Passenger's Behavior in Response to an Unplanned Transit Disruption

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INTRODUCTION

Offering affordable, efficient, and green service, the public transportation infrastructure of every municipality acts as the veins of its transportation system. In the Chicago metropolitan area, the Chicago Transit Authority (CTA) provides service to over 3.5 million riders in the city of Chicago and 35 suburbs surrounding the city (Chicago Transit Authority, 2017). CTA provides the nation’s second largest public transportation system which operates under the budget of over $1.5k million. Also, the rail transportation system connects both major airports to the transit system in Chicago (Chicago Transit Authority, 2017).

However, maintaining the competing quality of transit service is challenging. Private vehicles are typically the biggest competitor to transit service. Compared to private vehicles, service reliability, privacy, convenience, availability, and travel time are among the significant dis-utilities of transit service. Further, ride-hailing and ride-sharing services have changed the game in the transportation market. Today, not only does the transportation network companies (TNCs) take market share from private transportation options, but also, they are strong competitors of the transit system. These services provide a wide variety of affordable, door-to-door options and, thereby, encourage transit users to substitute their conventional choice (i.e., public transit) with TNCs.

The discussion above, along with the fact that transit service would not be economically viable unless it is adopted by enough customers (Berechman, 1993), demands to shed light on the transit users’ satisfaction. Service disruptions, as one of the boldest dis-utilities of transit system, could cause serious damage to the riders’ experience (Lin et al., 2016a). Various internal and external factors might cause transit disruption (Lo and Hall, 2006; Mattsson and Jenelius, 2015). Examples of internal factors include the staff strikes, technical failures, periodic maintenance actions such as station renovations and railway signaling changes, and strategic planning efforts such as minor or major reroutes. External issues, on the other hand, are by nature less preventable. Natural disasters such as heavy snowfalls and thunderstorms, for instance, would considerably hinder the regular operation of the fleet, imposing delays to the whole system. Terrorist attacks could be considered as an instance of such disruptions. Depending on the design of the transit system and its schedule, subtle issues on the operation might end up in huge and considerable deterioration of the users’ experience (Lo and Hall, 2006; Luo et al., 2018; Saxena et al., 2019).

1. LITERATURE REVIEW

The research on pre-planned or unplanned transit disruptions is a relatively new topic of research gaining growing attention in the past decade. A wide range of studies is found in the literature focusing on different aspects of transit disruption. Some scholars have focused on the effect of disruption on transportation network and transit ridership (Cadarso et al., 2013) and analyzed how transit authorities could recover the disrupted service efficaciously, while others have
provided insight into the issue from passengers’ point of view and analyzed how such disruptions could impact their travel behavior (Murray-Tuite et al., 2014; Saberi et al., 2018).

Two types of transit disruption are considered in the literature. First, pre-planned disruptions that may occur because of pre-planned activities such as maintenance and labor strikes (see, for instance, (Pnevmatikou et al., 2015; van Exel and Rietveld, 2009; Yap et al., 2018)). For instance, fracture critical bridges need to be inspected every two years using the “arms-length” approach which causes traffic disruption and potential safety hazards (M Abedin et al., 2019; Abedin and Mehrabi, 2019). Second, unplanned disruptions that are mostly due to natural disaster, bridge collapses (due to cracks in structural members such as girders and bracings or failure of the bridge deck (Mohammad Abedin et al., 2019; Ghoddousi et al., 2019), and terrorist attacks. This study is focused on the first one. As the goal of transit authorities is restoring and managing the disrupted service efficaciously, disregarding passenger’s behavior and perceptions could lead to adopting a management strategy that is not optimal (Currie and Muir, 2017). Therefore, a couple of studies collected data and develop behavioral models for unplanned disruptions. A comprehensive literature review on transit disruption can be found in Rahimi et al. For instance, Lin et al. revealed that travel cost, waiting time, duration of delay, income, and type of incident could affect transit users’ commuting mode choice during a subway service disruption in Toronto (Lin et al., 2016b). Yet, little is known about how the users’ choices would affect the stability of the road network. This study aims at filling the gap using activity-based simulation.

Generally, three types of survey are used in the literature of transit disruption including revealed-preference (RP), stated-preference (SP), and revealed preference-stated preference (RP-SP) survey.

