ESTIMATING DEMAND FOR AN ELECTRIC VERTICAL LANDING AND TAKEOFF (EVTOL) AIR TAXI SERVICE USING DISCRETE CHOICE MODELING

A Thesis
Presented to
The Academic Faculty

by

Sreekar Shashank Boddupalli

In Partial Fulfillment
of the Requirements for the Degree
MASTERS in the
SCHOOL OF CITY AND REGIONAL PLANNING AND
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Georgia Institute of Technology
AUGUST 2019

ESTIMATING DEMAND FOR AN ELECTRIC VERTICAL LANDING AND TAKEOFF (EVTOL) AIR TAXI SERVICE USING DISCRETE CHOICE MODELING

Approved by:

Dr. Laurie Garrow, Advisor
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Timothy Welch
School of City and Regional Planning
Georgia Institute of Technology

Dr. Satadru Roy
School of Aerospace Engineering
Georgia Institute of Technology

Date Approved: July 26, 2019

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Laurie Garrow for supporting, guiding and encouraging me at every step of the process. I would also like to thank Dr. Timothy Welch, my advisor from the School of City Planning for the constant feedback and involvement. This document wouldn’t have been produced without the immense contributions of my fellow research assistants, research engineers and the entire team working with Dr. Garrow.

I owe my utmost gratitude to my parents, family and friends, because of whom I have been blessed with the opportunity to be a part of this research group.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

UAM	Urban Air Mobility
eVTOL	Electric Vertical Take-off and Landing
DCM	Discrete Choice Modeling
MNL	Multinomial Logit Model
FAA	Federal Aviation Administration
IIA	Independence of Irrelevant Alternatives
CSA	Combined Statistical Areas
IVTT	In-Vehicle Travel Time
OVTT	Out of-Vehicle Travel Time
ASC	Alternative Specific Constant
CPI	Consumer Price Index

SUMMARY

Urban Air Mobility (UAM), often referred to in the press as "flying cars," is slated to be the next big thing in transportation. As congestion continues to increase on our roads and transit systems are in dire need of maintenance, commuters are looking out for other alternatives that can save time, and be cost-efficient, safe, and comfortable. With numerous companies vying to launch their service in the early part of the next decade, it is essential to analyze the effectiveness of UAM solutions and model how UAM could compete against the other, more established modes of transportation. A travel demand modeling study, on the basis of the utility maximization theory, has been conducted based on a stated preference survey of 2,500 commuters living and working in the Atlanta, Boston, Dallas-Ft. Worth, San Francisco, and Los Angeles areas. The study provides estimates of market share for the new air taxi service assuming current market conditions (i.e., no autonomous ground vehicles). The results highlight the reasons behind people's travel behavioral choices, and factors like frequency of air travel and presence of congestion influence demand for air taxi service for commuters, apart from the traditional mode choice determinants like travel time and cost. The results also reveal a distinct market segmentation: those who always choose the flying taxi, those who would never switch from their typical commute mode to a flying taxi, and finally, the group that makes tradeoff decisions between the modes available. A set of multinomial logit models and a latent class model have been estimated to explain the taste heterogeneity.

CHAPTER 1. INTRODUCTION

Humans have come a long way since the invention of the wheel. What started off as a simple, circular, mobile disc, has today come to define the field of transportation. The horse-drawn carriage was the first documented modern mode of transportation, initially designed for individual ridership and eventually moving on to create public transit. The steam engine opened up the possibility of exploring other sources of power which didn't involve physical human (or animal) labor. Some tinkering, a couple of explosions and a war later, the automobile was invented. Fast forward to today, where we can glide over the road in an eco-friendly electric car, share space with a hundred other people over a fixed rail network, or zip down the sidewalk on a flimsy two-wheeled battery operated toy – we have so many options to choose how we travel. Autonomous vehicles (AVs) can be a common sight in the not-so-distant future – the transportation world is sitting at the cusp of revolution.

Researches have contemplated and published their work on the potential for smaller, less powerful aircraft buzzing around the downtown skyline, making multiple trips along a network of premeditated routes, aka, urban air mobility (UAM). The possibility of environment friendly, quick aircraft coupled with the growth in on-demand mobility under the shared economy model, opens up the market for "flying taxis". Uber for example, has taken keen interest in such a reality, and has proposed to be a pioneer in the field by launching Uber Air. The idea is that people can book an aircraft the same way they book a cab, and cover large distances over a city's traffic. This revolutionary mode of transportation has the potential to reduce travel times and reduce the stress of commuting, while creating a minimal environmental footprint. In order to assess UAM's impact on the transportation system, evaluating its demand is important. Modeling what influences people to choose a travel mode over another and quantifying this behavioral aspect of a representative sample of individuals is the primary objective of this study.

Funded by NASA, the research team at Georgia Tech is creating a framework for predicting demand for urban air mobility for commuting purposes, and also identify the most feasible locations to launch for maximum profit. The following paper is a documentation of the efforts made towards the above mentioned goal, written as a process-oriented manuscript entailing the steps the author has taken towards the fulfillment of the objective. The journey has been described until the current progress made in the project with the expectation of completion in the near future. The rest of the report is organized as follows: chapter 2 is a summary of the literature reviewed, chapter 3 outlines the data collected, chapter 4 is the methodology employed and the process followed, chapter 5 is a compilation and explanation of the results obtained, chapter 6 is a detailed discussion on the implications of the results and finally, chapter 7 concludes the report.

The key findings from the project were that there are at least three distinct populations within the representative sample of survey respondents – the highly excited group likely to always choose to avail the benefits of the flying taxi, the highly skeptical group likely to never shift from the traditional commuting modes, and a third oscillating group making travel decisions based on the utility each alternative offers. A latent class model specification can account for this organic segmentation and each class' value of time indicates their propensity to experiment with the flying taxi.

CHAPTER 2. LITERATURE REVIEW

While progress is being made towards the early deployment of AVs (Fagnant & Kockelman, 2015), either privately owned or as the shared autonomous vehicle (SAV), a parallel branch of study is advancing on the implementation of urban air mobility (UAM). The combination of UAM combined with a strategically computed on-demand network creates opportunity for a new mode of transportation, the flying taxis that can ferry people across densely populated urban landscapes (Urban Air Mobility, 2019).

The proposed transportation service relies on electric vertical take-off and landing (eVTOL) aircraft to ferry commuters from point A to point B. The aircraft would be piloted in its first stages, with a total occupancy of four people inside the cabin (A Vision for the Future of Urban Air Mobility). Willing consumers would book their eVTOL taxi the same way that they would book a typical ridesharing service today, with the click of a button. The aircraft would operate out of a network of vertiports – infrastructure that allows for unobstructed takeoff and landing, with terminal facilities for ingress and egress (Aerial Ridesharing at Scale, 2019). The service would complement existing road transportation systems in that commuters can drive or take a train to the vertiport closest to their origin, and the aircraft can fly them to the vertiport closest to their destination. Traveling to and from vertiports, i.e., last mile connectivity, can be a challenge, based on the average distance between households and the vertiport. Multi-level parking lots, skyscrapers with helipads, and other empty plots next to interchanges can be retrofitted and reused as vertiports, instead of investing in traditional, capital heavy infrastructure projects (Aerial Ridesharing at Scale, 2019).

