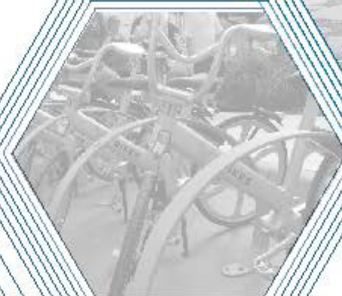

Where to? Origins and Destinations of TNC (Transportation Network Company) Trips in Context of Available Transit Options

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FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

WHERE TO? ORIGINS AND DESTINATIONS OF TNC (TRANSPORTATION NETWORK COMPANY)TRIPS IN THE CONTEXT OF AVAILABLE TRANSIT OPTIONS

FINAL PROJECT REPORT

By:

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Sponsorship:
CTEDD

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In cooperation with United States Department of Transportation's Office of Research, Development, and Technology (RD&T)

Acknowledgments

The authors wish to thank Dr. Timothy F. Welch, who conceived the initial idea for this work, and Dr. Carole Voulgaris, who helped develop it to secure funding. Cal Poly students Ms. Amanda Tran, Ms. Peyton Ratto, and Mr. Nick Sauciur helped with data analysis, literature review, and citation formatting. This work was supported by a grant from the Center for Transportation Equity, Decisions, and Dollars (CTEDD), funded by the US Department of Transportation Research and Innovative Technology Administration (OST-R) and housed at The University of Texas at Arlington. All opinions are of the authors alone.

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Technical Report Documentation Page

1. Report No.
CTEDD 019-11

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle
Where to? Origins and Destinations of TNC Trips in the context of available transit options: A Case study of Transportation Network Company (TNC) Users in Chicago

5. Report Date 5/20/2022

6. Performing Organization Code

7. Author(s)
Daniel DeFoe
Shams Tanvir, Ph.D., P.E.
Sean Barbeau
Alex Galano
Anurag Pande, Ph.D.

8. Performing Organization Report No.

9. Performing Organization Name and Address
Civil and Environmental Engineering, Cal Poly San Luis Obispo
Center for Urban Transportation Research (CUTR), University of South Florida

10. Work Unit No. (TRAIS)

11. Contract or Grant No.
USDOT - 69A3551747134

12. Sponsoring Organization Name and Address
Center for Transportation, Equity, Decisions and Dollars (CTEDD)
USDOT University Transportation Center
The University of Texas at Arlington
Woolf Hall, Suite 325
Arlington TX 76019 United States

13. Type of Report and Period Covered
Final Report

14. Sponsoring Agency Code

15. Supplementary Notes
Additional project information is available at https://ctedd.uta.edu/research-projects/where-to-origins-and-destinations-of-tnc-and-transit-trips-based-on-mobile-devices/

Project performed under a grant from the US Department of Transportation's University Transportation Centers (UTC) Program.

16. Abstract

Over the past decade, the rapid development and adoption of mobile phone and telecommunications technology have disrupted established business models by providing mobility services that were previously available primarily through the public sector (particularly public transit agencies) or were privately provided through directly owned and operated vehicles by firms (traditional taxis) or households (private automobile). Transportation has entered an era of immense change, with many transportation network companies (TNCs, e.g., Uber and Lyft) both complementing and competing with public transit. To best serve their communities, public-sector transportation agencies need better information about the degree to which these new mobility services complement or substitute publicly-provided fixed-route mass transit service. A lack of information on TNC usage is a significant barrier to efficient transportation planning and decision-making.

This project attempted to address this lack of information by trying to contextualize TNC use data with available transit options. Publicly available TNC trip data from the City of Chicago is used in this study in addition to a framework to come up with available transit options for those same trips. The results show a large majority of trips made using TNCs would have taken at least 30% longer using the alternative transit mode. Examining the TNC trip patterns within the nine Chicago districts showed that ~40% of the TNC trips were intradistrict trips. The research shows that meaningful conclusions to address the last-mile problem may be drawn using TNC trip data provided by the city of Chicago. It may be worth exploring why more cities do not provide similar data. Future research in this area should involve a survey of communities nationwide to examine the barriers/challenges due to which other cities do not make TNC trip data specific to their communities publicly available.

<table>
<tr><td colspan="2">17. Key Words
Data analytics, Big data, Transportation network companies, Mobility as a service
Public transportation, Transit</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available to the public through the Transport Research International Documentation (TRID) repository.</td></tr>
<tr><td>19. Security Classification (of this report)
Unclassified.</td><td>20. Security Classification (of this page)
Unclassified.</td><td>21. No. of Pages
55</td><td>22. Price
N/A</td></tr>
</table>

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Executive Summary

Almost all major cities are grappling with the issue of managing the seemingly unorganized TNC sector. It is upon the transportation professionals to understand the issues clearly and come up with policies and infrastructure changes accordingly. This research is aimed at supporting the goals of innovative transit agencies interested in promoting multimodal transportation in collaboration with TNCs. To best serve their communities, public-sector transportation agencies need better information about the degree to which these new mobility services complement or substitute publicly-provided fixed-route mass transit service. While Transportation Network Companies provide convenient mobility, whether or not they serve as an effective last-mile solution remains an open question. Lack of information on TNC usage, especially with respect to its role as a complement or competition to transit is a significant barrier to efficient transportation planning and decision-making by agencies.

This research analyzed the detailed TNC pickup and drop-off information from the City of Chicago data portal. A metric to define 'equitable access' to transit for the TNC users is developed and tested using the TNC database and comparable transit trips as queried from OpenTrip Planner 2 (https://www.opentripplanner.org/) software. Based on the analysis, we conclude that a large majority of trips made using TNCs would have taken at least 30% longer using the alternative transit mode. Examining the TNC trip patterns within the nine Chicago districts showed that ~40% of the TNC trips were intradistrict trips. TNC trips of less than 15 minutes duration (classified as short trips in this analysis) had a very high proportion of trips for which the potential transit alternative would have taken more than 200% of the TNC travel time. Micromobility options may be able to serve the travel needs of these users in a more sustainable way compared to TNC. The research shows that meaningful conclusions to address the last-mile problem may be drawn using TNC trip data provided by the city of Chicago. It may be worth exploring why more cities do not provide similar data.

Chapter 1. Introduction

Over the past decade, many private firms established business models based on providing mobile app-supported mobility services that were previously available primarily through the public sector (particularly public transit agencies) or that were privately provided through households' and firms' directly-owned and operated vehicles (i.e., taxis or airport van service). Transportation network companies (TNCs) that connect owners/operators of vehicles (typically not considered employees of these firms) to people who need rides have rapidly risen in use over the past decade. These TNCs are commonly referred to as rideshare, but we note that ride-hail may be a more appropriate term. Even though the large companies in this space, i.e., Uber and Lyft, provide options to share rides, in most cases, these companies serve single riders or riding parties. While the rideshare model proliferates and becomes increasingly ingrained as one of the travel mode choices, little data exists about the use and movement of these vehicles, especially with respect to how these trips complement or replace (or cannibalize transit trips). These questions are relevant because aligning TNCs to be complementary to transit service supports the sustainability goals of reducing VMT. Previous research including by the PI (Principal Investigator), has shown that the status quo with regard to the TNCs leads to a meaningful increase in VMT (Choi et al., 2022). There remain many unanswered questions about TNCs and their relationship with transit, including to what extent TNC trips cannibalize transit trips, and what are the factors that contribute to the competition between TNCs and transit. The data required to answer these questions include:

- How and where the TNC vehicles operate
- When people use rideshare and where do they start and end the trips
- What other mode choices are available to users choosing TNC as their mode of travel

In this project, publicly available data provided by TNCs to the City of Chicago is used to isolate rideshare trips to determine where and when they travel. Using these data, we have attempted to answer the questions above, adding significantly to the body of knowledge about TNC trips and contextualizing them with available transit options.

TNC's popularity is driven by the cost-effective yet convenient rides these companies are able to provide. The convenience is due to the widespread adoption of smartphones with GPS technology that make it easy for travelers to use mobile apps to request rides, check how long they have to wait and pay without cash. However, the proliferation of TNCs has been a disruptive force in the mobility landscape, and many questions have been raised about negative externalities, e.g., increased VMT(see Choi et al., 2022).

In particular, public transit agencies would benefit from better information on the degree to which new mobility services complement or substitute for publicly-provided fixed-route mass transit service. The lack of data on the use of these relatively new mobility services represents a barrier to sound decision-making on the part of agencies. We seek to address this challenge by combining the publicly available TNC trip data from Chicago with the Open Trip Planner data to explore the TNC trips in the context of available transit mode options.

The report is organized as follows; the next chapter provides background research and literature on questions relevant to this study. The next chapter provides the preparation of data from Open Trip Planner and Chicago's TNC trip database. Analysis of the data to address the research questions is provided in Chapter 4, followed by Conclusions and Future Scope in the Final chapter.

Chapter 2 Literature Review

Transportation network companies (TNCs), commonly referred to as rideshare, have rapidly risen in use over the past decade. While the rideshare model proliferates and becomes increasingly engrained as a normal travel mode, little data exists about the use and movement of these vehicles. Recent declines in transit ridership (even prior to COVID-19 pandemic) that have coincided with the introduction of TNCs into transit markets have motivated several studies on the potential relationship between transit and TNCs ((Boisjoly et al., 2018); (Clewlow & Mishra, 2017); (Hall et al., 2018); (Rayle et al., 2016)). While the residential location is a primary determinant of transit ridership ((Ralph et al., 2017); (Voulgaris et al., 2017)), the connection between residential location and TNC use is less clear.

In this project, we first explored the use of cell-phone-based GPS data to isolate rideshare trips to determine where and when the ride share users travel.

Use of Call Detail Records

Few studies have explored the viability of call detail records (CDRs) to specifically infer rideshare trips. In this section, we present a brief overview of studies using CDRs and built-in GPS data from mobile phones to infer mode choices to illustrate how researchers have leveraged this data. We then focus on the studies that have included an analysis of ridesharing and transportation network companies (TNC's).

Gurumurthy & Kockelman (2018) utilize AirSage GPS data to determine the feasibility of pairing when using rideshare services. Using the dataset, trip routes and purposes were inferred from origins and destinations. These trips were then used to determine the percentage of existing rides that can be shared via the use of a TNC. This process determines not only the optimum sharing of rides but also the optimum fleet size to accommodate the number of rides. Calabrese et al. (2011) similarly utilized AirSage datasets to determine origin-destination matrices and compared the data to existing census tract data to evaluate the effectiveness of using AirSage data and similar GPS data. The study found that using GPS datasets allowed for a better understanding of time-based travel trends.

Other research used GPS data to analyze traffic impacts. Zhang et al. (2020) used GPS records in Tokyo to look at the impacts of implementing rideshare from an environmental perspective. They determined that the implementation of rideshare programs could decrease the amount of CO_2 emitted by 84%. However, the study did not analyze the impacts of transit riders' views towards ride sharing or if its implementation would be accepted by the public. Ma & Wolfson (2013) studied the impacts of implementing a specific type of ridesharing known as slugging. Slugging is when one person involved in a rideshare will share rides with someone who covers a decent amount of their trip length and makes up the difference themselves. They base their main trip on the trip they're merging with and will figure out how to get to and from the merged trip origin and destination to their intended destination. Using GPS trajectory data taken from a taxi dataset, the model determined that the implementation of slugging would reduce 71 tons of carbon dioxide emissions as well as savings of up to 144,963 kilometers. Similar to the study from Zhang et al. (2020), this study did not examine the effects of rider preferences and opinions on the model.

GPS records from taxis were taken to determine how to better optimize taxi fleets for rideshare programs in places like New York City and Nanjing, China. Santi et al. (2014) analyzed the benefits of implementing a shareability network into its taxi fleet, or a model that would determine trips that could be combined with one taxi to reduce the number of fleet vehicles on the road. Dai (2016) analyzed the data in a similar fashion but took the data one step further and used it to determine optimal places for pickup to ensure the maximum efficiency of a taxi rideshare program. Spieser et al. (2014) also used taxi GPS records to determine the potential for replacing personal vehicles with an autonomous vehicle fleet. Through using travel records, the study was able to determine an optimal fleet size for an autonomous vehicle fleet meant for ridesharing services.

Reddy et al. (2010) use data from mobile phones with built-in GPS and accelerometers to estimate whether a user was stationary, walking, running, biking, or in some type of motor vehicle. A trained classifier model derived from a Hidden Markov approach is used to infer users' travel mode. Patterson, Liao, Fox, & Kautz (2003) similarly use GPS data to estimate mode choice, using knowledge of real-world constraints to distinguish between walking, driving, or riding the bus. Bayes filters are employed to create a probabilistic estimate of the user's next state based on their previous one, accounting for their geographic location. This process allows the authors to detect a change in modes, such as a user getting off the bus and starting to walk.

Wang, Calabrese, Lorenzo, & Ratti (2010) propose that CDRs can be used to detect travel mode considering the difficulties posed by collecting data of a finer resolution from GPS, which may provide better geographical accuracy than CDR-derived data but is not available in as large a volume. The approach to detecting travel mode involves three primary steps. First, the origin and destination of each trip are estimated. After noise is removed from the data, the second step sorts similar trips into subgroups based on travel times. Third, the results are validated by comparing the resultant travel times with the Google Maps estimates of travel times for driving, public transit, and walking as a means to estimate which mode of travel was used.