As one of the first studies that conducted an RP survey to capture transit users’ behavior in response to unplanned transit disruption, Murray-Tuite et al. investigated the long-term impact of the deadly Metrorail collision on passengers’ behavior in 2009 in Washington D.C (Murray-Tuite et al., 2014). Using a web-based survey, respondents, who had used the Metrorail six months before the incident, were asked to specify what changes they made to their transit trips in terms of mode and seat location after the collision and found that 10% and 17% altered their mode of travel and seating location in the same train, respectively.

Due to a couple of limitations of RP survey such as insufficient variation in the RP data to investigate all variables of interest (Kroes and Sheldon, 1988) and possibly strong correlations between explanatory variables (Kroes and Sheldon, 1988), some scholars suggested SP survey to reveal transit users’ behavior during a service disruption. In an SP survey, respondents are asked to indicate their decisions when faced with hypothetical scenarios. For instance, Bachok conducted an SP survey from train passengers in Klang Valley, Malaysia to reveal the modal shift of rail users based on information of alternative modes (Bachok, 2008). In this study, the train passengers were asked to choose among a set of alternatives including other trains, shuttle bus, private vehicles, and wait for the restoration of the rail system in hypothetical scenarios. Fukasawa et al. investigated the effect of providing information such as estimated arrival time,
arrival order and congestion level on the modal shift in response to unplanned transit disruption using a data from an SP survey (Fukasawa et al., 2012). They found that train users, who have accessibility to the information, have a higher frequency of shifting to other trains in comparison with those passengers without access to the information. In contrast, Bai and Kattan conducted an SP survey on light rail transit riders in Calgary, Canada and revealed that respondents have more willingness to switch their transport mode if there is no information provided to them regarding possible recovery period (Bai and Kattan, 2014).

Due to the idea that RP surveys are not able to investigate a wide range of variables of interest while SP surveys may not necessarily represent transit users’ behavior in a real service disruption (Kroes and Sheldon, 1988), some studies suggested combining both survey methods. For instance, Lin et al. conducted a combined RP-SP survey in Toronto to analyze transit users' mode behavior in response to a subway disruption (Lin, 2017; Lin et al., 2016a). The RP section devoted to respondents’ last experience with an unplanned service disruption and the SP section provides hypothetical disruption scenarios in which respondents were asked to either choose among alternative modes or cancel their trip. They revealed that travel cost, waiting time, duration of delay, income, and type of incident could affect transit users’ commuting mode choice during a subway service disruption (Lin et al., 2016a). Also, Rahimi et al. (2019) utilized a SP-RP survey to investigate transit users’ willingness to wait during an unplanned disruption.

2. SURVEY DESIGN

In order to investigate the behavior of transit riders to an unplanned service disruption, an RP-SP survey of Chicago Metropolitan area transit riders was conducted. For a complete discussion on the survey, please refer to (Auld et al., 2018). In this survey, a web-based questionnaire was implemented which was accessible through a survey link and PIN. Respondents were intercepted at CTA bus and rail, Metra train, and Pace bus stations by employing a sampling plan developed considering average daily ridership as well as the information of boarding/alighting (Auld et al., 2018). Participants who agreed to participate were given a contact card with a unique PIN which identifies the service, contact time and contact stop (Auld et al., 2018). By entering the survey link and the PIN, respondents were directed to the online questionnaire to provide the details corresponded to the intercepted trip.

The survey has four primary components including 1) person and household socio-demographic variables, 2) transit trip characteristics such as distance, travel time, travel cost, in-vehicle activities, access/egress to transit, etc., 3) transit users’ preferences towards transit and other modes, and 4) hypothetical scenarios for disruption based on the intercepted trip. This survey uses Google Maps API to gather reliable information about the origin and destination of the transit trip, transit routes, and travel time (see Figure 1). By employing Google Map APIs, travel times, waiting times, number of transfers, etc. were automatically saved.

This survey, also, collected information about transit users' experiences in using other mobility services in the Chicago Metropolitan Area including transportation network companies
(e.g. Uber, Lyft, etc.), taxis, car-sharing services (e.g. Car2go, Zipcar, etc.), and the city bike-sharing program (DIVVY). For each mobility services, the respondents were asked to provide information regarding the frequency of usage (in the Chicago Metro as well as while traveling), the duration of usage, which service they use if multiple options exist, and in-vehicle activities. Figure 2 presents an example of experience questions regarding TNC and taxi.

3. DESIGN OF STATED PREFERENCE CHOICE SETS

The SP disruption response questions were constructed by considering the characteristics of the intercepted trip as the basis for a set of SP questionnaires with the random configuration of modal characteristics according to an experimental design. For a complete discussion on the design of the survey, please refer to (Auld et al., 2018). Figure 3 shows an example of an SP disruption response scenario.