While it may seem that the future is just a couple years away, there's still coordination efforts yet to materialize. Legal challenges related to accountability, the FAA's involvement in air traffic control and airspace allocation, noise concerns and technological restrictions are just some of the barriers noted to successful implementation (Lineberger, Hussain, Mehra, & Pankratz, 2018). The flying taxis have the potential to change our perceptions about travel, provided they have significant market penetration. If the service is aimed at tapping into the everyday travel market, its competition is predominantly the automobile, followed by transit and in recent times, rideshare. In order to predict whether there exists a market for eVTOL taxis, i.e., estimate demand for the service, it is essential to analyze the current market split among the three existing modes of transportation, and how its introduction will change status quo. This can be done by the process of discrete choice modeling (DCM).

Existing literature entailing market research studies on UAM are suggestive of factors affecting mode choice and their impact on eVTOL demand. Airbus conducted a perception study to observe people's responses to eVTOL and arrived at positive and negatively influencing factors (Yedavalli & Mooberry, 2019). A market study conducted by Booz, Allen and Hamilton, a consultancy firm revealed that in the best case scenario, air taxis constitute a viable, $500 billion market (Urban Air Mobility (UAM) Market Study, 2018). Researchers at the Technical University of Munich, Germany have explored the behavioral aspect of mode choice modeling through a stated preference survey (Fu, Rothfeld, & Antoniou, 2019). The explanatory variables in traditional travel demand modeling literature can be categorized into three sections.

Travel characteristics like cost and time are primary determinants of mode choice (Train, 2003). More detailed logit models analyzing the mode split between public transportation and driving alone has described the greater distaste towards waiting time for non-privately owned vehicles (Koppelman & Bhat, 2006). Socio-economic variables like gender, age and income have effects on the affordability and accessibility towards different modes of available modes (Atasoy, Glerum, & Bierlaire, 2011). Some literature points towards the strong positive correlation between younger population and enthusiasm to try SAVs (Bansal, Kockelman, & Singh, 2016), while other researchers dismiss the effects as inconclusive (Fu, Rothfeld, & Antoniou, 2019). A NASA survey revealed a generally neutral to positive sentiment towards UAM (Urban Air Mobility (UAM) Market Study, 2018). Finally, personality traits like awareness about technology, concern for the environment and fear have been found to affect mode choice (Howard & Dai, 2014). The process used by most literature involves the development of multinomial logit models (MNLs), and other more advanced logit models to measure the influence of above stated explanatory variables on mode choice.

CHAPTER 3. DATA

The objective of the study was to estimate demand for a new mode of transportation, by identifying and analyzing trends in existing travel patterns. The first section of this chapter details the initial data that were collected to understand trends in commute characteristics. The second chapter is an overview of the stated preference survey that was conducted in five densely populated urban areas in the U.S.

3.1 eVTOL index database collection

It was imperative to determine suitable study areas covering all the largest cities and their surrounding metropolitan areas. A large portion of American commute patterns involve single occupancy auto travel from suburbia to downtown (Ingraham, 2017). Therefore, it was decided that data would be collected at the combined statistical area (CSA) level. A CSA encompasses "several adjacent metropolitan statistical areas (MSAs) or micropolitan statistical areas or a combination of the two, which are linked by economic ties" (Piven, 2018). The first step was to create an eVTOL index – a ranking system that could be used to compare American cities and their feasibility of introducing such a service.

The boundaries of the 40 largest CSAs by population were plotted and taken into consideration for analysis, as shown in Figure 1 below:

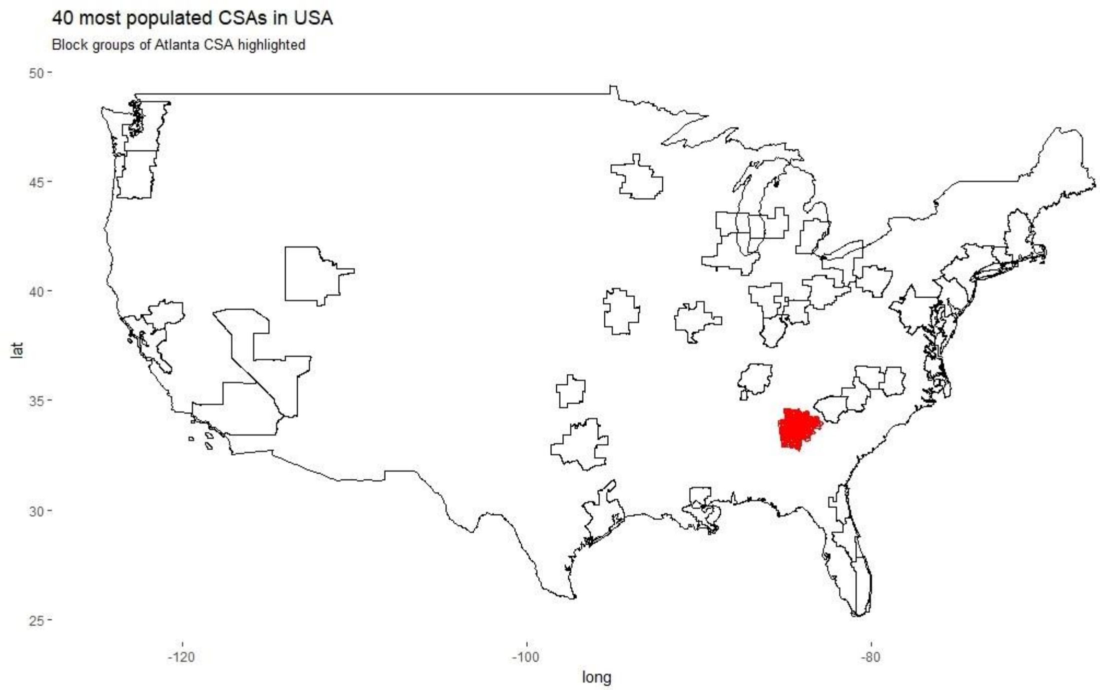


Figure 1 – 40 most populated CSAs analyzed for the eVTOL index

The smallest plausible unit at which data could be collected for this index, that could also suitably contained within a given CSA boundary was a block group; therefore, the data collected were mostly at the block group level. The block groups of the Atlanta-Athens-Clarke-Sandy Springs CSA have been highlighted in red as an example in Figure 1. The research team, influenced by Uber's initial presentations about eVTOL at their annual summit (Aerial Ridesharing at Scale, 2019), created some rational assumptions as to the general demographic groups that would be most likely to experiment with a flying taxi service. The eVTOL index would be a function of census variables like income, age, gender, education level, etc. and typical travel characteristics like average origin-destination (O-D) travel times, number of trips and mode split.

