RT station to your destination in minutes? (egress time) | 5 |
| What is the average daily parking cost in Canadian Dollars at the destination? *(please put 20 if you don't know about the parking cost)* | 20 |
| What is your general perception of the reliability of the TTC subway and RT system? | Neutral |
| Do you use any online tools (apps or websites) that provide real-time information on the transit service? | No |

Save and Next Page

# Page 5 / 15

In this part, we will gather information on your last commuting trip that was affected by a subway or Scarborough RT service disruption. This includes the disruption details (e.g. time, duration, location and type), any information provided by the transit agency, and your choice of travel mode in response to the disruption.

How long ago was your most recent encounter of a **subway or Scarborough RT disruption** that affected your trip to work or school (**same itinerary and direction** as the trip you just filled out)? A service disruption is defined here as a single event (or cause) that results in a subway delay of **15 minutes** or longer and generally includes an official announcement or alert addressing the disruption. help?

Within the last 2 weeks

Some examples of disruption are injury at track level, emergency situation, fire investigation, police investigation, mechanical problem, signal problem, power problem, communication outage, power outage, flooding. Please note that regular crew change, crowding, and slower train speed are not considered as service disruptions in this study.

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You may find the subway map helpful in recalling where the disruption occurred (source: http://www.ttc.ca/PDF/Maps/Subway_Map.pdf)


What was the approximate time of the disruption? 08:30 AM

Which subway line did the disruption occur on? Line 2: Bloor-Danforth

Which subway station did the disruption occur at? Christie

What was the cause of the disruption?

- ( ) Passenger related accidents: illness, injury, false alarm activation. <u>Announcement</u>: injury at track level, emergency situation
- ( ) Fire or smoke detection on track, train or station. <u>Announcement</u>: fire investigation
- ( ) Passenger related acts: suicide attempt , aggression, security issues. <u>Announcement</u>: police investigation, injury at track level, emergency situation
- (•) Mechanical, signals, brakes, track, traction power, door. <u>Announcement</u>: [mechanical, signal, …] problem
- ( ) Weather related incidents and communication or power outage due to weather. <u>Announcement</u>: communication outage, power outage, flooding, heavy snow
- ( ) Other types of incidents.
- ( ) I don't know.
- ( ) I knew but I don't remember anymore.

| | |
|---|---|
| Were replacement (shuttle) buses dispatched as a result of the incident? | Yes |
| What was the weather condition? | Comfortable |
| At what stage of your trip did you find out or learn about the disruption? | After boarding a subway train but before e |
| Which subway station was closest to your location when you learned or found out about the disruption? | Osington |

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You may find the subway map helpful in recalling where the disruption occurred (source: http://www.ttc.ca/PDF/Maps/Subway_Map.pdf)


To the best of your knowledge, what disruption information was available during your trip, via any communication channels such as station announcement, station TV update, TTC alert, TTC tweets (regardless of whether you knew or remembered the disruption information)?

- [x] Time of disruption
- [x] Cause of disruption
- [x] Disrupted location (station or segment of a subway line)
- [ ] Expected duration
- [x] Availability of replacement (shuttle) bus

How did you first find out about the disruption?

TTC announcement on train

Which travel mode choice did you choose to get to your destination as a result of the disruption?

Took a taxi

How much delay (in minutes) did you incur beyond the normal travel time due to the service disruption? (If you travelled by car and arrived faster than your usual transit trip, please put in a negative value.)

5

What was the additional total travel cost incurred due to the service disruption (including taxi fare, gas, and parking)?

$ 10

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In this section, you are provided with 7 **hypothetical major disruption** scenarios. In each scenario, you are to place yourself into your routine **commuting trip** and consider a service disruption that takes places at a location that your subway (or Scarborough LRT) train passes through, making your uninterrupted trip no longer possible. You are asked to familiarize yourself in that situation with relevant background information and use the attributes provided in the table for all feasible travel modes to choose the most preferred travel mode option. Please take your time and consider each scenario carefully. Definitions of column and row headers are available by hovering over the ❓ icon. Please note that the table may take up to ten seconds to load to generate all values.