As it mentioned in section 3, the real-time information of the intercepted trip such as actual time of departure, real-time traffic congestion, and current transit schedule were collected.
by taking advantage of Google Maps API and then these values considered as a basis for when generating the scenario values (Auld et al., 2018). In this survey, each respondent was faced with four random transit disruption scenarios.

In order to generate SP disruption scenarios, two sets of parameters are defined. The first group of parameters which are observed using the Google Maps API includes the drive time \( T_{Drive}^t \), drive distance \( D_{Drive} \), and the transit time \( T_{Transit}^t \) based on the intercepted trip (Auld et al., 2018). The latter group of parameters which are generated randomly for each SP scenario includes the status of the original trip which is either cancelled or delayed \( S \), the transit travel time delay as a percentage of the original trip \( D \), the TNC surge pricing factor as a percent of increase in the base fare \( P \), taxi waiting time \( W_{taxi} \), TNC waiting time \( W_{TNC} \), Shuttle service waiting time which is the percent of \( D \) due to waiting for the shuttle \( W_{Shuttle} \) (Auld et al., 2018).

Figure 2. an example of experience questions regarding TNC and taxi (Adapted from (Auld et al., 2018))
The parameter of transit travel time delay ($D$) is identified based on a random value $r$ using the following rule (Auld et al., 2018):

$$D = \begin{cases} 
\in (0.15,0.3) & r \leq 0.33 \\
\in (0.5,1) & 0.33 < r \leq 0.66 \\
\in (1.5,3) & r \geq 0.66 
\end{cases}$$

Similar to the delay parameter, the TNC surge pricing factor is identified as follows (Auld et al., 2018):

$$P = \begin{cases} 
\in (0.15,0.25) & r \leq 0.33 \\
\in (0.5,1.5) & 0.33 < r \leq 0.66 \\
\in (2.5,4) & r \geq 0.66 
\end{cases}$$

Further, the taxi waiting time is identified as follows (Auld et al., 2018):

$$W_{\text{taxi}} = \begin{cases} 
\in (5,15) & r \leq 0.50 \\
\in (30,45) & r \geq 0.50 
\end{cases}$$
Also, the TNC waiting time is identified as follows (Auld et al., 2018):

\[ W_{TNC} \in (3, 15) \]

Finally, the shuttle service waiting time is generated as follows (Auld et al., 2018):

\[ W_{Shuttle} = \begin{cases} 
  \in (0.25, 0.4) & r \leq 0.50 \\
  \in (0.5, 0.75) & r > 0.50 
\end{cases} \]

The values of the parameters above are then shown to the respondent. Note that both “change of destination” and “trip cancellation” as alternative options for disrupted services have no specifics (Auld et al., 2018). The “ask for ride” option uses the drive time, with no additional cost. By selecting this option, the respondent is directed to enter the estimated waiting time for the pick-up (Auld et al., 2018). The “auto drive” alternative considers the drive time along with an additional travel time to pick up the vehicle based on its location, but this option is only available when the transit user indicates that there is an available vehicle (Auld et al., 2018). The rest of the parameters are estimated as follows:

The wait times for a delayed transit trip and a shuttle transit trip would be (Auld et al., 2018):

\[ T^W_{transit} = D * T^t_{transit} \]

\[ T^W_{Shuttle} = W_{Shuttle} * T^W_{transit} \]

For the shuttle trips, the new travel times would be (Auld et al., 2018):

\[ T^t_{Shuttle} = T^W_{transit} + T^t_{transit} - T^W_{Shuttle} \]

The taxi and TNC fare (in dollars) are calculated considering the drive distance (\(D_{drive}\)) as follows (Auld et al., 2018):

\[ C_{taxi} = 3.25 + D_{Drive} * 2.25 \]

\[ C_{TNC} = (1.75 + D_{Drive} * 1) * P \]
4. DATA ANALYSIS

In our RP-SP survey, the information of 659 individuals and 659 transit-based trips was successfully collected. The data have four primary components including 1) person and household socio-demographic variables, 2) intercepted transit trip characteristics such as distance, travel time, travel cost, in-vehicle activities, access/egress to transit, etc., 3) transit users' preferences towards transit and other modes, and 4) hypothetical scenarios for disruption based on the intercepted trip. For a complete discussion on the data, please refer to (Auld et al., 2018).