The index would be determined by threshold limits defined by observing the ranges of the data collected. Subsets of this large dataset can be taken based on which O-D pairs have a high volume of trips, high income households and high travel time or distance.

3.2 Survey design and deployment

The next step in estimating a demand model was to deploy a stated preference survey, primarily analyzing the decision rules employed by a sample set of commuters in mode choice.

3.2.1 Overview

The survey was conducted using the Qualtrics Research Suite (also known as Survey Platform), a site license of which is maintained by Georgia Tech. The survey posed questions related to typical travel characteristics, personality traits and demographic variables. It was circulated to respondents in five CSAs – Atlanta-Athens-Clarke-Sandy Springs (GA), Boston-Worcester-Providence (MA-RI-NH-CT), Dallas-Fort Worth (TX-OK), San Jose-San Francisco-Oakland (CA) and Los Angeles-Long Beach (CA). These CSAs were chosen among the as they belonged to the top 10 most populated CSAs (ACS Estimates Population by CSA, 2017), and each exhibited a unique travel pattern. The survey design was implemented with careful consideration of the grammar used and strategic ordering of the questions, arranged so to improve clarity and prevent survey fatigue. The questions asked could be either binary, categorical or value-specific. Depending on the nature of the questions, they would be converted into variables that would eventually feed into the discrete choice models as explanatory factors for determining mode choice. The purpose of estimating these models was to obtain parameters that can estimate demand for eVTOL. By throwing a new mode of transportation into the mix the existing mode splits between auto, transit and rideshare, the three primary modes available today are expected to change. The models help understand the extent to which the market share between the modes will change, i.e., the elasticity of mode choice to the introduction of a fourth alternative.

3.2.2 Stated preference questions

The most critical part of the survey for this study was the stated choice section. Traditional discrete choice modeling involves scenarios where respondents are presented with two or more alternatives, with the travel characteristics of each alternative as determinants of mode choice. For this study, since eVTOL demand is the primary objective, respondents were given eVTOL as one alternative. Since eVTOL is an unheard-of concept, a brief description of the proposed service, with details about the aircraft, typical commute comfort levels and images were provided to the respondents. The other option presented was their everyday commute mode, asked as a question initially in the survey – it could either be their personal automobile, transit or rideshare (Uber/Lyft). Rideshare as an alternative was included as an experiment, to observe how frequent rideshare users respond to the introduction of new technology. The two alternatives were presented side by side, with the travel characteristics accompanying each mode. The in-vehicle travel time (IVTT) and travel cost are two variables that are associated with all four alternatives. Since transit, rideshare and eVTOL are not personal vehicles, there's an additional wait time, or out-of-vehicle travel time (OVTT) associated with them. OVTT is a travel construct that adds a higher proportion of disutility to the alternative, and it is a crucial determining factor. More details on the survey instrument and design can be obtained in (Garrow, Binder, & German, 2018).

eVTOL is a flying taxi service that cannot function in poor weather conditions. In the event that takeoff isn't possible, a discounted rideshare guarantee is offered. This ride guarantee variable can also be accompanied with the transit alternative, in case the bus takes longer than expected to arrive or the system is undergoing a maintenance issue. It is expected that the presence of a guaranteed rideshare conditional on the failure of the given mode would increase its utility. Finally, the transit alternative has a fifth variable, "transfer" - transfers during travel would be more exhaustive and take longer, thus, reducing transit's utility. Below in Figure 2 is the screenshot of a sample question from the survey:

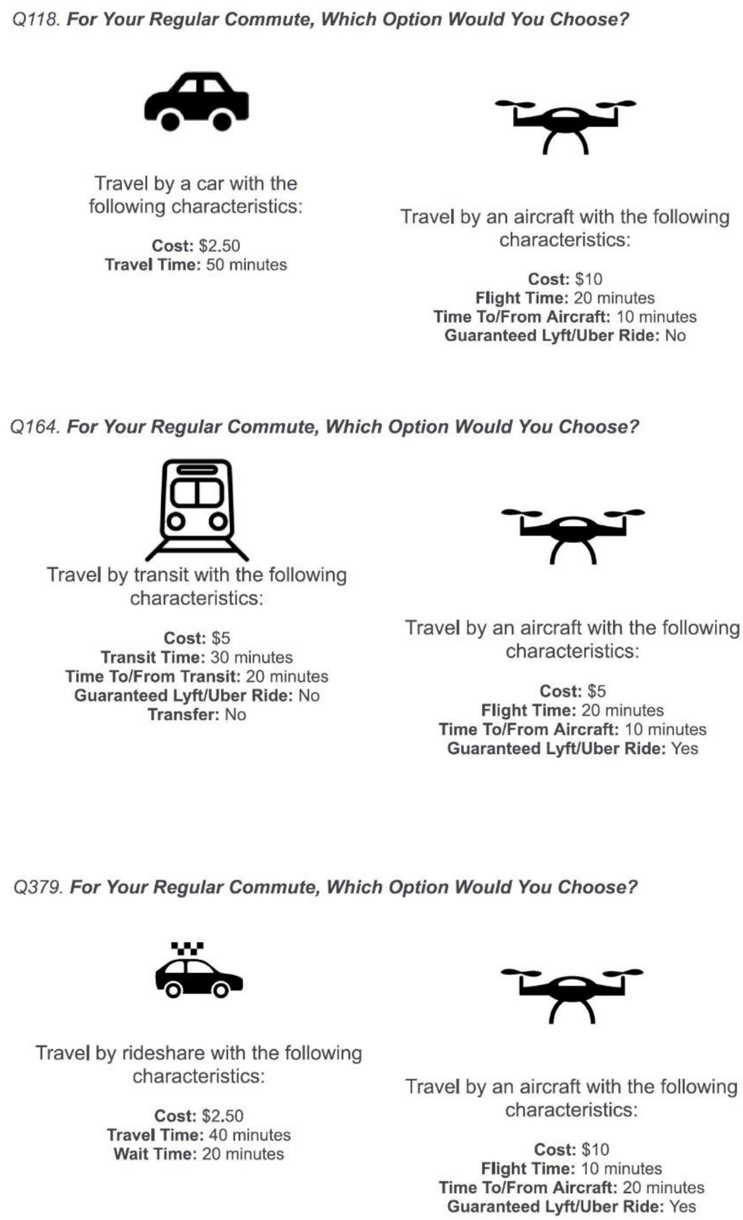


Figure 2 - Stated preference questions between typical mode of commute (auto, transit and rideshare respectively) and eVTOL

The stated choice section would be presented to each respondent based on their responses to the "typical commute mode" and "average commute distance" questions. Each individual was presented with two alternatives - one alternative would be their typical commute mode (asked as a question in earlier in the survey), and the other alternative would be eVTOL. The travel characteristics of both modes, like cost, time, wait time and transfer (for transit), would be provided, and the respondent can make their choice between the two. The research team divided the choice questions by mode and distance ranges – the ranges were created by using the reported home and work zip codes. Each mode versus distance range cell would have four sets of eight questions (making it a total of 32), with different values for each variable. Every respondent was presented with one random set of eight questions from the four levels corresponding to their stated distance versus mode cell. A schematic detailing the levels in blocks is shown below (Garrow, Binder, & German, 2018).