Research by Cici, Markopoulou, Frias-Martinez, & Laoutaris (2014) is among the early studies that attempt to use cell phone data to infer ridesharing trips. The primary contribution of this study is the combination of CDRs and social media data (Twitter and Foursquare) to estimate home-work commuting trips. Similarly, Alexander & González (2015) use CDRs to attempt to infer ridesharing trips and assess their impacts on the larger urban context. The authors estimate the mode share of three travel modes (drive-alone or taxi, carpool, and non-driving modes) by linking the origin and destination derived from the CDRs with the Census Transportation Planning Products (CTPP). In the absence of cell phone data, Cooper, Castiglione, Mislove, & Wilson (2018) conducted a simulation study by generating synthetic ridesharing requests to estimate the number of TNC vehicles, trips, and VMT. This method was considered the most appropriate option in light of the lack of meaningful, accessible, and objective data on TNC trips.

Conclusions from Literature Review

While there are providers such as AirSage that can provide a packaged version of useable data, cell phone location aggregators are naturally limited in scope by the number of cell phone service providers from which they receive data. Furthermore, a cleaned and trajectory-based sample for our study area is required to sufficiently enhance the quality of the data, but at the expense of data coverage. Ultimately, it was decided that cost of the data required for appropriately sampling the population for the analysis was not worth it. The research team instead focused on TNC trip data provided by the city of Chicago. Providing a framework for using publicly available data in future transit planning decision-making may encourage other cities to gather and make these data available.

All trips, starting November 2018, reported by Transportation Network Providers (sometimes called rideshare companies) to the City of Chicago as part of routine reporting required by the ordiance that governs the TNC operations in the city. The city has taken careful steps to address privacy of the individual users in the data, details of which may be found on the data portal (*City of Chicago | Developers*, n.d.). In the next chapter, we provided details of the datasets used in this study along with the way they are integrated with each other to address study questions.

Chapter 3 Data Description for Travel Pattern Analysis

This research used data from the following three sources:

- The Chicago Data Portal Transportation Network Providers (Transportation Network Companies (TNC) Trips dataset[1]
- The Chicago Transit Authority (CTA) General Transit Feed Specification (GTFS) dataset published on September 4, 2020, archived by OpenMobilityData.org[2]
- OpenStreetMap data for the area of Chicago[3]

The Chicago TNC dataset includes trips by ride-hailing providers in Chicago, with each record having the latitude and longitude of the center of the pick-up census tract or the community area if the census tract has been hidden for privacy for trip origins and destinations. Note that all start and end times of trips are rounded to the nearest 15 minutes. This rounding is part of the effort to protect individual user privacy.

The CTA GTFS dataset represents scheduled transit service in Chicago from September 1, 2020, to November 30, 2020. CTA does not include fare information in their GTFS datasets, and therefore fare cost for transit trips was not estimated. CTA does not provide a GTFS Realtime feed, and therefore archived real-time transit information for this time period was not considered. More information about the GTFS and GTFS real-time formats can be found at the home of the specification on the GitHub google/transit repository[4]. OpenStreetMap data was used for pedestrian paths (e.g., sidewalks) and streets which form the routes taken by users between transit legs of trips (e.g., origin to the first stop, transfers between stops, last stop to destination).

[1] https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p
[2] https://openmobilitydata.org/p/chicago-transit-authority/165/20200904
[3] https://www.openstreetmap.org/
[4] https://github.com/google/transit

The application created as part of this work is made available for future use and may be found on the links provided as footnotes in this chapter.

Planning for Transit Trip

To plan a transit trip, the OpenTripPlanner[5] open-source multimodal trip planning engine was used. The v2.0.0 release of OTP[6] was initially used for analysis. However, while testing, a bug was encountered[7] that mistakenly prioritized long walk trips over transit trips. As a result, a prerelease version of OpenTripPlanner v2.1.0 was used[8] that included a fix for this issue. OpenTripPlanner was configured to process transit data for the aforementioned time period using the graph build configuration options[9].

Two open-source software applications were created as part of this project to process data and interact with OpenTripPlanner:

1. opentripplanner-client-library[10] - A Kotlin Multiplatform library for making Application Programming Interface (API) requests and parsing responses from an OpenTripPlanner v2 server. It supports Android, iOS, and Java Virtual Machine languages (Java, Kotlin) for the following OTP2 REST API endpoints:
    a. /plan - Trip planning from an origin to a destination
    b. /bike_rental - List of bike rental stations
    c. /otp - Provides information about the OTP server (version, etc.)
2. otp-ride-hailing-analyzer[11] - A Java/Kotlin application for calculating scheduled transit trips that have the same departure time, origin, and destination as a given dataset of TNC

[5] https://github.com/opentripplanner/OpenTripPlanner
[6] https://repo1.maven.org/maven2/org/opentripplanner/otp/2.0.0/
[7] https://github.com/opentripplanner/OpenTripPlanner/issues/3289
[8] dev-2.x branch at commit https://github.com/opentripplanner/OpenTripPlanner/commit/8555ca87ef0019f3f050cf3079e9beb0fd367d7d
[9] https://docs.opentripplanner.org/en/latest/Configuration/#graph-build-configuration
[10] https://github.com/CUTR-at-USF/opentripplanner-client-library
[11] https://github.com/CUTR-at-USF/otp-ride-hailing-analyzer

trips. This application uses the opentripplanner-client-library to interact with an OpenTripPlanner server.

opentripplanner-client-library and otp-ride-hailing-analyzer software projects are both open-source and have been made available on GitHub, as shown in Figure 1 and Figure 2.

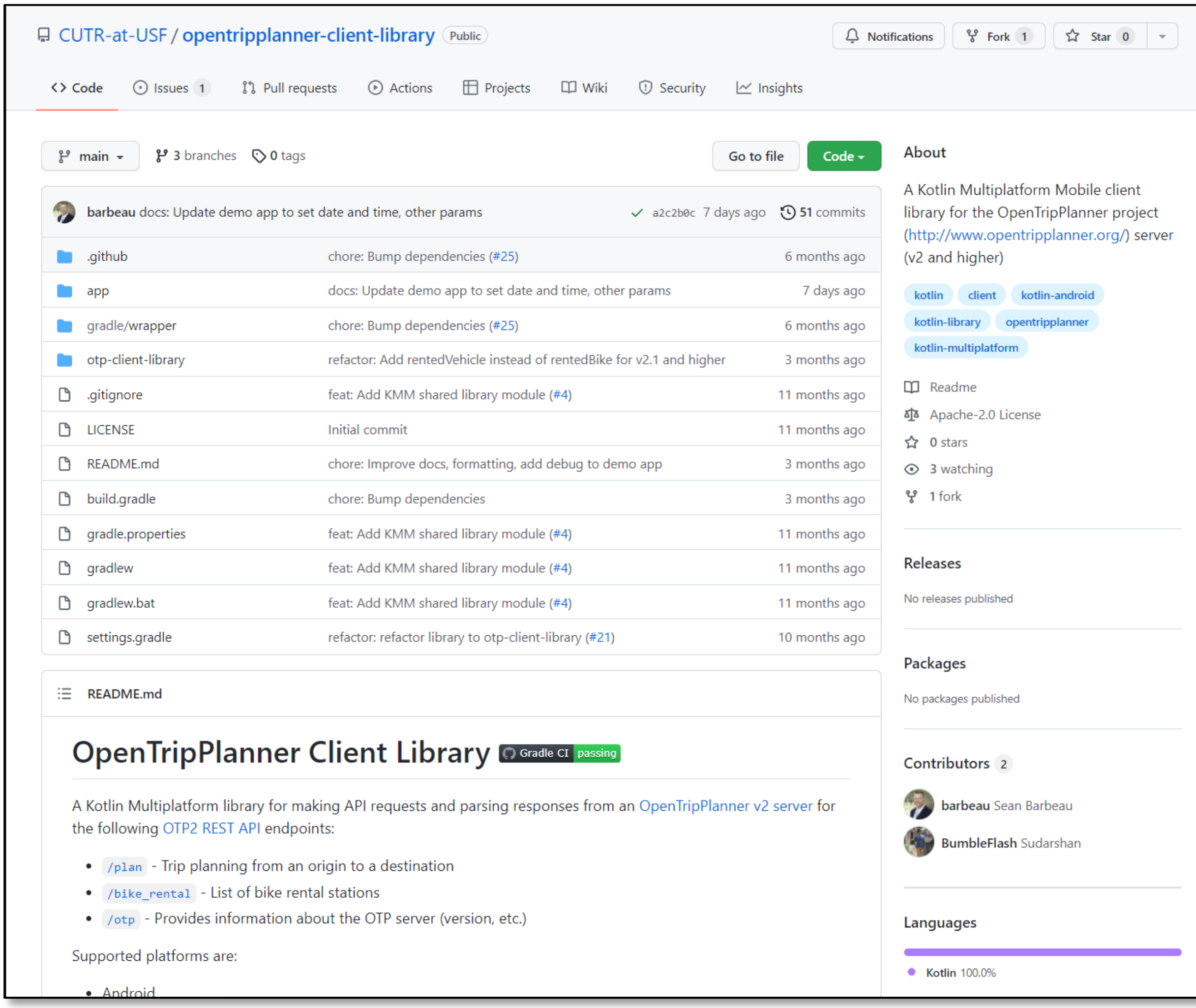


Figure 1 - The opentripplanner-client-library is a Kotlin multiplatform software project that communicates with an OpenTripPlanner v2 server

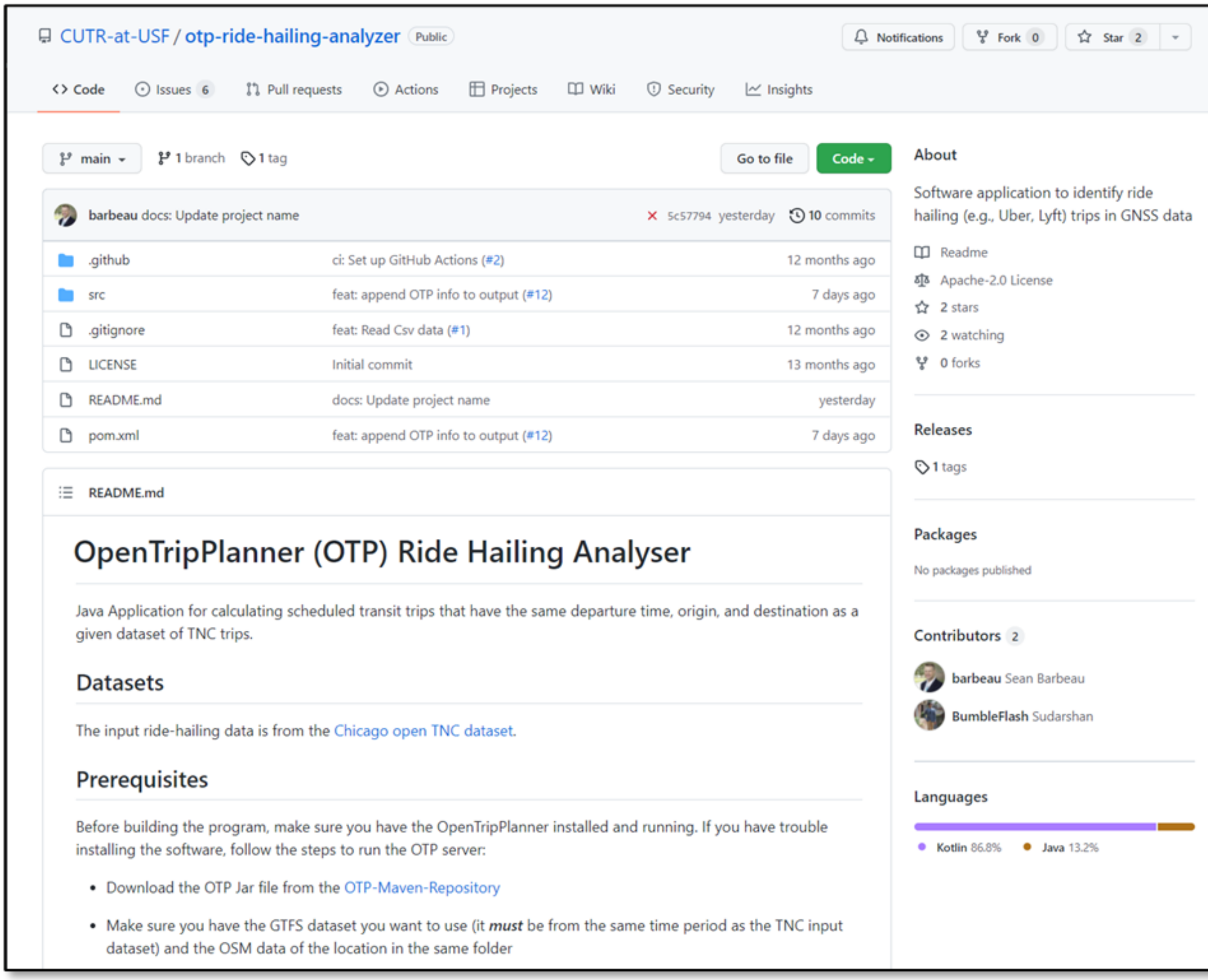


Figure 2 - The otp-ride-hailing-analyzer project is a software application that adds transit trip options to historical ride-hailing trip datasets

System architecture

A high-level system architecture of how the software and data components interact is shown in Figure 3.