You are **on your way** to your destination and the weather is **not comfortable** outside with rain, snow or extreme temperature. You are approaching *St George Station on the train* and you have just found out that there is a "**Signal or Train Breakdown**" at *Museum Station*, causing the subway service to be suspended between *St George Station* and *Union Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from St George Station given the situation.***

*Questions about the survey? Contact us at info@nexus-utoronto.ca*

| | Taxi ❓ | Other TTC Routes ❓ | Shuttle ❓ | Walk ❓ | Wait ❓ | Cancel Trip ❓ |
|---|---|---|---|---|---|---|
| Length of Delay (minutes) ❓ | 5 | 5 | 10-30 | | 25-55 | 0 |
| Cost (CAD) | $5.75 | $0 | $0 | $0 | $0 | $0 |
| Number of Transfers ❓ | | 0 | 0 | | 0 | 0 |
| Access Time (minutes) ❓ | | 5 | 0 | | 0 | 0 |
| In-vehicle Travel Time (minutes) ❓ | 3 | 3 | 6 | | 3 | 24 |
| Transfer Time (minutes) ❓ | | 0 | 0 | | 0 | 0 |
| Egress Walking Time (minutes) ❓ | | 6 | 7 | | 7 | 13 |
| Total Travel Time (minutes) ❓ | 8 | 18 | 22-42 | 12 | 35-65 | 38 |
| Choice | ○ | ○ | ○ | ◉ | ○ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Very Likely

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You are **on your way** to your destination and the weather is **comfortable** outside. You are approaching *Kipling Station* and you have just found out that there is a "**Fire Investigation**" at *Kipling Station*, causing the subway service to be suspended between *Kipling Station* and *Islington Station*. *You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from Kipling Station given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Wait | Cancel Trip |
|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 5 | 20-40 | 25-35 | 0 |
| Cost (CAD) | $31.00 | $0 | $0 | $0 | $0 |
| Number of Transfers | | 2 | 2 | 1 | 0 |
| Access Time (minutes) | | 1 | 0 | 0 | 0 |
| In-vehicle Travel Time (minutes) | 26 | 53 | 31 | 28 | 0 |
| Transfer Time (minutes) | | 11 | 9 | 4 | 0 |
| Egress Walking Time (minutes) | | 3 | 7 | 7 | 13 |
| Total Travel Time (minutes) | 31 | 73 | 67-87 | 64-74 | 13 |
| Choice | ○ | ○ | ○ | ◉ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Likely

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You are **at your origin** and the weather is **comfortable** outside. You are on your way out and you have just found out that there is a "**Medical Emergency**" at *High Park Station*, causing the subway service to be suspended between *Jane Station* and *Keele Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from your origin given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Bike | Wait | Cancel Trip |
|---|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 0 | No Information Provided | | No Information Provided | 0 |
| Cost (CAD) | $39.25 | $2.9 | $2.9 | $0 | $2.9 | $0 |
| Number of Transfers | | 4 | 3 | | 1 | 0 |
| Access Time (minutes) | | 2 | 13 | | 13 | 0 |
| In-vehicle Travel Time (minutes) | 26 | 46 | 31 | | 28 | 0 |
| Transfer Time (minutes) | | 27 | 14 | | 4 | 0 |
| Egress Walking Time (minutes) | | 6 | 7 | | 7 | 0 |
| Total Travel Time (minutes) | 31 | 81 | At least 65 | 53 | At least 52 | 0 |
| Choice | ○ | ○ | ○ | ◉ | ○ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Neutral

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You are **at your origin** and the weather is **comfortable** outside. You are on your way out and you have just found out that there is an "**Unknown Incident**" at *Islington Station*, causing the subway service to be suspended between *Kipling Station* and *Jane Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from your origin given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Bike | Wait | Cancel Trip |
|---|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 0 | 20-25 | | No Information Provided | 0 |
| Cost (CAD) | $39.25 | $2.90 | $2.90 | $0 | $2.90 | $0 |
| Number of Transfers | | 4 | 2 | | 1 | 0 |
| Access Time (minutes) | | 2 | 13 | | 13 | 0 |
| In-vehicle Travel Time (minutes) | 26 | 46 | 36 | | 28 | 0 |
| Transfer Time (minutes) | | 27 | 9 | | 4 | 0 |
| Egress Walking Time (minutes) | | 6 | 7 | | 7 | 0 |
| Total Travel Time (minutes) | 31 | 81 | 85-90 | 53 | At least 52 | 0 |
| Choice | ○ | ○ | ○ | ◉ | ○ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Neutral