Table 1 - Distance versus mode blocks

	Level 1			Level 2			Level 3			Level 4		
Range (miles)	Auto	Transit	Ride Share	Auto	Transit	Ride Share	Auto	Transit	Ride Share	Auto	Transit	Ride Share
0-24												
25-39												
40-54												
55+												

The same choice question corresponding to each distance vs mode block as shown in Table 1 was asked eight times with different travel characteristics and values for each of the variables mentioned above, to observe inter-respondent taste heterogeneity in the responses (Hess, Stathopoulos, & Daly, 2011). The research team was also keen on looking at trends in people's choices, and what values of travel time and cost prompted them to switch from one mode to the other. The values for cost were calculated based on a schema generated by observing typical gas prices and transit pricing in the five cities surveyed. Travel times were for the non-eVTOL modes were comparable to those reported by the respondent, while the travel times and costs for eVTOL were specified by a range of values that Uber is experimenting with for profitability (Garrow, Binder, & German, 2018). Since we would arrive at eight choice responses per person, the number of cases to be estimated for the logit models would be 8*n, where n is the total number of survey respondents.

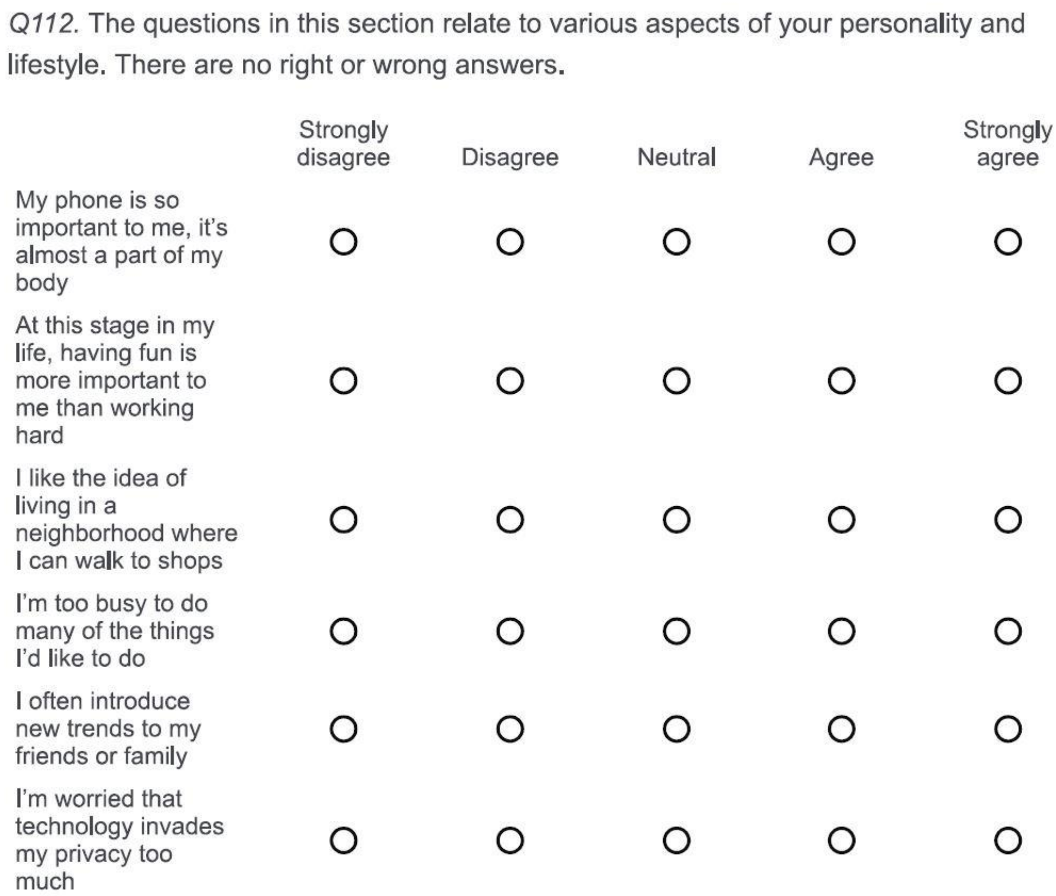
3.2.3 Other questions

The demographics and commute characteristics questions were converted into variables that could be used as independent factors that contribute to the utility function. For example, if the question asked was “Which of the following age category best describes you?", and given four categories, the variable associated with this question would be “AGE", with 1, 2, 3 and 4 as the values describing the above mentioned categories. Similarly, we had questions related to congestion on their way to work, income, presence of kids in the household, rideshare frequency, air travel frequency and many more. Appropriate categories were chosen for each of the variables, and their importance and usage is outlined in the paragraphs below.

Other than the stated choice section and the demographics/commute characteristics questions, the survey also contained personality-based questions, related to their attitude and behavior. These questions were primarily used later to conduct a cluster and factor analysis, which essentially categorized the respondents into mutually exclusive groups – a method to quantify each person’s individual characteristics into malleable scores.

3.3 Preliminary analysis

The survey would be distributed to a wide demographic spectrum, across five geographic areas. It is evident that the choices the respondents make would be based on different decision rules, influenced by a variety of individual characteristics, surrounding environment and other factors that cannot be explained by a simple survey question. Instead, the personality-based questions as mentioned above can be used as a proxy to attach a score to each individual, defined by a factor. These questions ranged from understanding their technology usage, lifestyle, environment friendliness, to name a few. The responses were quantified on a five-point Likert Scale, ranging from “Strongly Disagree” to “Strongly Agree”. A sample question is shown in Figure 3.


Q112. The questions in this section relate to various aspects of your personality and lifestyle. There are no right or wrong answers.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
My phone is so important to me, it's almost a part of my body	O	O	O	O	O
At this stage in my life, having fun is more important to me than working hard	O	O	O	O	O
I like the idea of living in a neighborhood where I can walk to shops	O	O	O	O	O
I'm too busy to do many of the things I'd like to do	O	O	O	O	O
I often introduce new trends to my friends or family	O	O	O	O	O
I'm worried that technology invades my privacy too much	O	O	O	O	O

Figure 3 - Likert Scale used for personality questions

The responses would then be aggregated and factors would be created by assigning a score to each observation. The factor analysis function in SPSS, a statistical software tool was used to generate the factors. They would later be used as explanatory variables in the discrete choice modeling.