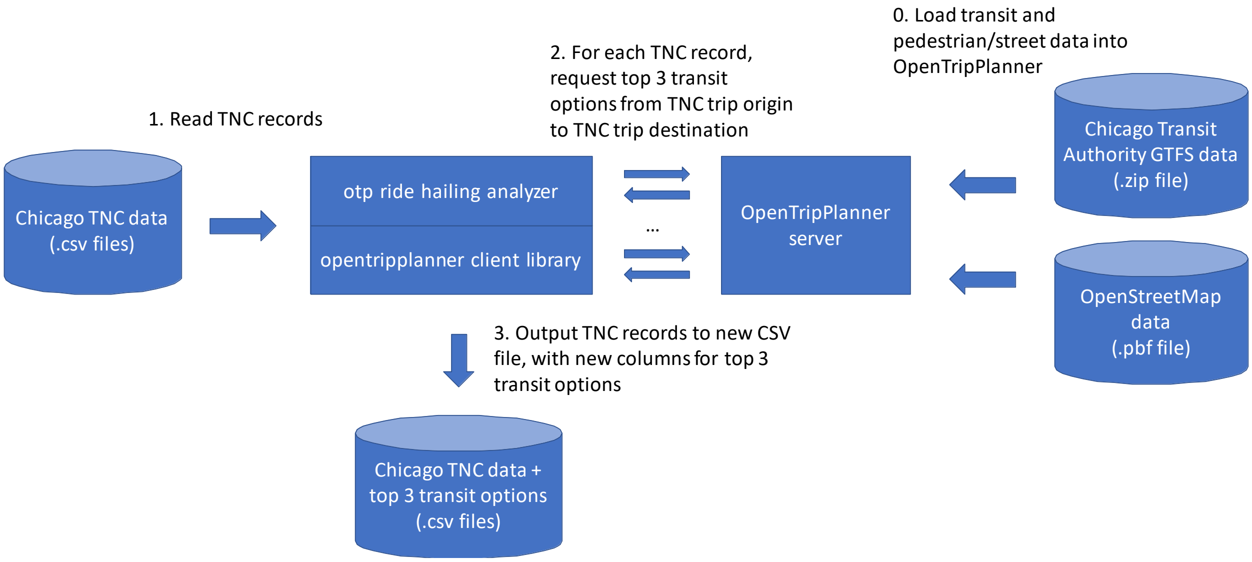


Figure 3 - System architecture and protocol for generating transit trip options from TNC trip origins and destinations

The first step that must be performed prior to running the software analysis tools created for this project is to set up and run an OpenTripPlanner server with the GTFS and OSM data. Instructions for this process can be found on the OpenTripPlanner Basic Tutorial page[12]. Note that the GTFS service period should match the dates of the Chicago TNC data trips to use the scheduled transit service for that time period.

Next, the otp-ride-hailing-analyzer application is executed on the computer where the OTP server is running (the tool could also be configured to send requests to a remote OTP server) with the name of the Chicago TNC data file to be processed. The application will read in the TNC data, and for each trip record in the TNC data, it will send a transit trip request to the OpenTripPlanner server using the TNC trip origin as the transit trip origin, the TNC trip destination as the transit trip destination, and the TNC trip start date and time as the transit trip start date and time. Note that the application can execute these trip planning requests to the OTP server in parallel so a larger amount of trips can be simultaneously processed. The application will then receive a set of multimodal trip itineraries from OTP for each origin and destination

[12] http://docs.opentripplanner.org/en/latest/Basic-Tutorial/

pair and will write a new CSV file that mirrors the original input file, but with new columns appended that represent various characteristics of the top three trip options returned by OTP for that origin and destination pair. The new columns include the following data for each of the top three transit trip options:

- Total travel time of the trip, in seconds
- Total distance of the trip, in meters
- Total wait time, in seconds
- Total altitude change, in meters
- Number of transfers
- Modes used for the trip
  - For example, [WALK, SUBWAY, WALK] for a trip starting with walking to a subway line, taking the subway, and then walking to the destination. Similarly, [WALK, BUS, WALK, BUS, WALK] would represent a trip walking to a bus and then transferring to another bus with walking in between. Several non-walk modes such as bus and subway with transfers in between can also be combined (e.g., [WALK, SUBWAY, WALK, BUS, WALK]).
- Total walk time, in seconds
- Total walk distance, in meters
- Total time on bus, in seconds
- Total distance on bus, in meters
- Total time on subway, in seconds
- Total distance on subway, in meters
- Total transit time (bus, subway combined), in seconds
- Total transit distance (bus, subway combined), in meters

Other data is also returned from OTP for each trip and is included in the output as a placeholder for future analysis for additional modes of travel beyond transit. Note that fields corresponding to these additional modes were always "0" for the analysis in this report given the lack of additional input data (e.g., no historical bikeshare data, lack of tram and rail service in Chicago given that all CTA GTFS options are categorized as bus or subway):

- Total bicycle time, in seconds

- Total bicycle distance, in meters
- Total rental (e.g., bikeshare) bicycle time, in seconds
- Total rental (e.g., bikeshare) bicycle distance, in meters
- Total time used to park a bicycle, in seconds
- Total distance used to park a bicycle, in meters
- Total time in a car, in seconds
- Total distance in a car, in meters
- Total time used to park a car, in seconds
- Total distance used to park a car, in meters
- Total time spent on a tram, in seconds
- Total distance on tram, in meters
- Total time spent on rail, in seconds
- Total distance on rail, in seconds

Figure 4 shows an example output from the otp-ride-hailing analyzer, with the original ride-hailing trip origins and destinations in the columns on the left and with new columns to the right showing characteristics for transit trip options for those same origins and destinations. The suffix "1" indicates that the columns pictured in Figure 4 all refer to the first of the top three transit options – additional columns with suffixes "2" and "3" refer to the second and third of the top three transit options aren't pictured in Figure 4.

pickupCentroidLatitude	pickupCentroidLongitude	dropoffCentroidLatitude	dropoffCentroidLongitude	totalTravelTimeSec1	totalDistanceMeters1	totalWaitTimeSec1	transfers1	Modes1	walkTime	busTime1
41.92268628	-87.64948873	42.00962288	-87.67016686	3262	13290.13792	0	0	WALK, SUBWAY, WALK	1732	0
41.9442266	-87.65599818	41.9442266	-87.65599818	640	1010.201323	0	0	WALK, BUS, WALK	599	41
41.968069	-87.72155906	41.968069	-87.72155906	354	626.0036892	0	0	WALK, BUS, WALK	316	38
41.9442266	-87.65599818	41.9442266	-87.65599818	640	1010.201323	0	0	WALK, BUS, WALK	599	41
41.90837867	-87.67094508	41.87101588	-87.63140653	4901	6312.221	0	0	WALK	4901	0
41.76157791	-87.57278199	41.74124273	-87.5514282	2865	3637.854	0	0	WALK	2865	0
41.77887686	-87.59492544	41.70658788	-87.62336651	4105	10409.94772	0	0	WALK, BUS, WALK	2969	1136
41.81294894	-87.61785968	41.7632468	-87.61613411	1058	5741.788196	0	0	WALK, BUS, WALK	212	846
41.94779159	-87.68383494	42.00962288	-87.67016686	3297	9129.181992	491	1	WALK, BUS, BUS, WALK	1707	1099
41.9386662	-87.71121059	41.77887686	-87.59492544	3978	24306.58179	147	1	WALK, SUBWAY, WALK, BUS, WALK	1108	1523
41.92434708	-87.73473975	41.92726096	-87.76550161	2302	2986.489	0	0	WALK	2302	0
41.90120699	-87.67635599	41.95358213	-87.72345239	2264	8429.716538	0	0	WALK, SUBWAY, WALK	1574	0
41.9000696	-87.72091824	41.9000696	-87.72091824	1058	1487.301777	0	0	WALK, BUS, WALK	1025	33
41.94269184	-87.65177051	41.95340004	-87.64600707	1237	1591.803	0	0	WALK	1237	0
41.94779159	-87.68383494	41.96581197	-87.65587879	3319	4285.802	0	0	WALK	3319	0
41.968069	-87.72155906	41.9442266	-87.65599818	3389	8298.019299	131	1	WALK, BUS, WALK, BUS, WALK	2289	969
41.79409025	-87.59231086	41.77592883	-87.66659627	2563	8557.718171	778	1	WALK, BUS, WALK, BUS, WALK	405	1380
41.9442266	-87.65599818	41.92268628	-87.64948873	2128	2751.064	0	0	WALK	2128	0

Figure 4 - Example output from the otp-ride-hailing-analyzer, showing original ride-hailing trip origins and destinations in the columns on the left with appended transit and walk options in columns on the right

Transit trip characteristics

OpenTripPlanner transit trips are planned using the TNC trip start time as the departing transit time of the trip (as opposed to using the TNC trip destination arrival time as the "arrive by" time of the transit trip).

When boarding the first transit vehicle in the trip plan, the OTP assumes that the traveler timed their walking trip perfectly to arrive exactly when the first scheduled transit trip departs. As a result, OTP assumes that there is no waiting time on the first transit leg of the trip. However, the wait time for subsequent transit legs (e.g., getting off one bus and waiting to transfer to another) is defined by the difference in the scheduled arrival time of the first vehicle and the scheduled departure time of the second vehicle. Similarly, the TNC trip dataset does not include TNC wait times, and therefore the wait times for the TNC trips are unknown.

OpenTripPlanner v2.0 (i.e., OTP2) uses well-known algorithms for pedestrian and transit routing[13]:

> *OTP1 uses a single time-dependent (as opposed to time-expanded) graph that contains both street and transit networks. Walk-only and bicycle-only trips are generally planned using the A-star algorithm with a Euclidean heuristic. Walk+Transit or Bike+Transit trips are planned using A-star with the Tung-Chew heuristic (i.e., a graph grown backward from the destination providing a lower bound on aggregate weight) for queue ordering. For speed reasons, we are performing single-variable generalized cost optimization, which is not ideal. We should be performing Pareto optimization on at least two variables (generalized cost and time).*
>
> *OTP2 splits the search into three segments: access from the origin to transit stops, egress from transit stops to the destination, and transit service connecting the two. For the transit segment, OTP2 uses the Multi-criteria Range Raptor algorithm. For the access and egress searches, it uses the same approach as OTP1. Both splitting the search into three parts and the use of a table-scanning algorithm like Raptor improve OTP2's performance significantly while increasing result quality by producing true Pareto-optimal sets of results.*

[13] http://docs.opentripplanner.org/en/latest/Bibliography/

As previously discussed, OTP2 (and specifically a prerelease version of v2.1.0) was used in this analysis. Additional details on algorithms used in OpenTripPlanner can be found in the OpenTripPlanner Routing Bibliography[14]. In the next chapter, an analysis of these data in combination with each other is presented.

[14] http://docs.opentripplanner.org/en/latest/Bibliography/

Chapter 4 Data Analysis and Results

As mentioned previously, we downloaded the TNC trip data for all *weekdays* (excluding holidays and weekends) between October 1, 2020, to November 30, 2020 (43 days). We also removed all the TNC trips that were in shared or carpooled mode. The weather filtering was based on matching the TNC trip database with a weather database for the City of Chicago. The weather database reports whether a particular day is one of the 11 categories – Cloud, Rain, Clear, Mist, Snowy, Drizzle, Thunderstorm, Smoke, Haze, Fog, and Squall. Among the 11 categories, we selected the days that are Clear, Cloud, and Fog. The resulting filer provided us with 2,810,334 trips with 135 variables associated with each trip. Each trip was matched to one of the 77 community areas of Chicago as the origin and destination zone. The city of Chicago further divides its community areas into the following nine districts: Far North Side, North Side, Central, Northwestern Side, West Side, South Side, Far Southwest Side, Southwest Side, Far Southwest Side (Heldt, n.d.). These community areas are formal designations and have unique demographic characteristics and cultural significance. The origin-destination analysis presented in this report is based on these nine districts.

Descriptive Statistics

The merged database of TNC trips and OTP trips resulted in 1,289,890 trips. As described in the methodology section, there were three (3) Open Trip Planner (OTP) options provided corresponding to each trip made in TNC. The average trip distance for the TNC trips was 5.19 miles. The average trip duration was 14.6 minutes (874 seconds). The average total cost of TNC trips was $14.54. Table 1 shows the summary statistics of the key variables included in the merged TNC and OTP database.