With respect to the gender, 46% male and 54% female participants who live in the Chicago metropolitan area completed the survey. Also, the data includes 72% full-time workers, 11% part-time workers, 3% unemployed, 9% of students, and 2% other categories. As for the household income level, 17.87% of participants’ households have an annual income less than $35k, 46.16% have an annual income between $35k and $100k, and the other 35.93% earn more than $100k per year. A full description of the sample with respects to household and individual demographic characteristics of the respondents are presented in Table 1 and Table 2, respectively.

The survey collected detailed attributes for a randomly intercepted transit trip in a typical day. Respondents were intercepted at a transit station (i.e., CTA bus, CTA rail, Metra, and Pace) in the Chicago metropolitan area and were asked to provide information about the characteristics of transit trip as well as its access and egress trips (Auld et al., 2018). Among all respondents, 53% were intercepted in CTA rail stops, 16% in CTA bus stops, 26% in Metra stops, and the remaining 5% were in Pace. With respect to the activity type, approximately 37% and 42% of the respondents were working or doing an in-home activity, respectively, at the origin of their intercepted trip. Also, more than 50% of the respondents had working activity at the destination of their intercepted trip. Fig. 1 presents the distribution of activity types in both the origin and destination of the intercepted trip.
Table 1. Descriptive statistics of household demographic characteristics.

| Variables                          | Frequency | Percentage |
|-----------------------------------|-----------|------------|
| HH size: one                      | 188       | 28.70%     |
| HH size: two                      | 315       | 48.09%     |
| HH size: three                    | 90        | 13.74%     |
| HH size: four                     | 39        | 5.95%      |
| HH size: five or more             | 23        | 3.51%      |
| HH income: < $15,000              | 42        | 7.43%      |
| HH income: $15,000 - $35,000      | 59        | 10.44%     |
| HH income: $35,000 - $50,000      | 79        | 13.98%     |
| HH income: $50,000 - $75,000      | 85        | 15.04%     |
| HH income: $75,000 - $100,000     | 97        | 17.17%     |
| HH income: > $100,000             | 203       | 35.93%     |
| Housing type: mobile/manufactured | 5         | 0.78%      |
| Housing type: apartment           | 247       | 38.29%     |
| Housing type: condo               | 96        | 14.88%     |
| Housing type: townhome/duplex     | 47        | 7.29%      |
| Housing type: single family       | 238       | 36.90%     |
| Housing type: other               | 12        | 1.86%      |
| Housing tenure: own/mortgage      | 288       | 46.01%     |
| Housing tenure: rent              | 322       | 51.44%     |
| Housing tenure: other             | 16        | 2.56%      |
| Housing payment: < $500           | 37        | 6.60%      |
| Housing payment: $500 - $1,000    | 157       | 27.99%     |
| Housing payment: $1,000 - $1,500  | 153       | 27.27%     |
| Housing payment: $1,500 - $2,000  | 106       | 18.89%     |
| Housing payment: $2,000 - $3,000  | 69        | 12.30%     |
| Housing payment: > $3,000         | 39        | 6.95%      |
Table 2. Descriptive statistics of individual demographic characteristics.