Survey respondents were also asked questions related to their perceptions about air travel in general, and eVTOL appeal and usage, based on the description provided. A five-point Likert Scale was again used for these questions. The responses were then plotted on an "eVTOL enthusiasm" versus "eVTOL concern" graph, to observe their potential likelihood of using the service. The clusters would then be assigned based on how the dot density of the responses transitioned across the graph. The cluster analysis results would later be fed into a chi-squared analysis. A chi-squared analysis is a statistical method employed to observe correlation between a given set of variables, at given significance levels (Using Chi-Square Statistic in Research). In this case, the Pearson correlation coefficient is computed for the explanatory variables (derived from the initial set of questions asked) and the clusters as allocated above. Consequently, the percentage splits, row percentages and column percentages for responses to the questions are also calculated by cluster.

Once all the categorical and binary variables were created, a preliminary descriptive statistics analysis was performed to get a clear picture of the frequency description of the responses. The number of observations per category helps to understand the demographic breakdown of the dataset, along with an idea of how each question's responses are divided. Its importance is later seen in the MNL estimation section.

CHAPTER 4. METHODOLOGY

Discrete choice modeling (DCM) is a science that helps predict an individual's choice among a set of alternatives to choose from, the probability being a function of quantifiable variables that influence the choice. It works under the principle of the utility maximization choice-based theory, which states that given a set of alternatives, a rational individual will choose that alternative which provides the maximum utility (Koppelman & Bhat, 2006). In transportation, DCM can be applied to predict which mode would an individual use to make an everyday trip. The mathematical form of one discrete choice model – namely the multinomial logit model (MNL) is determined by the assumptions that are made regarding the error components in the utility function. The MNL serves as a tool that helps calculate the probability of choosing one of the given alternatives.

4.1 Data format

The alternatives in this choice set were auto, transit, rideshare and eVTOL. The variables in the utility function include in-vehicle travel time, out-of-vehicle travel time, and cost (all of which differ across the alternatives) and other variables like age, income, rideshare frequency (all of which remain constant across alternatives for each individual). The raw data obtained from the survey is reshaped and restructured to be compatible with logit model estimation software. There are two types of datasets which can be used to estimate MNL models – IDCASE only and IDCASE-IDALT. The IDCASE-only data format, contains each alternative's specific travel characteristics in separate columns, and each individual's choice is recorded in the same row by an assigned alternative number. Since each variable is represented by a column, this dataset tends to be wide.

Table 2 - IDCASE example

				Alternative 1		Alternative 2		Alternative 3		Chosen
Case	Person ID	Income	Age	Time (min)	Cost ($)	Time (min)	Cost ($)	Time (min)	Cost ($)	
1	1	30000	28	30	2.5	40	1.5	20	5	3
2	1	30000	28	25	2.5	35	1.5	30	2	1
3	1	30000	28	60	1	20	5	40	2	3
4	2	45000	30	45	2.5	30	5	35	3	2
5	2	45000	30	15	10	20	5	30	2	2

The IDCASE-IDALT format contains a column outlining all the available alternatives (by their assigned number), with the travel characteristics for each alternative in the corresponding rows, but under the same column. The case number repeats for each person, by the number of alternatives provided to them, in separate rows. The choice is represented as a binary variable, and since each alternative's characteristics are represented by a row, this dataset is long.

Table 3 - IDCASE-IDALT example

Case Number	Person ID	Income	Age	Alternative	Time(min)	Cost($)	Chosen
1	1	30000	28	1	30	2.5	0
1	1	30000	28	2	40	1.5	0
1	1	30000	28	3	20	5	1
2	1	30000	28	1	25	2.5	1
2	1	30000	28	2	35	1.5	0
2	1	30000	28	3	30	2	0
3	1	30000	28	1	60	1	0
3	1	30000	28	2	20	5	0
3	1	30000	28	3	40	2	1
4	2	45000	30	1	45	2.5	0
4	2	45000	30	2	30	5	1
4	2	45000	30	3	35	3	0
5	2	45000	30	1	15	10	0
5	2	45000	30	2	20	5	1
5	2	45000	30	3	30	2	0

For the models run in this study, the IDCASE-IDALT data format was preferred. Unlike the example shown above, the dataset used in this study would have only two alternatives to choose from for each case, either eVTOL or the mode they typically use to commute.

4.2 Utility equation

MNL models are generated based on the maximum utility theory. To put it simply, given a set of alternatives, a rational consumer would choose the alternative which provided them with the highest utility. The predictive capabilities of the analyst are representative of the difference between the estimated utility values and the actual utility values used by the commuter. Theoretical utility for each alternative *i* can be defined as a function of the explanatory variables as mentioned earlier (Koppelman & Bhat, 2006).

$$U_{it} = V_{it} + \varepsilon_{it} \qquad (1)$$

In the above equation, U_{it} is the theoretical utility, while V_{it} is the observable (also called deterministic) portion of the utility, for individual t. The third component, ε_{it} is the difference between the unknown utility used by the individual, and the utility estimated by the analyst, i.e., the unobservable component, or the error term. Since the error could be a result of inadequate information, measurement inaccuracy, omission of explanatory variables or errors in the utility, it is represented by a random variable. The deterministic portion of utility can be written as a function of three or more components:

1. attributes related to each alternative's characteristics (travel time, travel cost, number of transfers for transit, wait time for rideshare, and others),
2. attributes related to the individual's characteristics (age, income, gender, typical commute distance, etc.),
3. inherent preferences for alternatives that cannot be explained by their observable characteristics, or bias.

The error term's presence in the utility function is an acknowledgement of the analyst's limitations in completely and accurately accounting for all the factors that affect an individual's mode choice. Since the error terms are unmeasurable, certain assumptions are made that lead to the mathematical form, the multinomial logit model (MNL) where the error term is assumed to be:

1. extreme-value (or Gumbel) distributed,
2. identically and independently distributed across alternatives, and
3. identically and independently distributed across individuals (Koppelman & Bhat, 2006).

Thus, by applying the above assumptions on the error term, the deterministic portion of the utility for alternative i can be written as follows:

$$V_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots \ldots \ldots . \beta_n X_{ni} \tag{2}$$

In the above equation, X_{ni} are the explanatory variables like travel time, income for each individual. The corresponding βs are the coefficients associated with the corresponding variable. The betas for each parameter are the desired output of this estimation. The direction and magnitude of the betas measure the extent of influence that the associated variable exerts on utility. The betas calculated for variables like IVTT, OVTT and cost, i.e., those that vary across alternatives, or the generic coefficients are a constant value across each alternative. The variables like age, income, or other individual specific characteristics which don't vary across alternatives, will yield alternative-specific coefficients – there is one beta associated with each alternative, measured in relative proportions to a specified reference alternative. The bias, β_0 associated with each alternative, known as the alternative specific constant (ASC), is also a result of the estimation measured against a reference. Both the generic variables and alternative-specific variables contribute to the utility, consequently influencing mode choice. Given k alternatives, each alternative i defined by the utility function V_i (as described in Equation 2), the probability of choosing an alternative is determined by

$$P_i = \frac{e^{V_i}}{\sum_{i=1}^{i=k} e^{V_i}} \tag{3}$$

The alternative with the highest probability (highest utility) is the alternative the model states that the person would have chosen. The optimal betas that maximize the utility are estimated by a function called the log likelihood. The log likelihood is a function of the choice made and the probability estimated above, as shown below

$$Log\ Likelihood = d_i^n \times \ln(P_i) \tag{4}$$

In Equation 4, d_i^n is the choice made for alternative *i* in case *n* and P_i is the probability of choosing alternative *i*.