Table 1: Summary Descriptive Statistics of the Merged TNC and OTP Databases (n= 1,289,890)

Variable	Label	Unit	Mean	Standard Deviation	Minimum	1st Quartile (Q1)	Median	3rd Quartile (Q3)	Maximum
TNC Trip Time	tripSeconds	Seconds	873.81	516.76	4	502	762	1124	17622
TNC Trip Distance	tripMiles	Miles	5.19	4.6	0	2	3.7	6.7	307.4
TNC Fare	fare	$	10.76	6.14	0	7.5	10	12.5	277.5
TNC Driver Tips	tip	$	0.44	1.52	0	0	0	0	500
TNC Extra Charges	additionalCharges	$	3.34	1.9	0	1.4	3.1	4.9	166.2
Total TNC Trip Cost	tripTotal	$	14.54	7.25	0	9.9	13	17.4	613.9
Start of Trip	tripStartHour	0-24 Hr	13.8	5.54	0	9	14	18	23
Travel Time for 1st OTP Option	totalTravelTimeSec1	Seconds	3161.19	1460.89	118	2157	3125	4133	13308
Waiting Time for 1st OTP Option	totalWaitTimeSec1	Seconds	98.46	214.01	0	0	0	0	3549
Travel Time for 2nd OTP Option	totalTravelTime2	Seconds	2320.46	1288.03	120	1397	2062	3040	19724
Waiting Time for 2nd OTP Option	totalWaitTime2	Seconds	146.66	225.11	0	0	0	248	13115
Travel Time for 3rd OTP Option	totalTravelTime3	Seconds	2396.28	1310.38	118	1455	2162	3131	18162
Waiting Time for 3rd OTP Option	totalWaitTime3	Seconds	128.61	222.65	0	0	0	210	12808
Total Time for fastest OTP Option	quickestTotalTravelTime	Seconds	2338.62	1344.89	118	1369	2092	3087	13893
Extra time in fastest OTP option over TNC	quickest_time_longer_than_uber	Seconds	1464.82	1009.18	-15446	783	1312	2019	11997
Fastest OTP time as % of TNC travel time	percent_of_time_quickest_alt_is_to_uber	%	286.88	127.62	3	215.3	271.1	338.2	15900

Trip Clustering

The first step in the analysis was clustering the trips using the k-prototype clustering method (Huang, 1998). It has been used to cluster TNC trip data recently (Soria et al., 2020). We used the Elbow method to select the optimal number of clusters that maximizes cost reduction for an increasing number of clusters. This analysis provided us with 4 clusters of trips. In the results section, we have discussed each cluster of trips separately and analyzed the variation of travel characteristics of trips in each one of these clusters separately. Table 2 shows the number and percentage of trips classified in the four different clusters.

Table 2: Number of trips in different traveler clusters

Cluster ID	Number of TNC Trips	Percentage
0	61,615	4.78%
1	520,050	40.32%
2	462,330	35.84%
3	245,898	19.06%

Figure 5 shows the boxplot of travel times under each cluster of the trip. The figure shows that cluster 0 consists of relatively longer trips, cluster 1 is short trips, and clusters 2 and 3 are somewhat medium-duration trips.

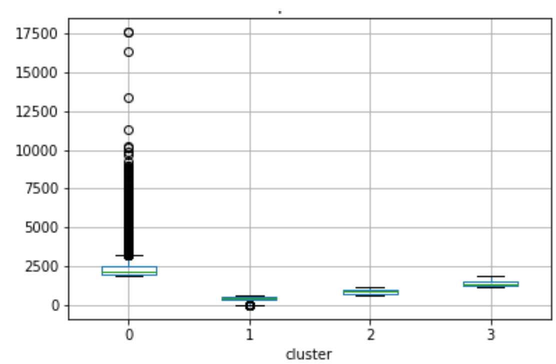


Figure 5: Boxplot of TNC Trip Travel Time in seconds (y-axis) for each cluster (x-axis)

In the next step of the analysis, we cross-matched these clusters with the transit database. This cross-matching resulted in three separate travel time and wait time estimates for the transit mode (i.e., a potential alternative to TNC). These travel times were different combinations of WALK, BUS, and SUBWAY. We estimated the quickest possible alternative way to complete the reported TNC trip using any one of these combinations. We then estimated the amount of excess time it would have taken for a comparable transit trip over the trip taken by TNC. Figure 6 shows the distribution of excess time in each one of the 4 clusters. A positive value on the x-axis means TNC trips were shorter than the quickest transit alternative. As expected, histograms corresponding to these clusters do have considerable overlaps. Cluster 1 is concentrated in the lower range, meaning that these trips taken by TNC had a higher potential to have been made through an alternative combination of modes for little to no travel time penalty. Therefore, these TNC trips constitute a lot of convenience trips. Another consideration is that Cluster 1 had the shortest trips, so another transportation method would have also likely gotten the traveler to their destination without too much excess travel time. The distribution for Cluster 3 had the maximum spread.

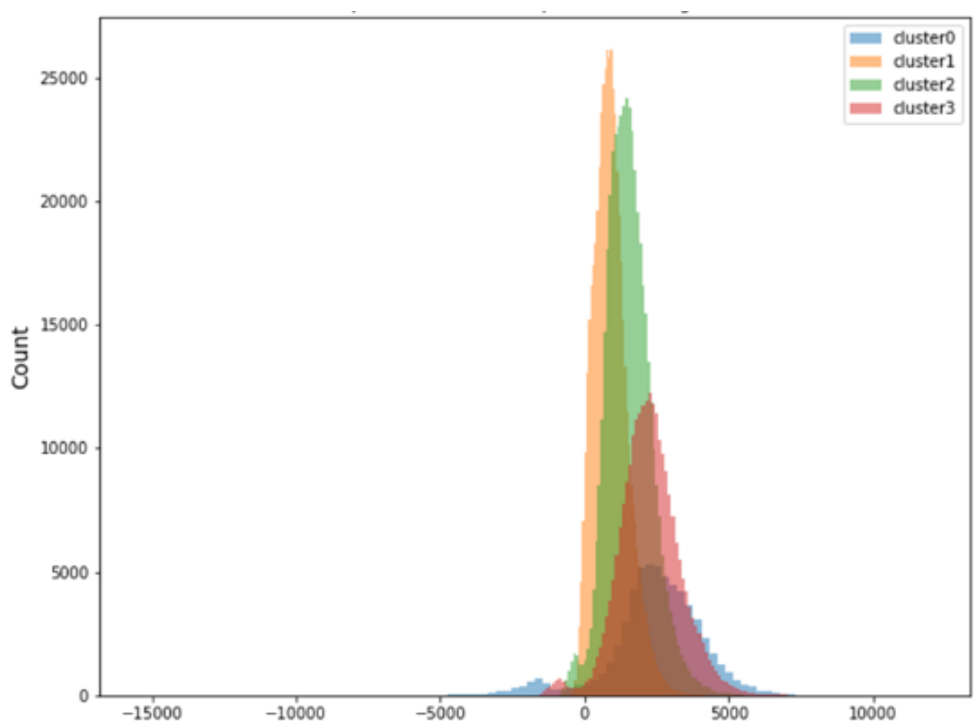
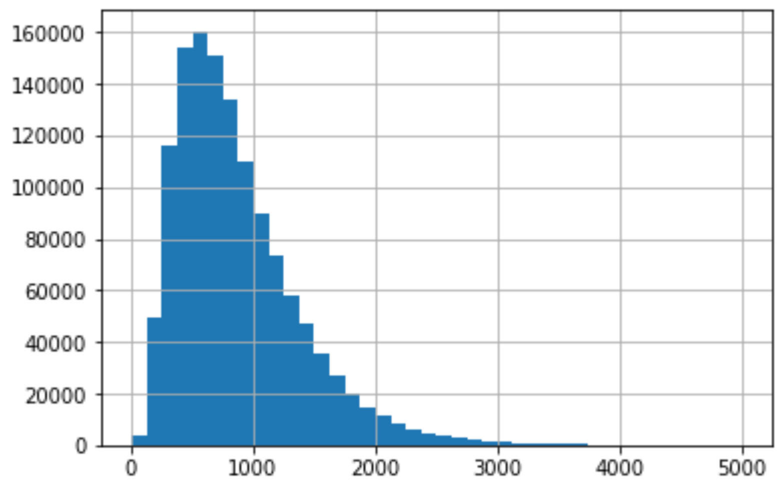


Figure 6 Histograms for excess travel time (in seconds on the x-axis) for the quickest alternative transit mode trip over the recorded TNC trip corresponding to the four clusters

Transit Time Sensitivity of TNC Users

In this section, we categorized the riders whose OTP trip times are comparable to TNC as Convenience Riders. The riders whose OTP trip times were within 30% of their TNC time [<1.3 times of the TNC trip time] as moderate convenience riders. Riders that needed to use more than 1.3 times their corresponding TNC trip time in a comparable OTP mode were termed as 'Largely Necessity Drivers.'



Trip Time in TNC (seconds)

Figure 7: Histogram of Total Trip Time in TNC (seconds)

Based on the 'Fastest OTP time as % of TNC travel time' variable, which shows how much extra time the fastest transit option would have taken to complete the same trip conducted using TNC, we arrived at three different classifications of TNC riders.

The categorization of the riders was based on the following logic:

```
if Fastest OTP time as % of TNC travel time < 110: #if they saved no more than 10% of their ride time
    return "Convenience Rider"
  elif Fastest OTP time as % of TNC travel time < 130: #if they saved no more than 30% of their trip
    return "Moderate Convenience Rider"
  else:
    return "Largely Necessity Rider"
```

Table 3 shows the distribution of riders in each one of the three categories. It is apparent that overwhelmingly (~95%) of TNC trips would have taken 30% or higher extra travel time.

Table 3: Number of Trips by Rider Type based on Transit Availability

Rider Type Category	Number of Trips	% of trips
Largely Necessity Rider	1,223,973	94.89%
Convenience Rider	45,760	3.55%
Moderate Convenience Rider	20,157	1.56%

Figures 8 through 11 explore the median household income of the census block groups corresponding to pick-up (or drop-off) locations and the variable defining convenience of the TNC trip ("Fastest OTP time as % of TNC travel time").

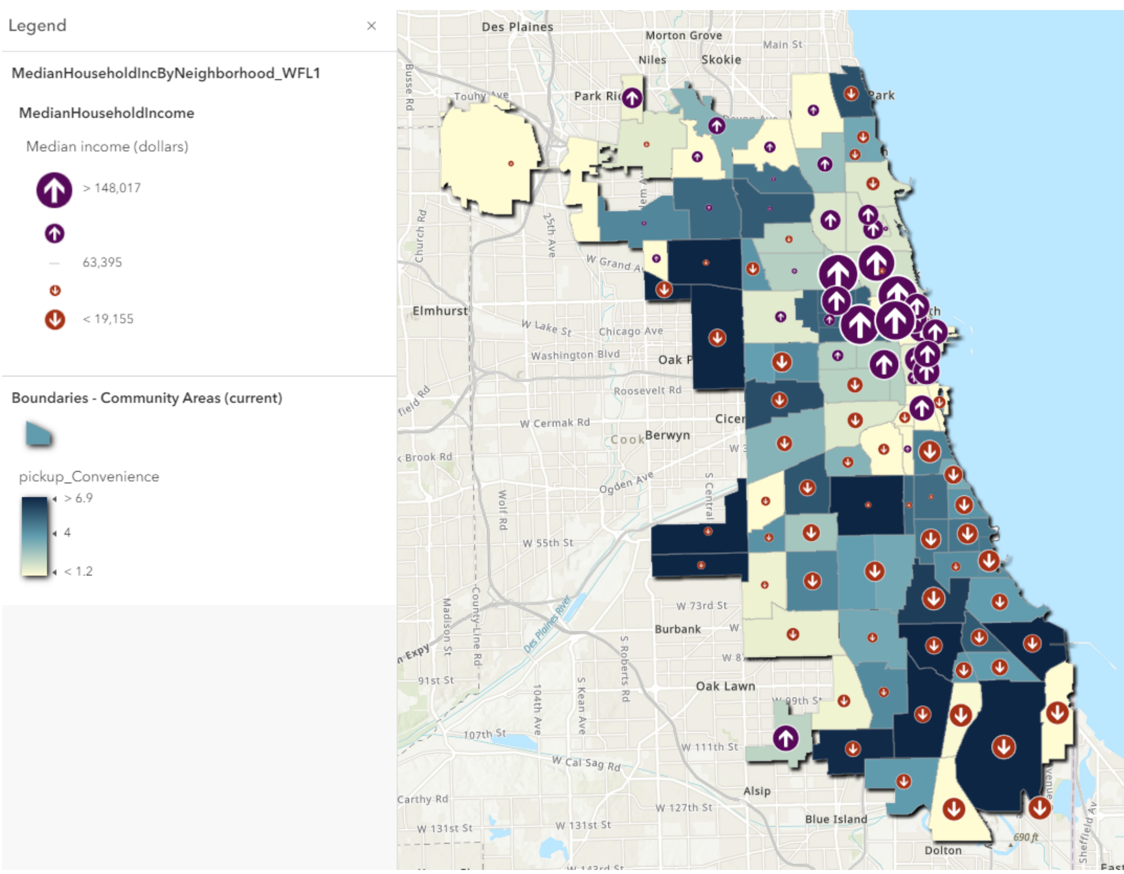


Figure 8: High Concentration of Convenience Trips at TNC Pickup Locations from Low Income Neighborhoods