| Variables                              | Frequency | Percentage |
|----------------------------------------|-----------|------------|
| Gender: male                           | 298       | 45.57%     |
| Gender: female                         | 356       | 54.43%     |
| Age: < 18                              | 1         | 0.15%      |
| Age: 18 - 24                           | 115       | 17.48%     |
| Age: 25 - 34                           | 216       | 32.83%     |
| Age: 35 - 44                           | 129       | 19.60%     |
| Age: 45 - 54                           | 99        | 15.05%     |
| Age: 55 - 64                           | 79        | 12.01%     |
| Age: 65 - 74                           | 15        | 2.28%      |
| Age: > 75                              | 4         | 0.61%      |
| Race: white/Caucasian                  | 375       | 57.43%     |
| Race: African-American                 | 109       | 16.69%     |
| Race: Hispanic/Latino                  | 69        | 10.57%     |
| Race: Asian                            | 56        | 8.58%      |
| Race: two or more ethnicities          | 27        | 4.13%      |
| Race: native American                  | 4         | 0.61%      |
| Race: other                            | 13        | 1.99%      |
| Marital status: single                 | 312       | 47.56%     |
| Marital status: married/domestic partnership | 275     | 41.92%     |
| Marital status: widowed                | 4         | 0.61%      |
| Marital status: separated              | 7         | 1.07%      |
| Marital status: divorced               | 40        | 6.10%      |
| Marital status: other                  | 18        | 2.74%      |
| Education level: no high school degree, 12 grades or less | 6 | 0.92% |
| Education level: high school graduate, diploma or the equivalent | 35 | 5.36% |
| Education level: some college credit, no degree | 92 | 14.09% |
| Education level: trade or vocational school certificate | 7 | 1.07% |
| Education level: associate degree      | 43        | 6.58%      |
| Education level: bachelor’s degree     | 250       | 38.28%     |
| Education level: graduate or professional degree | 220 | 33.69% |
| Employment status: full-time           | 475       | 72.08%     |
| Employment status: part-time           | 70        | 10.62%     |
| Employment status: student             | 57        | 8.65%      |
| Employment status: homemaker          | 4         | 0.61%      |
| Employment status: retired             | 22        | 3.34%      |
| Employment status: unemployed or looking for work | 22 | 3.34% |
| Employment status: other               | 9         | 1.37%      |
The survey gathered information regarding arrival/departure time flexibility of the above activities. The analysis of the sample revealed that approximately 21% and 29% of respondents had departure time flexibility from the origin and arrival time flexibility at the destination, respectively. Further, the majority of the departure times were between 6-9 a.m. and 3-6 p.m. Fig. 2 presents the distribution of departure time in the data.

With respect to trip characteristics, our survey also collected travel distance, travel time, number of transfers in the respondents’ transit trip. Fig. 3 presents the distribution of the number of stops in the intercepted trip. Per the figure, around 67% of the respondents had no transfer in their intercepted trip. Further, Fig. 4 and Fig. 5 show the distribution for travel distance and travel time in the data, respectively. According to Figure 4, approximately 22% of the intercepted trips were less than 5 miles while around 7% of the intercepted trips were more than 30 miles.
Fig 2. Distribution of departure time in the data (Adopted from (Auld et al., 2018)).

Fig 3. Distribution of the number of transfers during the trip.
Fig 4. Distribution of travel distance in the sample.

Fig 5. Distribution of travel time in the sample.
Respondents were also asked about the mode which they used to get from the origin to the initial transit station, and from the last transit station to the destination. Per the analysis, walking was the prominent mode of transport (67.83% for the trip to the initial transit stop and 85.13% for the trip from the last transit stop to the destination) due to the close proximity of the origin and destination to the transit stops (Figure 6 and Figure 7).

**Fig 6.** Distribution of travel distance between origin and initial transit stop.

**Fig 7.** Distribution of travel distance between the last transit stop and the destination.
In this survey, respondents were asked to indicate the amount of time they spent on different activity types while they were on board the intercepted transit vehicle. The activity types include reading book/newspaper, doing work or school-related activities, using a smartphone/tablet/laptop for entertainment, talking on the phone, socializing, and relaxing (Josh et al.). Table 3 shows the distribution of in-vehicle activity types and duration in the data. Per the data analysis, using smartphone/tablet/laptop, reading, and relaxing are the most preferred activities that respondents have conducted.

We also asked the respondents about their reasons to select transit as their mode of travel. We found that fastest option to reach the destination, no need to worry about parking, and lower travel cost are the most influential reasons on selecting public transit as they were important for more than half of the respondents.

Table 3. Distribution of duration of in-transit activity in the sample (Adopted from (Auld et al., 2018)).

| Activity type                  | None          | Very little of the time | Some of the time | Most of the time | All of the time |
|-------------------------------|---------------|-------------------------|------------------|------------------|----------------|
| Reading                       | 68.74%        | 6.22%                   | 10.17%           | 10.77%           | 4.10%          |
| Using a smartphone for entertainment | 20.03%        | 11.53%                  | 23.52%           | 28.83%           | 16.08%         |
| Talking on the phone          | 83.92%        | 7.28%                   | 6.53%            | 1.52%            | 0.76%          |
| Work related activity         | 79.21%        | 7.13%                   | 9.86%            | 2.73%            | 1.06%          |
| School related activities     | 91.50%        | 2.58%                   | 4.25%            | 1.21%            | 0.46%          |
| Socializing or talking with others | 81.18%        | 5.77%                   | 7.44%            | 3.49%            | 2.12%          |
| Relaxing / doing nothing)     | 44.31%        | 13.66%                  | 25.19%           | 10.62%           | 6.22%          |
| Other                         | 93.17%        | 2.12%                   | 3.03%            | 0.61%            | 1.06%          |

To explore respondents’ opinion about transit systems, they were asked attitudinal questions about potential benefits of and concerns of public transit and were asked to indicate their level of agreement to a couple of statements about public transit. Fig. 8 presents the distribution of respondents’ answers to these questions. We found that less concern about parking and traffic conditions and more productive use of time while traveling are the most common opinions about transit systems. On the other hand, people have mixed opinions with regards to privacy restrictions in the transit system. According to Fig. 9, approximately 30% of respondents somewhat agree or completely agree that public transit restricts privacy whereas about 40% disagree with this statement.
Fig 8. General opinions toward public transit in the sample.