In the IDCASE-IDALT format, the choice is a binary variable (1 for yes, 0 for no). Therefore, looking at Equation 4 log likelihood will always be either 0 or negative. Ideally, if the model specification is accurate and every explanatory variable is accounted for, the probability associated with the alternative actually chosen (choice = 1) will be very close to 1. In realistic models, it is accepted that if the chosen alternative has the highest probability compared to the alternatives, then the model is successful. In the ideal scenario, log likelihood should be 0. Now, taking the sum of log likelihoods for all the cases, we get the sum of log likelihoods, which is the function to be maximized. Since the log likelihood for each case is negative, the sum of log likelihood will be a negative value. The sum is the objective function to be maximized by an optimization algorithm like Berndt-Hall-Hall-Hausman (BHHH) or Newton-Raphson, with the variables specified in the utility equation as constraints that the objective function is subject to. The coefficients obtained after the estimation are those where the sum of the log likelihoods is maximized. The model with the sum of log likelihoods closest to zero (least negative, or maximum magnitude) is the model that best fits the data.

4.3 Process

The first set of MNL models chosen to be run was based on using a forward-step wide regression approach, in which explanatory variables (derived from the survey questions) were entered one-by-one and observing which of the parameters yielded significant betas, and which models had smaller log likelihoods. The best performing models were chosen for further estimation, with some modifications to the categories and the coefficients. The clusters identified from the cluster analysis were then used to segment the respondents, and the best performing models were run separately for each cluster, to observe variation in values of time (VOT) across the dataset. The research team then explored the possibility of a latent class model – a latent class model captures unidentified, hidden trends in decision rules that a certain subset of the dataset would've followed, otherwise invisible in a basic MNL. Finally, a mixed logit model – a model that assigns a distribution of values for a coefficient instead of computing an average effect – was estimated.

MNL model estimations can be conducted on any platform – Excel, R, Python. There are specific statistical tools like SAS, Stata and ELM which also support logit modeling functionality. The decision to pick one over the other is the tradeoff between convergence accuracy, speed and level of understanding. Excel is very visual, and for small datasets with less than five variables, the estimations will be fairly simple and quick. However, for large datasets like ours, we needed a more powerful tool. ELM is a click-based GUI developed by a former member of the research team, Jeff Newman. Its simple interface allows beginners to grasp the nuances of logit modeling, and the outputs are presented in a clean, succinct and readable format. ELM was used for the initial set of estimations.

Over the course of the study, the research team experimented with other modeling software as well. The challenges with MNL estimations aren't limited to poor model specifications alone. Even with an accurate model specification on a non-erroneous dataset, logit modeling faces problems ranging from lack of convergence of the maximization function, poor performance of the algorithm being used to achieve this convergence, the starting values provided forcing the convergence sequence to oscillate around identical betas, or getting stuck between multiple local optima. With so much possibility for inaccuracy in model estimation, it is advisable to experiment with multiple software. The research team expanded on its arsenal of modeling software and eventually moved on to estimations on Larch, which is an open source Python package, also created by Jeff Newman.

The decision to shift the estimations to Larch was undertaken to explore all the possible combinations within logit modeling and fully investigate its functionality through added flexibility. Scripting in Python allowed for more control over the specification, as well as estimation procedure. The increased user input meant that the research team could account for foreseeable challenges, as well as iterate with different maximization procedures, number of iterations and parameters. Stata, a powerful, licensed software package was tested to try running latent class and mixed logit models. Although the commands available in Stata allow for high performance computations, the version available to us wasn't suitable for our data. Historically, the research team has worked successfully on Biogeme, an open source statistical tool created by

Michel Bierlaire, now updated into an open source Python package. Having had experience with Biogeme, the team found that it tends to be excellent at finding the "optimal" solution owing to its advanced algorithms and detailed model specification structure. Therefore, to improve efficiency, the typical process followed by logit modelers is to iterate multiple combinations on faster software like Larch, and once satisfied with the parameters and results, the estimations can be carried out in Biogeme as a quality control measure.

CHAPTER 5. RESULTS

5.1 eVTOL index results and descriptive statistics

The eVTOL index was the initial step towards understanding the market size and estimating market share for such a service. The research team had certain logical assumptions as to who, where and under which circumstances would be most likely to switch from their traditional mode of commute to a flying taxi service. For example, Uber’s preliminary pricing strategy points at flight costs greater than those of driving or transit in phase 1 of implementation (Garrow, Binder, & German, 2018). The network of routes being planned include long distance O-D pairs. On the basis of just these two determining factors, it is evident that high income commuters with a long commute distance would ideally be the segment of the population the service can be directed at. Multiple influencing factors like other census variables, typical travel times and average number of trips between given sets of origins and destinations were accumulated and consolidated. The 40 CSAs for which the data has been collected are eventually to be ranked based on their feasibility for implementation of an urban air mobility service for commuting purposes, purely dependent on their score in the index.

The LODES data was used to assign a weight to each OD pair, based on the number of trips that are reported to occur between the pair. This is a crucial portion of the dataset as it forms the basis on which potential routes and itineraries can justifiably be modeled. A cumulative distribution frequency graph of the distances between all of the OD pairs was plotted.