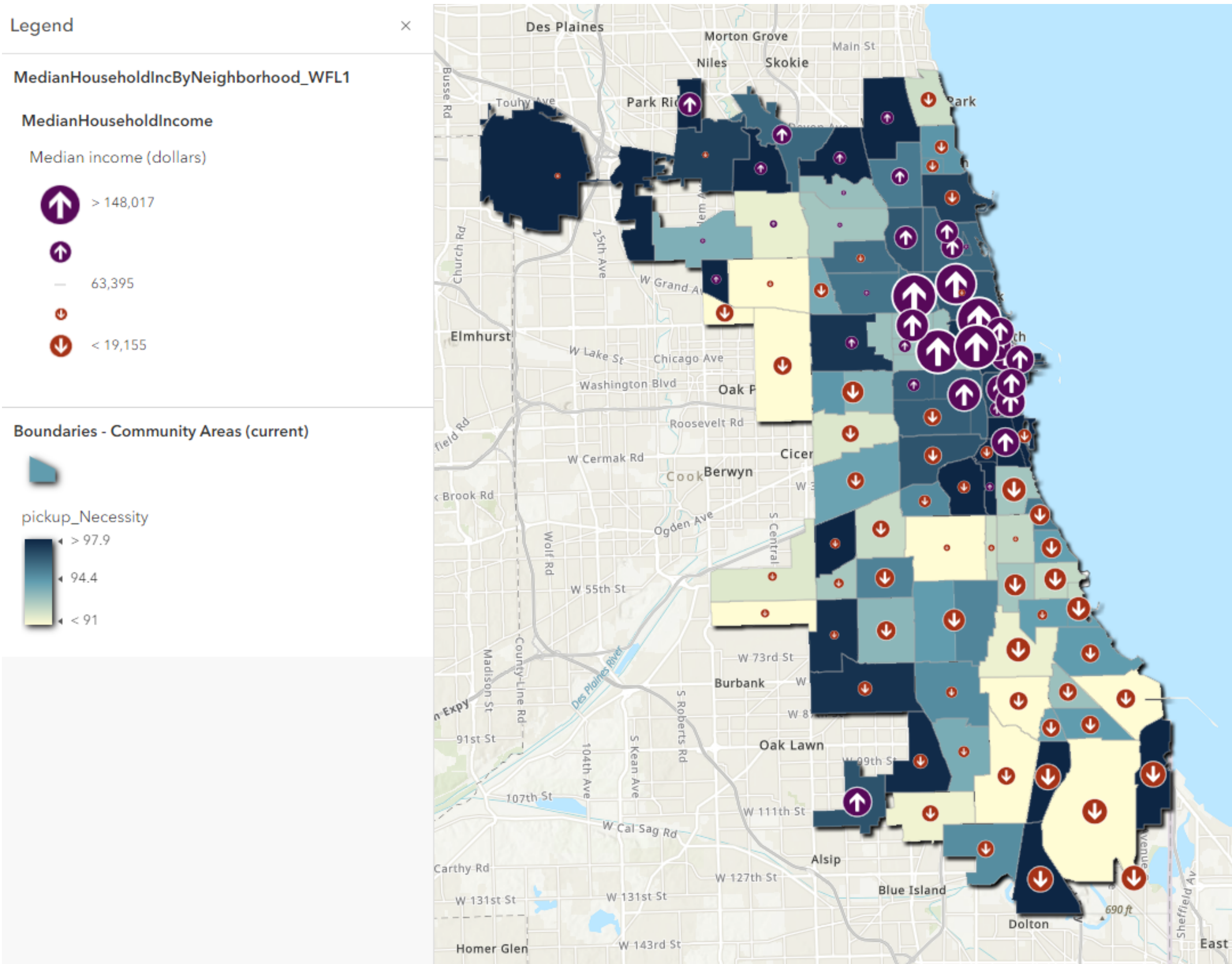


Figure 9. High Concentration of Necessity Trips at TNC Pickup Locations from High Income Neighborhoods

Figure 9 shows that riders getting picked up in higher-income neighborhoods are choosing TNC when they do not have a viable alternative that provides a comparable (within 30%) travel time . Whereas, in Figure 8, riders getting picked up in lower-income neighborhoods are choosing TNC even if they have higher availability of a comparative OTP option. It may be possible that higher-income neighborhoods have less availability of transit and, therefore, the comparative OTP option involves higher travel time. On the other hand, in low-income neighborhoods, the reliability and perceived quality of service may be lower. Therefore, low-income neighborhoods are generating more convenience trips.

The data shows the same trend if one examines the trip percentages of different categories of excess travel time at the drop-off locations (Figure 10 and Figure 11).

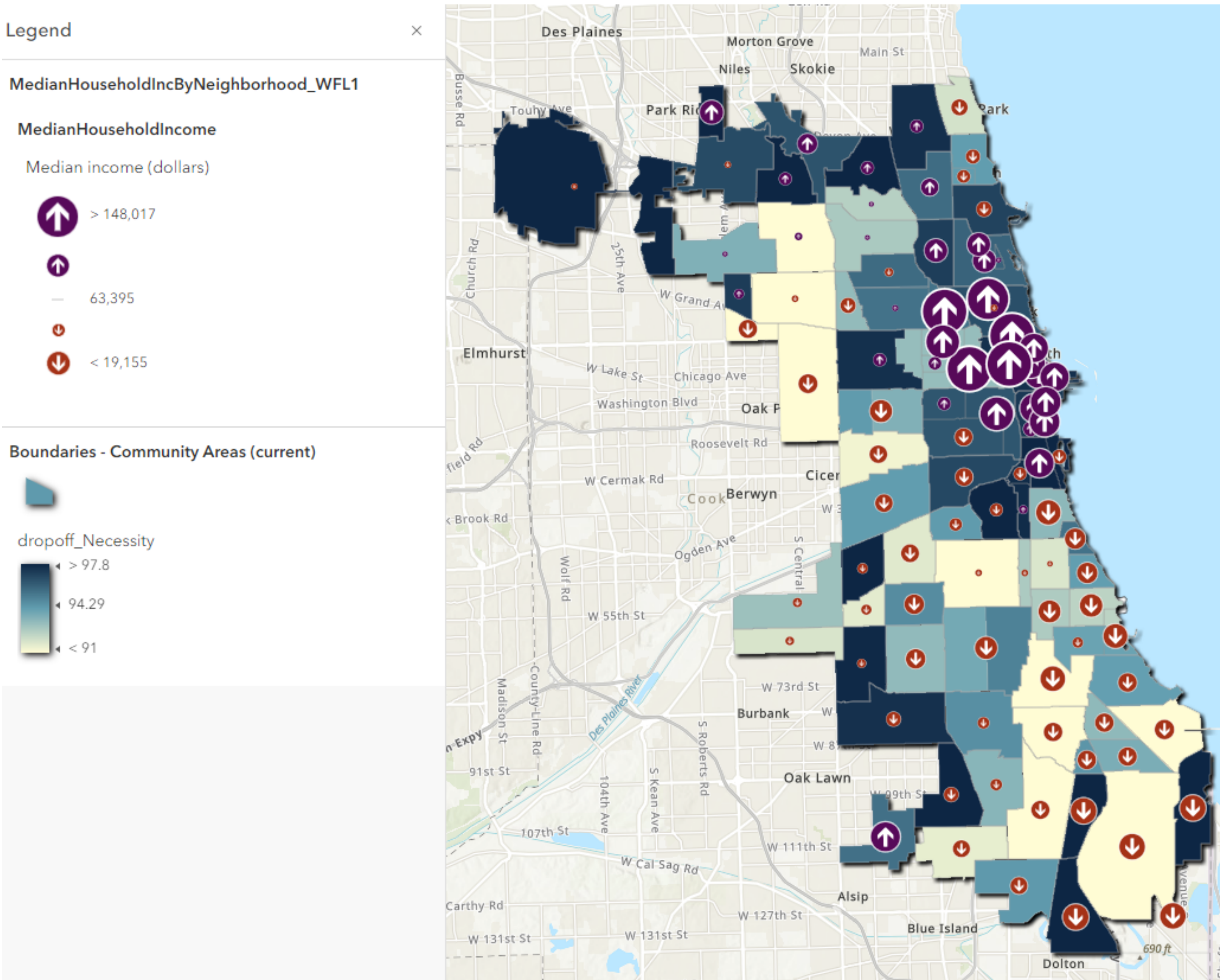


Figure 10: High Concentration of Necessity Trips at TNC Dropoff Locations from High Income Neighborhoods

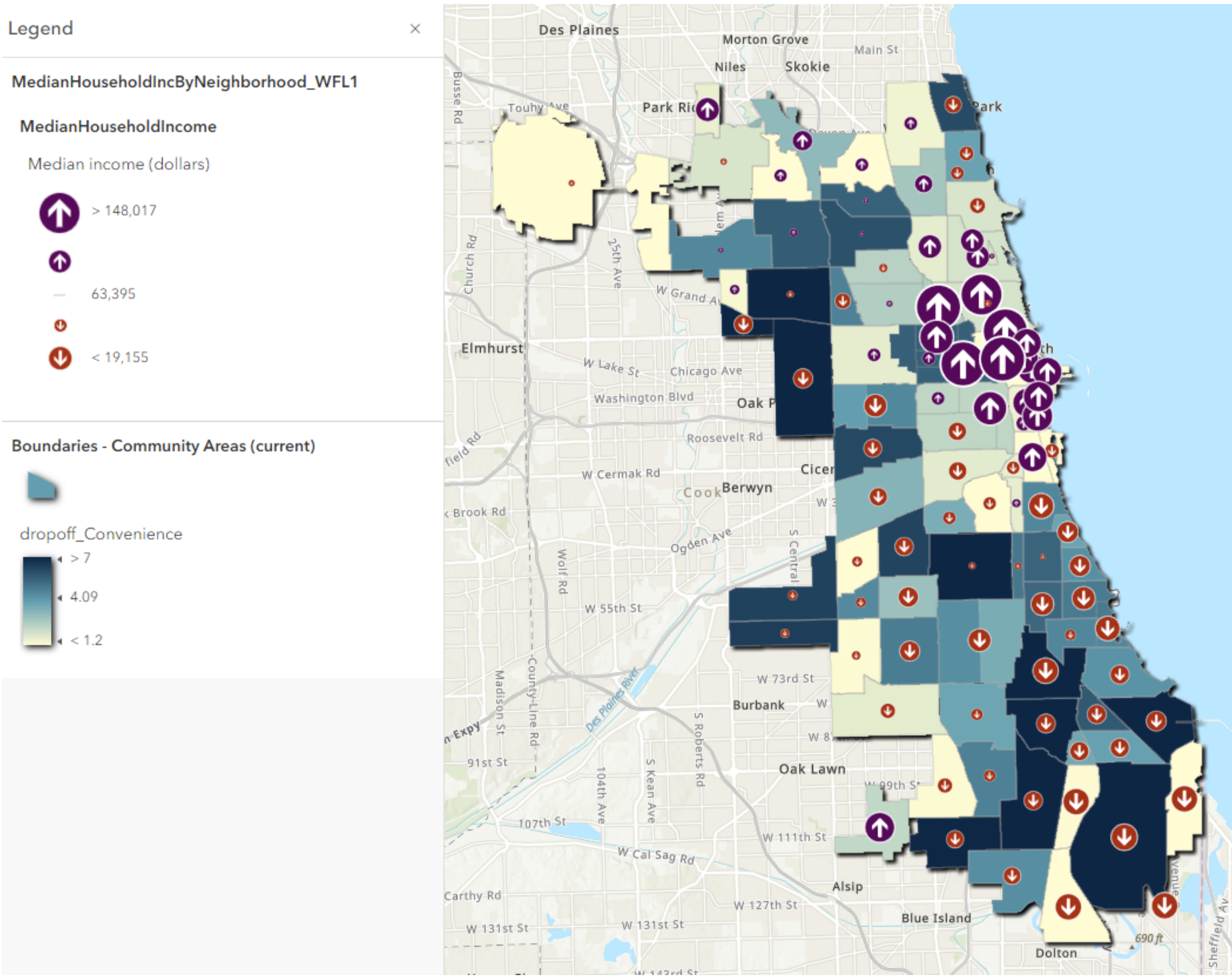


Figure 11. High Concentration of Convenience Trips at TNC Dropoff Locations from Low Income Neighborhoods

Rider Clusters by Rider Categories

We found the rider categories in each one of the four different clusters to ascertain the transit preference variability among the clusters. Table 4 shows the number of riders in different clusters.

Table 4: Percentage of different rider categories in the four clusters

	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Convenience Rider (Alternative trip travel time ≤ 110% of the TNC travel time)	0.39%	1.83%	0.85%	0.47%
Moderate Convenience Rider (Alternative trip travel time between 110% to 130% of TNC travel time)	0.11%	0.95%	0.31%	0.19%
Largely Necessity Rider (Alternative trip travel time between ≥ 130% of TNC travel time)	4.27%	37.53%	34.68%	18.41%

Spatial Analysis

The results of the spatial analysis are provided in Figure 12. In the figure, a darker shade of yellow means more drop-off-heavy neighborhoods. Darker red means more pick-up-heavy neighborhoods. The size of the circle shows the total number of pick-ups and drop-offs.