In addition to collecting information regarding the characteristics of transit-based trips, respondents’ attitudes in a possible disruption of the transit system were also collected. Respondents were first asked to state how long they are willing to wait for the transit system to be restored before they start to think about alternative modes in two conditions of 1) with no information from the transit agency, and 2) if the transit agency provides information regarding the delay. Fig. 9 presents the distribution of willingness to wait in the two conditions. We found that people tend to wait for higher durations when a transit agency informs them of the delay.

Fig 9. Willingness to wait for the transit system to be restored.

Moreover, because the respondents’ source of information for receiving emergency updates is significant in their behavior at the time of possible disruption, respondents were asked to indicate their level of agreement to statements regarding various sources of information. Fig. 10 illustrates the distribution of respondents’ level of agreement to the latter statements. According to the figure, approximately 75% of respondents indicated that they either somewhat
or completely trust emergency updates from officials and more than 90% indicates that they would somewhat or completely follow instructions from officials.

![Bar chart showing trust levels](chart.png)

**Fig 10.** Distribution of respondents’ trust to various sources of information.

Finally, participants were faced with four stated choice experiments for various hypothetical scenarios in which they were asked to select the most preferred choice given the designed attributes. The alternatives are:

- Wait for the shuttle bus
- Change other trip attributes
  - Change destination
  - Cancel trip
- Change mode
  - Ask for ride
  - Auto drive
  - Use taxi
  - Use TNC

Fig. 11 presents the distribution of the first level alternatives and Fig. 12 shows the distribution of different types of alternative modes in the sample.
5. MODEL ESTIMATION & RESULTS

In this study, we are interested in predicting and simulating the transit users’ behavior in response to an unplanned service disruption. According to the SP scenarios provided to each respondent, we propose a decision tree (DT) model structured in three-level. The upper level determines whether the transit user decides to cancel or perform his/her trip if the trip is disrupted. The next level determines if the user decides to change the destination provided that the trip is not canceled, and the last level estimates the alternative mode being chosen given that the destination is not changed. The alternative modes are waiting for the shuttle bus, transportation network companies (e.g., Uber and Lyft), friend/family pick up, personal vehicle, and taxi.
A decision tree is a classifier which generates a tree and a couple of rules, representing the model of different classes using a given data. A typical DT structure includes three elements: 1) each “internal node” represents a test on an attribute, 2) each “branch” denotes an outcome of the test, and 3) each “leaf node” represents the distribution of class(es) (Han et al., 2011). A couple of advantages stated in the literature for DT classification models. First, because of their intuitive representation, the outcome of a DT model is easy to implement (Breiman et al., 2017). Second, it is not required for a modeler to specify any parameter and thus DT models are suitable for investigative knowledge discovery. Third, DT models are relatively high in terms of accuracy; also, they are fast as far as model development concerned (Breiman et al., 2017; Han et al., 2011).

In DT models, a dataset is classified by directing them from the root of the tree down to a leaf with respect to the outcome of the tests along the path (Rokach and Maimon, 2008). In a DT structure, we start from the root node, and then we apply the test (i.e., a locally optimum decision about which attribute to use for subdividing the data) to the data and follow the appropriate branch based on the outcome of the test. Gini Index, Entropy and Misclassification Error are commonly used measurements to choose an appropriate attribute (Tan, 2018). Then, the branch leads us either to another internal node or a leaf node (Tan, 2018). When the leaf node is reached, the class label related to the leaf node is then assigned to the observation.

In order to develop a DT model, a dataset is divided into two different samples including a “training sample” and a “testing sample.” The training and testing samples are used to generate the tree and evaluate its performance, respectively. As the training sample size and the predictive performance are positively correlated, data scientists usually prefer to use the largest possible training sample (Rokach and Maimon, 2008). However, due to some dataset limitations, especially in small ones, the training sample might be limited because the rest of the sample (i.e., testing sample) should include all available classes adequately. In this study, we came up with 80% and 20% of the dataset for training sample and testing sample, respectively.