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You are **at your origin** and the weather is **comfortable** outside. You are on your way out and you have just found out that there is a "**Medical Emergency**" at *Lansdowne Station*, causing the subway service to be suspended between *Keele Station* and *Ossington Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from your origin given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Bike | Wait | Cancel Trip |
|---|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 0 | No Information Provided | | 25-35 | 0 |
| Cost (CAD) | $39.25 | $2.90 | $2.90 | $0 | $2.90 | $0 |
| Number of Transfers | | 4 | 3 | | 1 | 0 |
| Access Time (minutes) | | 2 | 13 | | 13 | 0 |
| In-vehicle Travel Time (minutes) | 26 | 46 | 33 | | 28 | 0 |
| Transfer Time (minutes) | | 27 | 14 | | 4 | 0 |
| Egress Walking Time (minutes) | | 6 | 7 | | 7 | 0 |
| Total Travel Time (minutes) | 31 | 81 | At least 67 | 53 | 77-87 | 0 |
| Choice | ○ | ○ | ○ | ○ | ○ | ◉ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Neutral

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You are **on your way** to your destination and the weather is **not comfortable** outside with rain, snow or extreme temperature. You are approaching *Kipling Station* and you have just found out that there is a "**Signal or Train Breakdown**" at *Kipling Station*, causing the subway service to be suspended between *Kipling Station* and *Islington Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from Kipling Station given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Wait | Cancel Trip |
|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 5 | 10-30 | 50-60 | 0 |
| Cost (CAD) | $41.50 | $0 | $0 | $0 | $0 |
| Number of Transfers | | 2 | 2 | 1 | 0 |
| Access Time (minutes) | | 1 | 0 | 0 | 0 |
| In-vehicle Travel Time (minutes) | 26 | 53 | 31 | 28 | 0 |
| Transfer Time (minutes) | | 11 | 9 | 4 | 0 |
| Egress Walking Time (minutes) | | 3 | 7 | 7 | 13 |
| Total Travel Time (minutes) | 31 | 73 | 57-77 | 89-99 | 13 |
| Choice | ○ | ○ | ◉ | ○ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Neutral

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You are **on your way** to your destination and the weather is **not comfortable** outside with rain, snow or extreme temperature. You are approaching *Ossington Station on the train* and you have just found out that there is a "**Fire Investigation**" at *Bathurst Station*, causing the subway service to be suspended between *Ossington Station* and *St George Station. You have the following mode options shown in the table with the associated attributes.* ***Please choose your most preferred option to get to your destination from Ossington Station given the situation.***

| | Taxi | Other TTC Routes | Shuttle | Walk | Wait | Cancel Trip |
|---|---|---|---|---|---|---|
| Length of Delay (minutes) | 5 | 5 | 10-15 | | 50-80 | 0 |
| Cost (CAD) | $13.50 | $0 | $0 | $0 | $0 | $0 |
| Number of Transfers | | 0 | 1 | | 1 | 0 |
| Access Time (minutes) | | 2 | 0 | | 0 | 0 |
| In-vehicle Travel Time (minutes) | 7 | 11 | 14 | | 10 | 19 |
| Transfer Time (minutes) | | 0 | 4 | | 4 | 0 |
| Egress Walking Time (minutes) | | 7 | 7 | | 7 | 13 |
| Total Travel Time (minutes) | 12 | 26 | 35-40 | 39 | 71-101 | 32 |
| Choice | ○ | ◉ | ○ | ○ | ○ | ○ |

In the future, how likely are you to get to your destination using your selected choice above if you encounter this scenario in real life?

Neutral

Please identify all the travel mode choices that you considered when making selections (if you thought about choosing an option in at least one of the scenarios, that means it was considered; if, for example, you would never bike, then it's not considered)

- [ ] Drive
- [ ] Take a Taxi
- [x] Other TTC Routes
- [x] Shuttle
- [x] Bike
- [x] Walk
- [x] Wait
- [x] Cancel Trip

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| | |
|---|---|
| How old are you? | 25-29 |
| What is your gender? | Male |
| What is the highest level of education you have completed? | Bachelor's Degree |
| What is your employment status? | Not employed |
| What is your student status? | Full time |
| Do you have a TTC monthly Metropass? | No |
| How many times on average do you take the TTC subway or Scarborough RT in a week (a round trip counts as two trips)? | 11-12 times per week |
| What is your housing (dwelling unit) type? | Apartment |
| Do you own or rent your place of residence? | Rented |
| How many people, including yourself, live in your household? | 1 |
| What is your total annual individual income before tax? | less than $20,000 |

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# Thank you for completing the survey.

Please let us know if you have any comments or suggestions for the survey.

Submit