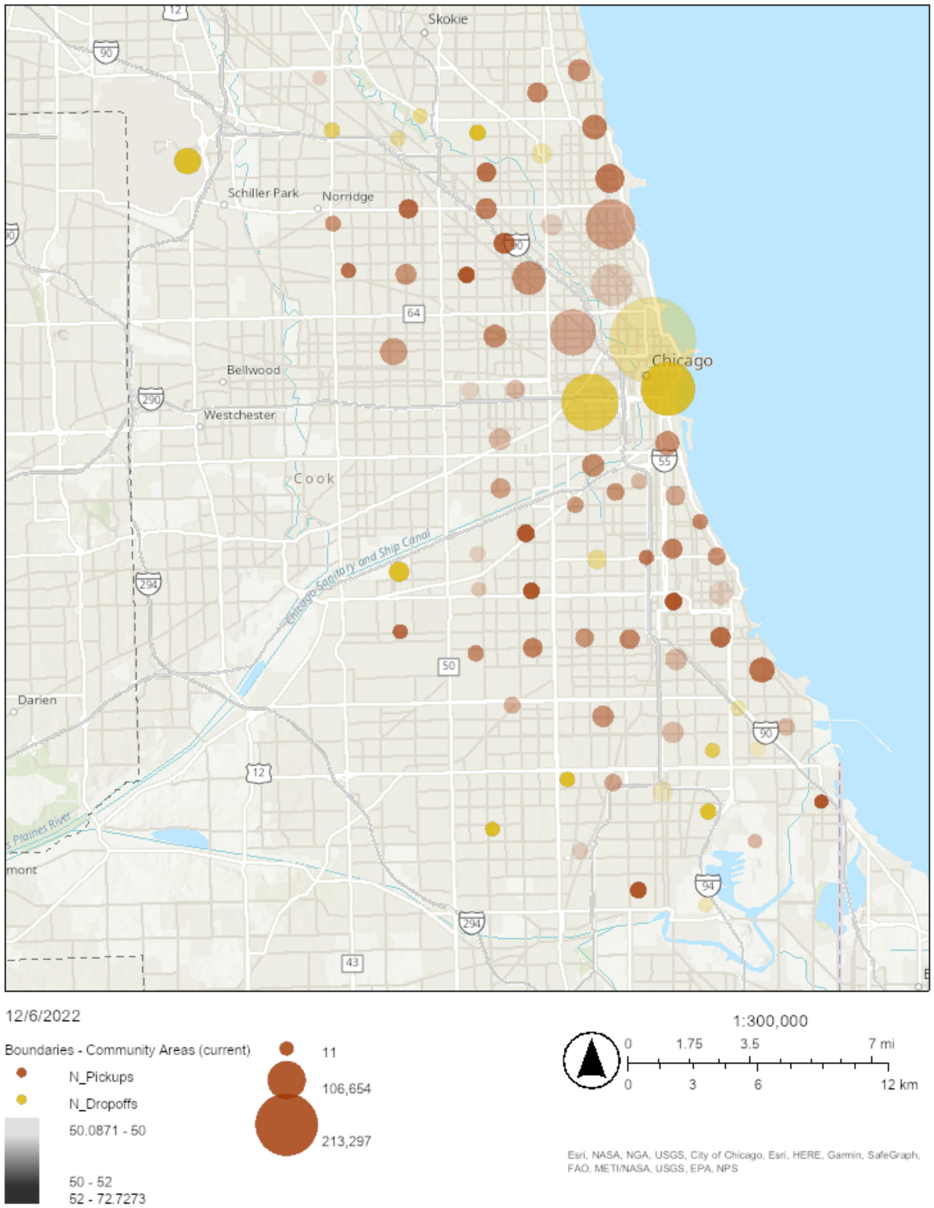
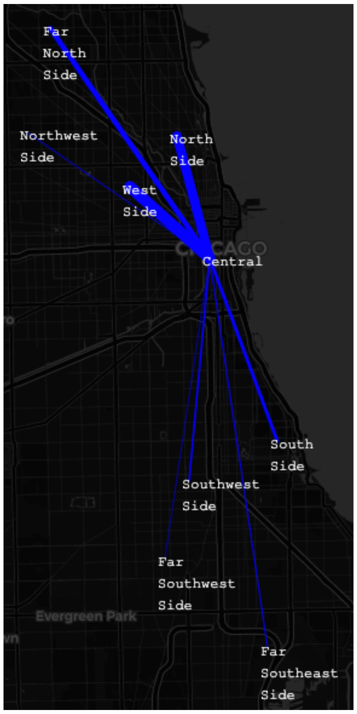


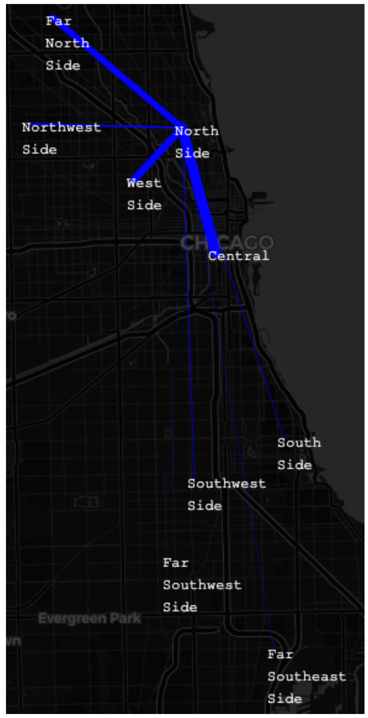
Figure 12 Pickup and Drop-off Density by Neighborhood

Accordingly, the maximum number of drop-offs are happening in downtown Chicago, Near North Side, Near West Jackson boulevard, O'Hare international airport, Far Southwest side, and West side. Pick-up locations are concentrated near the North side and South side of Chicago.

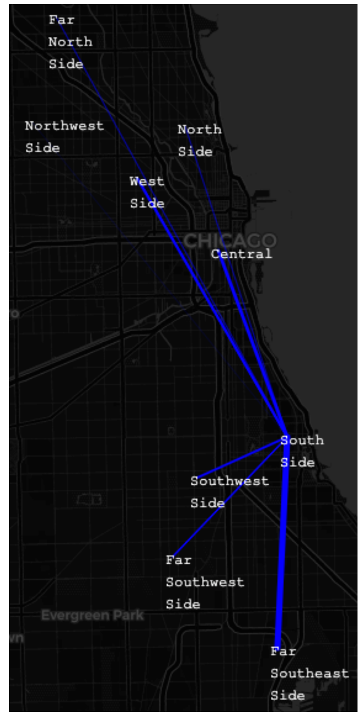
Figure 13 shows the origin-destination flow of trips generated from 9 districts of Chicago defined earlier (Heldt, n.d.) to the remaining eight districts as destinations.



(a) Central

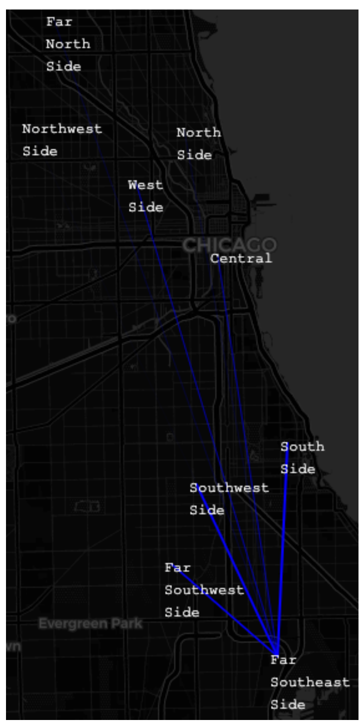


(b) North

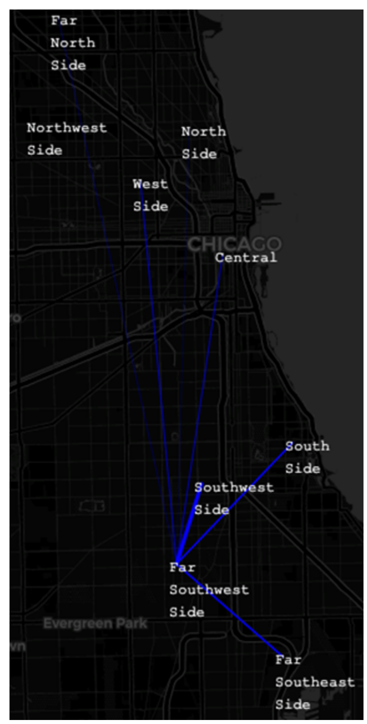


(c) South

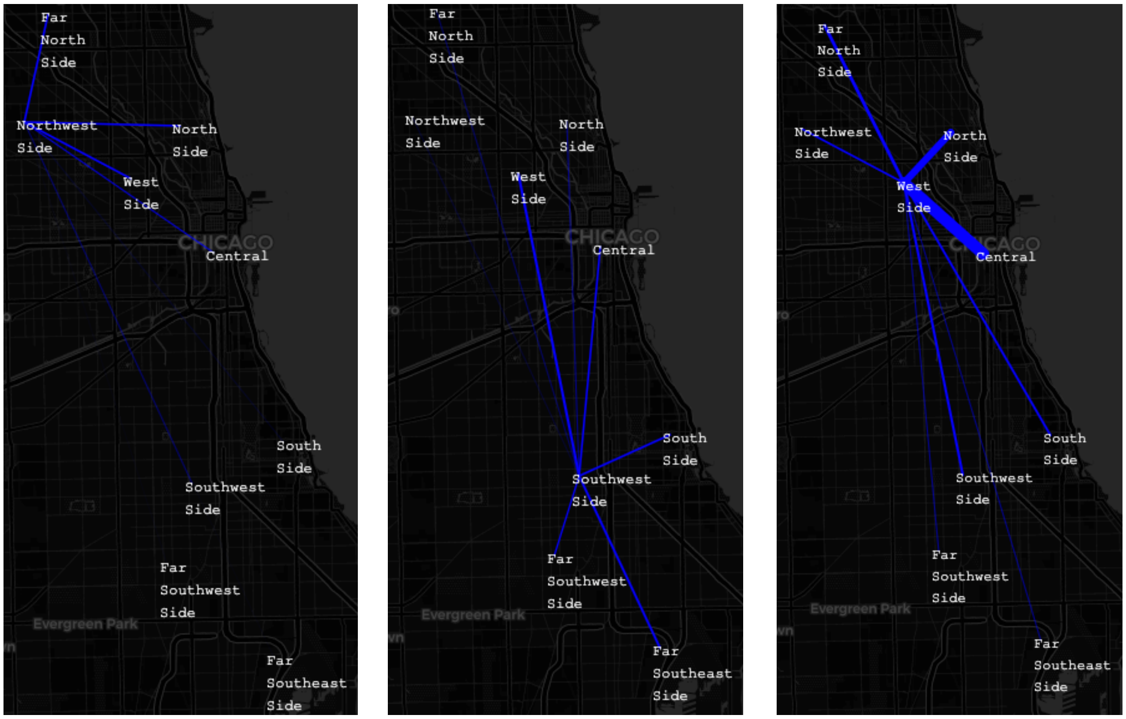
(d) Far North



(e) Far Southeast



(f) Far Southwest



(g) Northwest (h) Southwest (i) West

Figure 13 Distribution of origin-destination flows for the nine districts of Chicago

Each individual map only has one pickup location and visualizes the pairings with the remaining eight districts. The weight/thickness of the line measures the proportion of rides from the origin to the destination out of all rides. From these visuals, most trips from the Chicago West side are going to the Central side. Given the physical proximity between the two districts, the trips from West to Central often would not have taken that much additional time via the public transportation option. Trips from the West side to the other districts would have taken significantly longer except for the physically closer North side. Overall, TNC trips from West to Central and West to North side are more likely to be convenience trips given the presence of lower excess travel time public transit option that may have been available due to physical proximity between the districts.