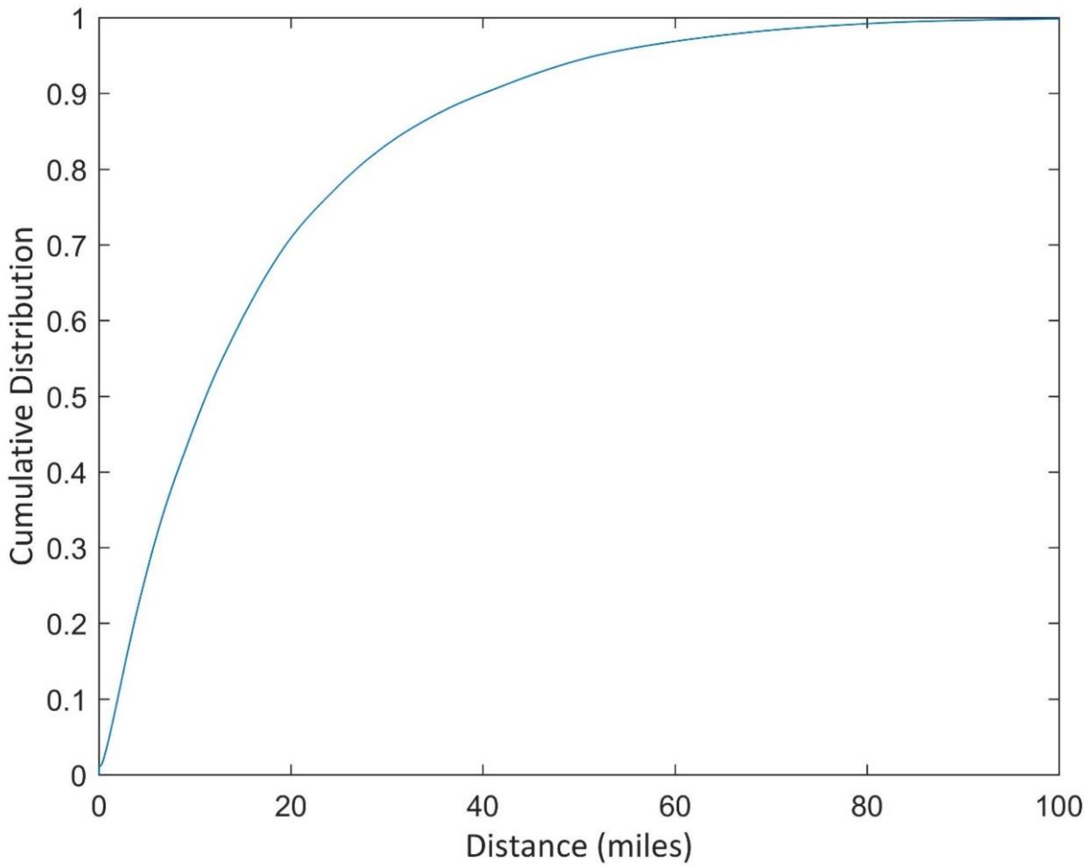


Figure 4 - Cumulative distribution frequency (CDF) of distances weighted by number of trips

An interesting takeaway from this curve is that about 70 percentile of all trips undertaken fall under the 20-mile distance mark. This distance range is important as it gives the research team a big picture view of what could potentially be the ideal commute distances and travel times to be looked at in the demand model estimation. It also helped the team categorize the distance to work variable in the survey accordingly.

The stated preference survey was conducted in the five CSAs as mentioned earlier. The agreement with Qualtrics (the agency conducting the survey) was to arrive at a total of 2500 responses, 500 from each CSA. The responses were downloaded in the .sav format, accessible in a readable format by the IBM provided software SPSS. Qualtrics has its own unique method of coding the responses to the questions asked. The question numbers were isolated and their labels were studied, to generate a list of variables that can be used in the factor and chi-square analysis, followed by the discrete choice modeling. The categories as defined by Qualtrics were modified to suit the research team's requirements, and a frequency distribution for each of the variables was generated. Below is an example of some of the variables generated:

Table 4 - Variables created from the survey

Variable Name	Type	Description	Values	Interpretation	Freq
DaysWorkedOutsideHome	Numeric				
		Days of the week worked outside home	1	2 to 4	551
			2	5	1685
			3	6 or 7	263
TotalHoursWorked Categories	Numeric				
		Total hours worked in a week (categories)	1	0-39 hours + unknown + missing	338
			2	40-49 hours	1141
			3	50+ hours	1020
HHIncomeCat	Numeric	Household Income (categories)			
			0	<100K	18
			1	100-149K	1023
			2	150-199K	661
			3	200K+	797
CongestionHomeLeave	Numeric				
		Congestion level near home when leaving for work	1	Little to no congestion	951
			2	Minor congestion	742
			3	Moderate congestion	577
			4	Heavy congestion	229
Hybrid	Numeric				
		Do you own or lease a hybrid?	0	Don't own vehicle	31
			1	Yes	449
			2	No	2019

Variable Name	Type	Description	Value	Interpretation	Freq
BothFuelAndBattery	Numeric				
		How likely if used both fuel and batteries?	1	Much less likely	44
			2	Less likely	93
			3	Would not affect my decision	1436
			4	More likely	644
			5	Much more likely	282

The "Value" column for the variables could either be categorical, binary or a numeric value. The survey can clearly be split into three parts – part 1: the demographic and personal information, including income, age, their commute characteristics, etc.; part 2: the personality based questions, quantified on a Likert scale; part 3: finally, the stated preference section, where each respondent was provided with 8 choice based questions between two alternatives.

Parts 1 and 2 were directly converted into explanatory variables. The stated preference part was converted into binary choice variables (1 for yes, 0 for no), associated with the alternatives each respondent was presented with. The end product was a dataset in the IDCASE-IDALT format, with each respondent answering 8 choice set questions, joined with the travel characteristics of both alternatives in each question, and finally joined to the master dataset of demographic, commute and personality variables, repeating for each person.

The data were subject to an initial cleaning and logical modifications were made. Some responses contained NULL values for the choice variable and recognizing that this is the most critical piece recorded from the survey, these were omitted. Some responses to the "AGE" question were blank due to an error that occurred during data transfer. The missing responses were populated with the mean of the rest of the recorded observations. It was assumed that observations with “zero adults in the household” were response errors, and were also filtered out. Other minor survey recoding errors and data were adjusted to suit the analysis.

The stated preference part of the survey forms the crux of the discrete choice models we estimated. Each set of eight questions that the respondents answered was followed by a response-based question, depending on the eight choices made. If the survey taker never chose eVTOL as their preferred alternative, they were asked for suggestions that would motivate them to potentially choose eVTOL in the future. Of those who responded positively to providing suggestions, 28 percent mentioned safety (fear), while cost was stated as the reason for not choosing eVTOL by 12 percent. A detailed breakdown of all reasons (aggregated by general themes) is presented below:

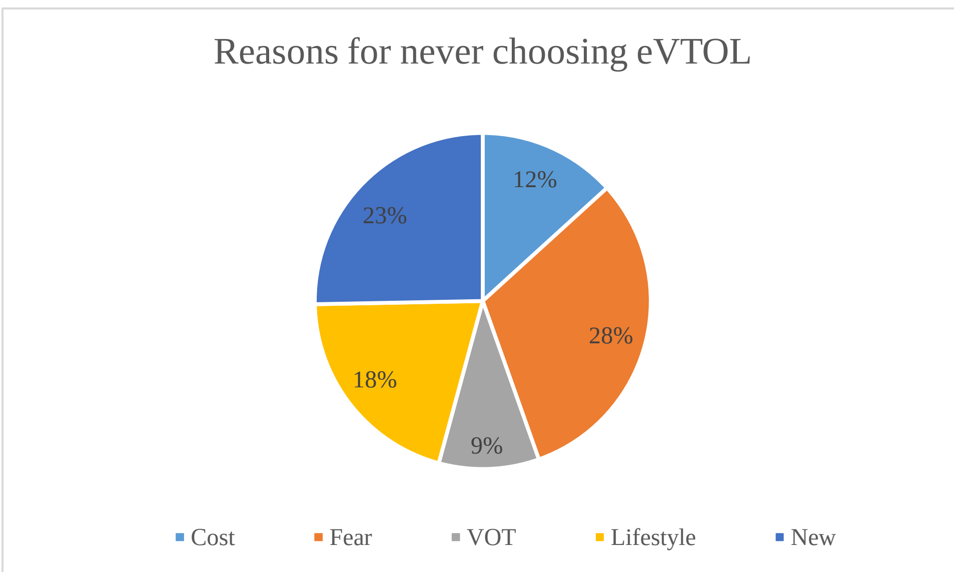


Figure 5 - Reasons for never choosing eVTOL

Category “new” includes those respondents who were uncertain about using it unless they received positive feedback from their friends who already used it – it’s too new to make a decision about without reviews. Considering that it is the second most popular reason, it is important to note that the first wave of publicity and marketing about Uber Air, the first impression created makes a difference – it could sway so many riders away from their traditional commute modes.