Biasedness in model development is one of the most critical issues in classification methods, and it usually occurs due to using an imbalanced dataset. A dataset is imbalanced if the classes are not approximately equally distributed. Our dataset is imbalanced because only around 10% of the respondents either canceled their trip or changed their destination. Then, before developing the first-level and second-level DT models, the problem should be addressed. A couple of methods are proposed in the literature to avoid the biasedness of DT models. For instance, assigning distinct costs to training samples (Pazzani et al., 1994) and either oversampling the minority class or under-sampling the majority class (Kubat and Matwin, 1997) are widely implemented in the literature to address the issue. In this study, the oversampling method is utilized using the SMOTE algorithm. This algorithm can be found in Chawla et al. (Chawla et al., 2002).

In this study, the three DT models are developed using Scikit-learn module (Pedregosa et al., 2011) in Python programming language. Table 4 presents the attributes used in the DT models. In the DT model developments, Entropy measurement is selected as the test condition.
Two different approaches are employed to develop the DT model for each level. In the first approach, the number of leaves and the depth of the tree are restricted, while in the other one, we do not set any value for those parameters, and the DT models are developed without restrictions. Figure 13 and Figure 14 represent an example of a restricted DT structure for the first-level (i.e., performing trip) and the second-level (i.e., changing destination).

Several performance measurements are suggested in the literature to evaluate a classification model. In this study, a couple of widely utilized performance measurements are estimated including Accuracy, Precision, Recall, and F-measure to select the outstanding DT model for each level. These are calculated by employing a coincidence matrix. Table 5 presents a coincidence matrix corresponding to a two-class classification model. The diagonal numbers are the representative of correct decisions, while the rest represents the errors (Olson and Delen, 2008).

| Predicted class | True class          |          |
|-----------------|---------------------|----------|
|                 | Positive            | Negative |
| Positive        | True positive count (TP) | False positive count (FP) |
| Negative        | False negative count (FN) | True negative count (TN) |

Table 5. An example of a two-class coincidence matrix for a classification problem.

Using coincidence matrix, Accuracy, Precision, Recall and F-measure equations for a classification problem would be (Olson and Delen, 2008):

Accuracy = \( \frac{TP + TN}{TP + TN + FP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

Recall = \( \frac{TP}{TP + FN} \)

F-measure = \( \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \)
Table 4. Variables used in the DT models.

| Category          | Name             | Definition                                                                 | Mean   | Std. Dev. |
|-------------------|------------------|---------------------------------------------------------------------------|--------|-----------|
| Demographics      | AGE_M65          | 1: If the age of transit user is more than 65 years old/ 0:                | 0.03   | 0.17      |
|                   | male             | Otherwise                                                                  |        |           |
|                   | Bachelor         | 1: If the transit user has a bachelor degree / 0:                         | 0.38   | 0.49      |
|                   | M_Bachelor       | 1: If the transit user has a master degree and more/ 0:                  | 0.34   | 0.47      |
|                   | inc_U15          | 1: if the household income is less than 15K/ 0:                         | 0.06   | 0.244     |
|                   | inc_15_35        | 1: if the household income is between 15K and 35 K / 0:                  | 0.09   | 0.29      |
|                   | inc_75_100       | 1: if the household income is between 75 K and 100 K / 0:                | 0.18   | 0.38      |
|                   | inc_M100         | 1: if the household income is more than 100 K/ 0:                       | 0.33   | 0.47      |
|                   | full_emp         | 1: if the transit user is a full-time worker / 0:                        | 0.72   | 0.45      |
|                   | Student          | 1: If the transit user is a student/ 0:                                 | 0.088  | 0.28      |
|                   | Dlicense         | 1: If the transit user has a driver license/ 0:                         | 0.86   | 0.35      |
| Trip characteristics | DriveDistance    | The distance between the trip origin and destination in miles (Ranged between 0.39 and 59) | 16.45  | 26.87     |
|                   | DriveTime        | The estimated travel time between origin and destination (min)           | 35.92  | 29.12     |
|                   | home_a           | 1: If the activity type at the destination is in-home activity/ 0:       | 0.23   | 0.42      |
|                   | work_a           | 1: If the activity type at the destination is work activity/ 0:          | 0.47   | 0.50      |
|                   | flexible_a       | 1: If the transit user has time flexibility for arrival at the destination/ 0: | 0.70   | 0.46      |
|                   | Activitydur_d    | The activity duration at the origin before going to a transit station in minutes (Ranged between 0 and 23 hours) | 7.17   | 5.06      |
|                   | trip_regular     | 1: If the transit user makes this trip regularly/ 0:                     | 0.84   | 0.37      |
|                   | trip_alone       | 1: If the transit user is traveling alone/ 0:                           | 0.86   | 0.35      |
|                   | veh_acc          | 1: If the transit user has accessibility to his/her car to make the trip/ 0: | 0.44   | 0.50      |
| SP variables      | OptTransitWait   | The waiting time for delayed/replaced transit service (min)              | 57.35  | 121.66    |
|                   | OptTaxiCost      | Taxi fare if the transit user wants to make the trip by using this option | 39.61  | 60.50     |
|                   | OptTNCCost       | TNC fare if the transit user wants to make the trip by using this option | 52.46  | 91.86     |
Figure 13. The restricted DT model for the first level (i.e., performing or cancelling trip)
Figure 14. The restricted DT model for the second level (i.e., changing the destination of trip)
With regards to the performance measurements, the unrestricted version of DT models for each level is utilized due to their higher accuracy in comparison with restricted ones. Table 6, Table 7, and Table 8 presented the performance measurements for our three-level DT model.