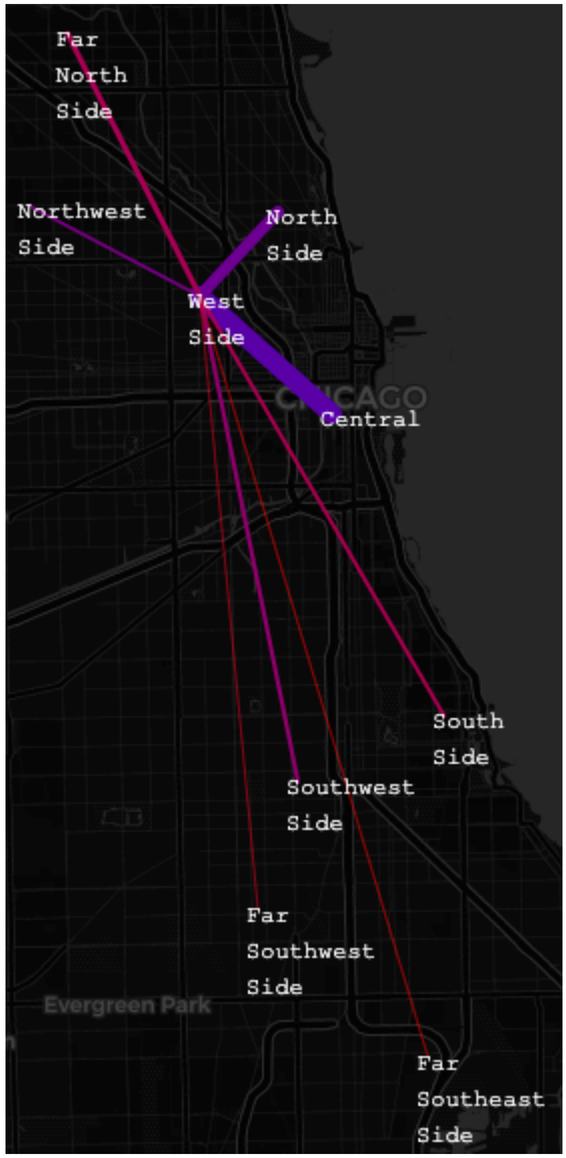


Figure 14: The farther apart zones have relatively higher travel time in OTP option than the TNC option

Figure 14 visualizes the TNC trips originating on the west side. A color gradient of the connecting lines between districts shows the average travel time the trips from the pick-up location to the drop-off district would have taken via the alternative transit mode. The lines with redder share are pairings where the alternate trip options had a higher average travel time, while bluer lines had a lower average estimated time for alternate trips. The thickness of the lines shows the number of trips. Here most TNC trips from the West side are to the Central side, and the blue shade of the connecting line shows trips from West to Central often would not have taken much longer via a public transportation method. Trips from the West side to the other districts would have taken significantly longer (except for the TNC trips from the West side to the North side). Overall, trips from West to Central and West to North may sometimes be seen as just more convenient via TNC.

Origin Destination Analysis

Figure 15 shows the relative proportion of all trips among the 9X9 possible origin-destination pairs. The TNC trip pick-up district is on the y-axis, while the drop-off district is on the x-axis. It is noteworthy that the greatest proportions of trips are within (to and from) the same districts. The greatest single OD pair is for trips within the West Side (9.2% on the bottom right). There were a relatively high number of TNC trips between the West Side and Central. The second most frequent trips were between the North side and Central Chicago. Nearly 40% of all trips were within the same districts, i.e., relatively short trips. This may also be potentially related to the hub and spoke transit system of Chicago, which may render intra-district trip O-D pairs in locations with relatively limited transit options.

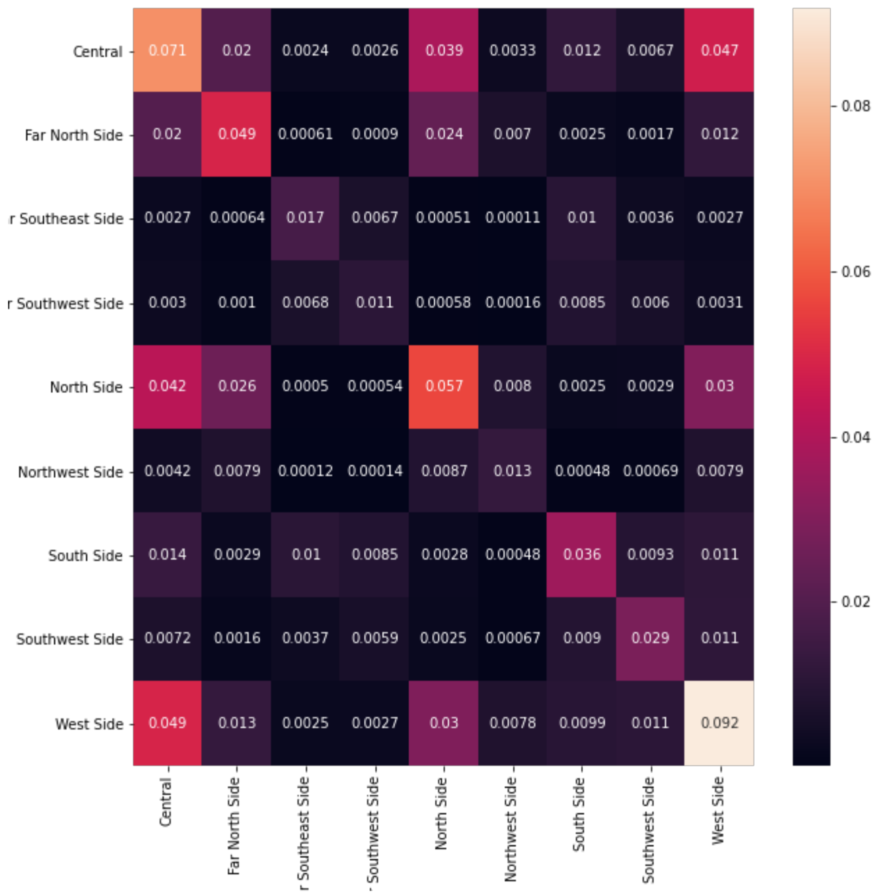
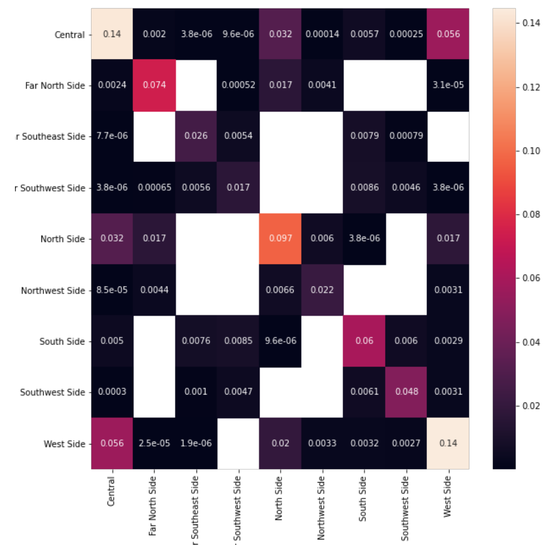


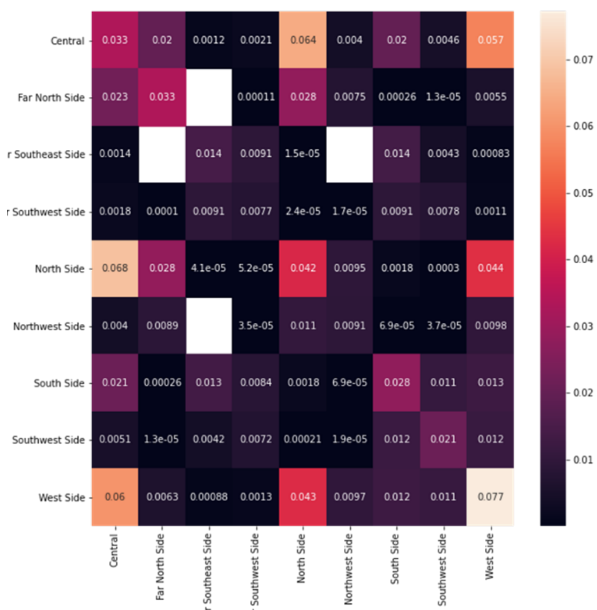
Figure 15: Relative frequency of all trips among the origin-destination pairs

The same OD analysis was repeated within each of the four clusters (See Figure 16). Most TNC trips in cluster 0 (the cluster with longer duration trips; See Figure 5) were from and to the Far North, especially between the Far North and the West side. Only about 10% of the trips for cluster 0 were within the same district, which is expected since this is the cluster with longer trips.

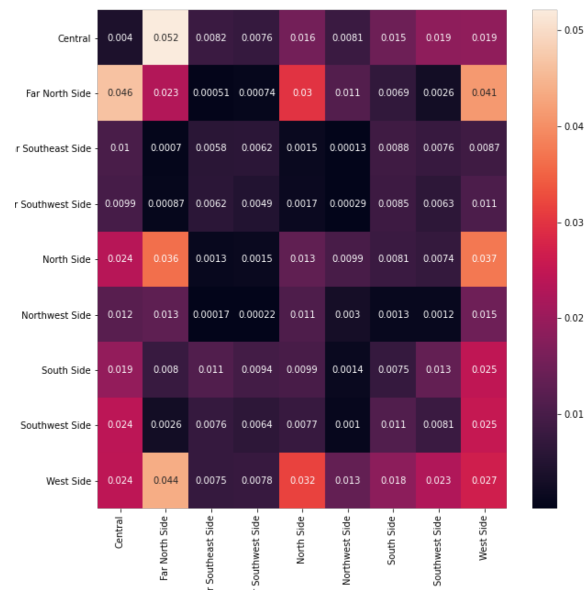
Cluster 0



Cluster 1



Cluster 2



Cluster 3

Figure 16 relative O-D distribution for trips in all four clusters

Next, we analyzed the TNC trips for which the comparable travel time for transit would have been shorter than the TNC travel time. The spatial distribution of those trips is shown in Figure 7. Note that the empty cells represent the O-D pairs for which no such trips exist. The west side, which has 29% TNC trips that would have had a lower transit travel time, is noteworthy.

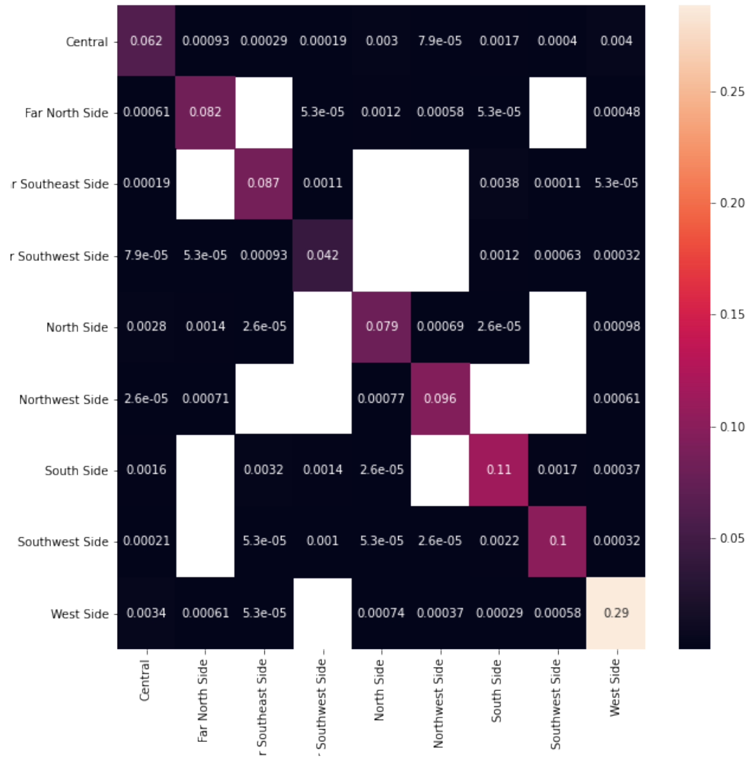
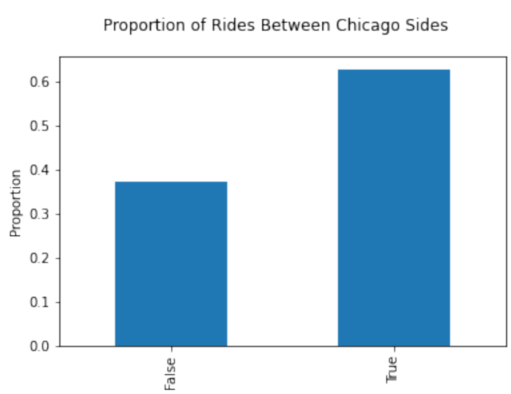
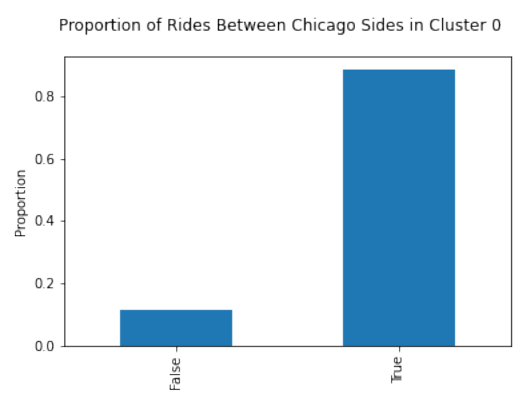


Figure 17 Spatial distribution of trips where a comparable transit trip would have been shorter

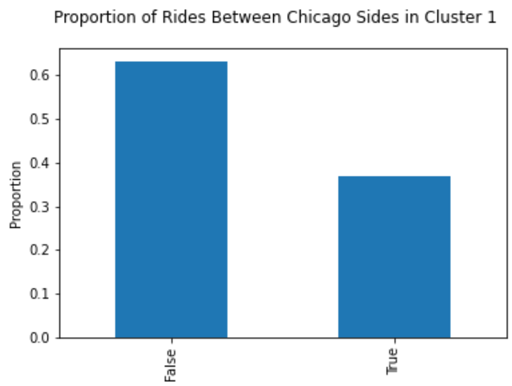
Figure 18 shows the proportion of inter-district trips in the four different clusters of TNC trips. Cluster 0 has the highest number of inter-district trips, followed by Cluster 3. However, cluster 1 has the highest number of intra-district trips, i.e., trips that were made within the same districts.



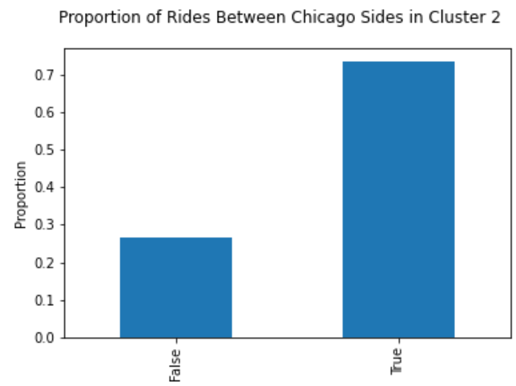
Total Trips



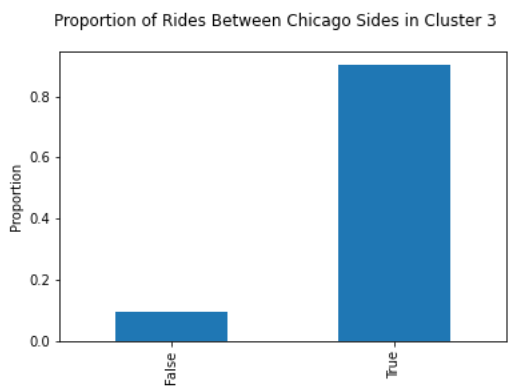
Cluster 0



Cluster 1



Cluster 2



Cluster 3

Figure 18. Ratio of Inter-district trips (represented by "True" bars) and Intra-district trips ("False") for all TNC trips and for TNC trips within each cluster

Convenience Duration Pairings

The trips were further classified by trip duration. Trips less than 15 minutes were categorized as short duration, trips between 15 and 30 minutes were medium duration, and trips over 30 minutes were categorized as long duration trips. Figure 19 shows the proportions of TNC trips based on different combinations of duration and convenience categorizations. The greatest proportion of rides was moderate convenience and short duration; this means that there are probably a good proportion of short rides that alternative transit trips may have been feasible (based on the OTP database). Most of the necessity rides were actually medium-duration trips. Most convenience riders were also short-duration. Short rides can likely have a public transit (or perhaps a micromobility mode such as escooter) alternative that could serve them nearly as quickly.

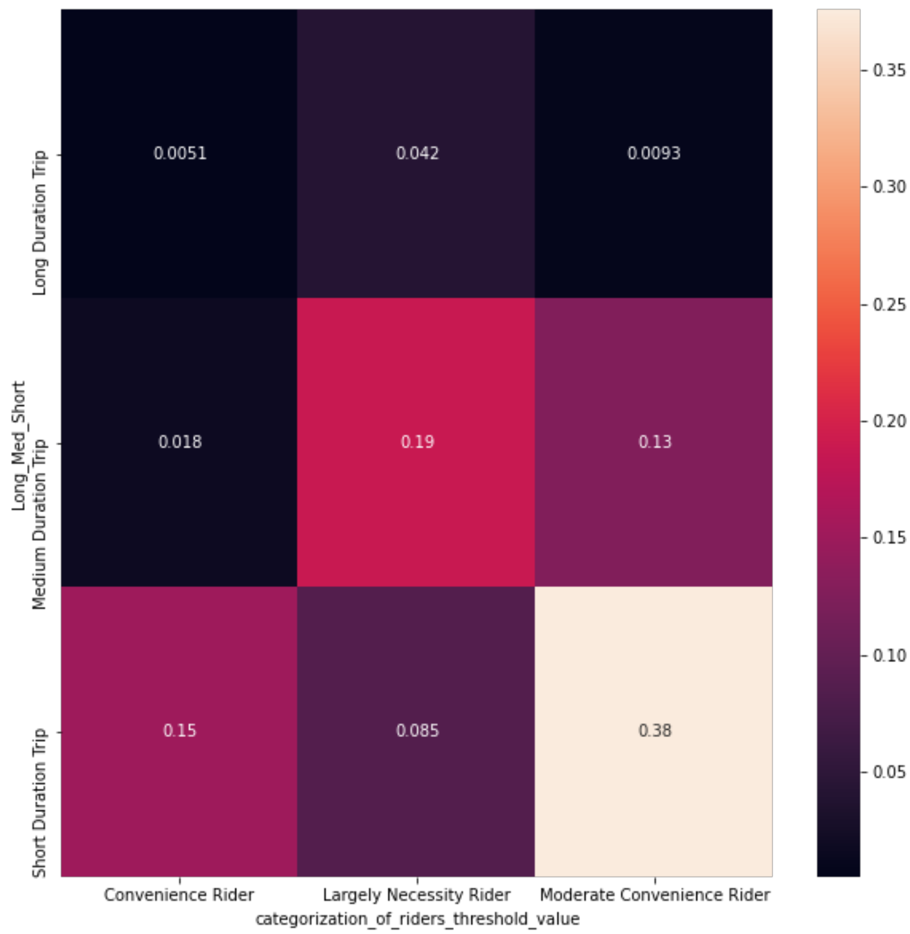


Figure 19. Relationship between rider types and trip duration

We further classified riders based on how much time they saved by choosing TNC over a comparable OTP option. Based on that classification, we created five classes of TNC users. The code to create the classes are as follows:

```
def categorize_riders_percentange_greater_valuesTest(percent_of_time_quickest_alt_is_to_uber):
    if percent_of_time_quickest_alt_is_to_uber < 110: #if they saved no more than 10% of their ride time
        return "10%Saver"
    elif percent_of_time_quickest_alt_is_to_uber < 125: #if they saved no more than 25% of their ride time
        return "25%Saver"
```

```
elif percent_of_time_quickest_alt_is_to_uber < 150: #if they saved no more than 50% of their trip
    return "50%Saver"
elif percent_of_time_quickest_alt_is_to_uber < 200: #if they saved no more than 100% of their trip
    return "100%Saver"
else:
    #Otherwise a greater than 100% saver
    return ">100%Saver"
```

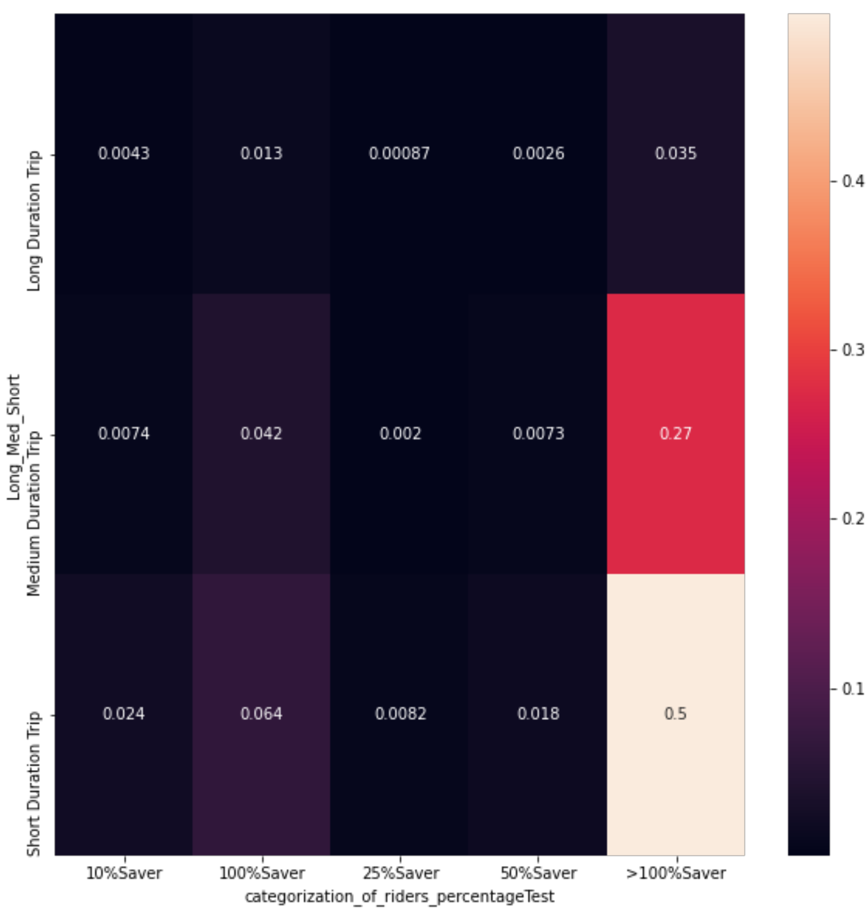


Figure 20. Trip duration categories by TNC Time Saving

Figure 20 shows the proportions of the pairings of duration categorization (short, medium, and long) with the percent of the trip time that a rider saved by taking TNC rather than taking the quickest transit alternative found in the OTP database. The high proportions of trips where comparable OTP trips would have taken more than 200% of the TNC travel time for the trips that were short (0.5) and medium duration trips (0.27) are noteworthy. It indicates that micromobility (e.g., e-scooters or e-bike rental) options may be helpful in converting these trips to more sustainable modes.

Summary of Findings

Data from the open-source multimodal trip planning engine (Open Trip Planner; OTP) combined with TNC trip data provided by the city of Chicago can help discern patterns about the potential alternative available to the TNC riders. The analysis of TNC trip data, along with potential transit alternatives on days not affected by inclement weather in this chapter, led to the following key findings:

- 95% of the trips made using TNCs would have taken at least 30% longer using the alternative transit mode.
- Riders starting in lower-income neighborhoods are choosing TNCs even when a transit trip option is available and would have taken no more than 30% excess travel time compared to transit. It is important to note that while the location of rides is known, the riders themselves may or may not be lower-income.
- When trips were clustered using the factors such as travel time, distance, and costs, we found four unique clusters. The cluster with the longest TNC trips on average (Cluster 0) was also the cluster that had disproportionately high convenience riders (i.e., riders for whom the available transit trip would have taken no more than 10% additional travel time).
- Examining the TNC trip patterns within the nine Chicago districts per the Chicago community research guide (Heldt, n.d.) shows that ~40% of the TNC trips were intradistrict trips. This may have to do with the hub and spoke system of the Chicago transit system (*Transit Deserts in Cook County*, 2014).
- TNC trips of less than 15 minutes duration (classified as short trips in this analysis) had a very high proportion of trips for which the OTP alternative would have taken more than 200% of the TNC travel time. Micromobility options may be able to serve the travel needs of these users in a more sustainable way.

In the next chapter, potential policy implications of these findings are discussed along with scope of future efforts for this research.

Chapter 5 Concluding Remarks, Policy Implications, and Future Scope

This work provided a framework to analyze the TNC trips made in the City of Chicago in the context of alternative trip choices available. The analysis used publicly available data underscoring the value of Cities such as Chicago working with TNC partners and making this data available. The alternative trip choices were derived based on the OTP tool that relied on the GTFS database and OpenStreetMap data for the City of Chicago. A summary of key findings was provided at the conclusion of the previous chapter. This chapter discusses the policy implications of those findings along with the future scope of this line of inquiry.

Policy Implications

Transnational Corporations (TNCs) provide a convenient mode of travel for those who are able to afford it but can be a source of planning issues for governments and communities. Researchers have documented the expected increase in VMT and congestion that resulted from the introduction of TNCs into the urban regional network (Choi et al., 2022; Diao et al., 2021). In addition to externalities, TNCs can exacerbate existing inequalities in transportation access (Harmon, 2018).

One way cities can attempt to address TNC issues is through the study of trip-making patterns and encouraging TNC usage where they complement transit and/or serve transit deserts. Policy measures should discourage TNC use at or near locations with ubiquitous transit and encourage them to operate where there is a lack of transit options. These measures may include limiting drop-off and pick-up locations, but most existing regulation has focused on passenger safety and driver wages, including, for example, the New York City Council (*The New York City Council - File #: Int 0890-2018*, 2018).

This research provided a framework to examine TNC use with respect to alternative transit options. The research helped categorize the TNC trips into trips of convenience or necessity based on the estimation of excess travel time the alternative trip would have taken. Patterns on these trips can help communities identify where the TNC use needs to be discouraged.

A critical step for cities in that direction would be to learn from the City of Chicago experience and provide TNC trip data publicly for anyone to analyze with adequate privacy protections.

Limitations and Future Scope

While using publicly available data to develop the framework for examining TNC trips in relation to the other available transit option produces more accessible research, there are some limitations of this work. First, due to privacy protection, the geolocation of the TNC trips is available at a scale that may make it harder to identify any localized transit desert. Furthermore, in examining the transit access for TNC users, users are precluded from TNC usage due to lower incomes and relatedly due to limited access to the use of smartphones and credit cards. Chicago region's hub-and-spoke transit system may be especially prone to leaving many transit deserts between the lines that radiate out from downtown (*Transit Deserts in Cook County*, 2014).
In the study, we also examined Chicago districts and examined if the convenience riders or necessity riders had any correlation with the neighborhood's income levels. However, neighborhood demographic data may differ from income characteristics of who is actually using TNCs in those neighborhoods.

Despite these limitations, we contend that it would be an excellent idea for cities to follow the lead of Chicago and provide TNC trip data for public usage as part of their agreement with TNCs to operate in their cities. With more cities making their data available, the analysis framework to contextualize those trips with transit options would expand the menu of options for the communities to address the negative aspects of TNCs. A study that involves city staff of communities of varying sizes on why this has not been a more common practice would also be of interest from a public policy standpoint.

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