**Table 6. The performance measurements for the first-level (performing trip) DT model**

| Performance measurement | Alternatives | Perform trip | Cancel trip |
|-------------------------|--------------|--------------|-------------|
| Accuracy                |              | 85.31%       |             |
| Precision               |              | 88.65%       | 53.33%      |
| Recall                  |              | 95.08%       | 31.58%      |
| F1-Score                |              | 91.75%       | 39.67%      |

**Table 7. The performance measurements for the second-level (changing destination) DT model**

| Performance measurement | Alternatives | Does not change destination | Change destination |
|-------------------------|--------------|------------------------------|--------------------|
| Accuracy                |              | 98.36%                       |                    |
| Precision               |              | 98.63%                       | 87.50%             |
| Recall                  |              | 99.54%                       | 70.00%             |
| F1-Score                |              | 99.08%                       | 77.78%             |

**Table 8. The performance measurements for the third-level (mode choice) DT model**

| Performance measurement | Alternatives | Ask for ride | Auto-drive | Shuttle bus | TNC | Taxi |
|-------------------------|--------------|--------------|------------|-------------|-----|------|
| Accuracy                |              | 58.27%       |            |             |     |      |
| Precision               |              | 37.84%       | 44.44%     | 74.59%      | 41.46% | 27.08% |
| Recall                  |              | 41.18%       | 47.06%     | 70.82%      | 38.64% | 39.39% |
| F1-Score                |              | 39.44%       | 45.71%     | 72.65%      | 40.00% | 32.10% |

DT models provide not only good accuracy but also offer rich attribute importance information that could be used where the interpretability of the model is paramount (Kazemitabar et al., 2017). For an attribute, the importance score (or tree weight) is calculated in a DT model by summing the impurity reductions over all nodes where a split is made on the attribute with respect to the size of the node (Kazemitabar et al., 2017).
Per our results for the first-level DT model, the dummy variable of work activity at the destination is the most influential attribute on the performing the disrupted trip. According to Figure 15, having the arrival-time flexibility at the destination, the dummy variable of in-home activity at the destination, the distance between the origin and the destination, and the waiting time of the delayed/replaced service are ranked in second to fifth place, respectively.

The second-level DT model reveals that the waiting time of the delayed/replaced service, having the arrival-time flexibility at the destination, and the dummy variable of in-home activity at the destination are the most important attributes to develop the second-level DT model (Figure 16). Besides, having the income more than $100k, the duration of activity at the origin, the trip distance, and the TNC fare as an alternative mode for the disrupted trip play a critical role in deciding whether to change the destination of the disrupted trip or not.

Per the results of third-level DT model, the TNC fare as an alternative mode for the disrupted trip and the waiting time of the delayed/replaced service are the most influential factors on the selecting the alternative mode for the disrupted transit service (Figure 17). Also, the trip drive time and distance, as well as the duration of activity at the origin, are the key attributes to predict the mode behavior of the respondents.

Figure 15. The importance of variables used in the first-level DT model.
Figure 16. The importance of variables used in the second-level DT model.

Figure 17. The importance of variables used in the third-level DT model.
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