5.2 Initial set of MNL models

The results from the survey are organized as a progression of experimental estimations, each subsequent model set an improvement from the previous set. In doing so, the lessons learned at each step are elucidated as nuances in discrete choice modeling.

The variables obtained from the survey were used in iterative combinations to create an initial set of models to get a feel of the dataset, its convergence stability, and to develop the first phase of the logit modeling for this study. The research group had its own set of intuitive assumptions as to each variable's magnitude and direction of influence, and the first draft of models were estimated to validate those assumptions or inspect the violations with greater care. The models' parameters were decided based on parameters that could theoretically influence mode choice and are somewhat similar in their deterministic character. For example, if a respondent answered yes to "the presence of heavy congestion on the commute to and from work" and no to "making stops on the way back from work", it is fair to assume that their utility to drive would be lower, compared to the other modes. Another method employed to group variables together in models was just experimental – the research group wanted to observe the combined effect of certain parameters on stated preference. For example, to observe if people would adopt lifestyle changes with the introduction of eVTOL, the variables describing whether respondents would change their residence (move farther to work, closer to work, or no change) was combined with the variable that described the activities they would undertake with the extra time gained (work more, with family or on oneself).

Traditional discrete choice modeling revolves around travel cost and travel time as definitive explanatory variables. Since the utility maximization theory has been formulated based on a "rational consumer", cost and time are mandatory inclusions, and are a regular occurrence across all the models. It is critical to note that the models include separate in-vehicle travel time (IVTT) and out of-vehicle travel time (OVTT) variables, as OVTT has higher disutility than IVTT – every one minute spent waiting for the bus feels like almost four minutes inside the bus (Koppelman & Bhat, 2006). The OVTT variable applies only to transit, eVTOL and rideshare, as auto is a personally owned mode, and the only time spent outside the vehicle is walking from the destination to the parking spot. OVTT for transit is the time spent waiting for the train or bus to arrive, while at the station, and for rideshare it would be the time waiting for your Uber/Lyft to arrive. Logically, the longer the wait time, the less likely an individual would be to select that alternative. The time and cost coefficients were used to calculate the value of time for the sample set, and the ratio of OVTT to IVTT tells us by how much the wait time for a mode reduces its attractiveness than the time spent inside the vehicle. The ride guarantee and transfer variables are the other two generic variables that feature across all the models. Ride guarantee is applicable only to transit and eVTOL, while transfer is applicable only to transit, i.e., the coefficients for these to variables only affect the utility of their respective, corresponding modes.

Below are the results from the first set of estimations, performed in ELM. The bolded coefficients are those with t-stats significant at the 95% confidence level ($t_{critical} = \pm 1.96$).

Table 5 - First set of 5 (out of 50) models

Category	Parameters		Model_1 (MNL)	T-stat	Model_2 (MNL)	T-stat	Model_3 (MNL)	T-stat	Model_4 (MNL)	T-stat	Model_5 (MNL)	T-stat
Generic parameters	In-vehicle travel time		**-0.039**	-36.661	**-0.038**	-36.584	**-0.039**	-36.626	**-0.039**	-36.739	**-0.039**	-36.793
	Out of vehicle travel time (not applicable to auto)		**-0.037**	-12.767	**-0.037**	-12.755	**-0.037**	-12.753	**-0.037**	-12.773	**-0.037**	-12.773
	Travel cost		**-0.091**	-32.842	**-0.092**	-33.116	**-0.091**	-33.052	**-0.091**	-32.861	**-0.091**	-32.773
	Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and Transit)		**0.370**	12.741	**0.371**	12.749	**0.372**	12.762	**0.372**	12.774	**0.373**	12.788
	If there's a transfer in the transit ride (applicable only to Transit)		**0.223**	2.501	**0.221**	2.465	**0.221**	2.473	**0.222**	2.477	**0.225**	2.508
Alternative specific parameters	eVTOL taken as reference alternative											
ASCs	Alternative specific constants	Auto	0.329	5.717	0.405	6.814	0.427	7.143	0.424	7.043	0.440	7.283
		Transit	0.247	3.304	0.440	5.392	0.397	4.707	0.437	4.949	0.424	4.783
		Ride Share	-0.505	-3.487	-0.523	-2.927	-0.668	-3.505	-0.579	-2.910	-0.684	-3.327
Number of days worked outside the home per week (categorical variable, three categories)	2-4 days a week worked outside home	Auto	0.063	1.534	--	--	--	--	0.044	1.064	0.098	2.222
		Transit	0.084	0.814	--	--	--	--	0.016	0.155	-0.129	-1.078
		Ride Share	0.339	1.391	--	--	--	--	0.381	1.513	0.284	1.114
	5 days in a week worked outside home (reference)		-	-	-	-	-	-	-	-	-	-

Categories	Parameters		Model_1 (MNL)	T-stat	Model_2 (MNL)	T-stat	Model_3 (MNL)	T-stat	Model_4 (MNL)	T-stat	Model_5 (MNL)	T-stat
	6-7 days a week worked outside home	Auto	-0.145	-7.802	--	--	--	--	-0.136	-7.172	-0.132	-6.934
		Transit	0.101	1.470	--	--	--	--	0.127	1.840	0.132	1.906
		Ride Share	-0.025	-0.330	--	--	--	--	-0.069	-0.835	-0.100	-1.192
	0-9 hours a week worked at home (reference)		-	-	-	-	-	-	-	-	-	-
Hours worked at home per week(categorical variable, with two categories)	10+ hours a week worked at home	Auto	--	--	--	--	-0.064	-3.249	--	--	-0.079	-3.815
		Transit	--	--	--	--	0.119	2.165	--	--	0.161	2.568
		Ride Share	--	--	--	--	0.289	2.548	--	--	0.294	2.518
Total hours worked per week(categorical variable, three categories)	Total hours worked in a week: 0-39 hours	Auto	--	--	-0.091	-1.753	-0.096	-1.852	-0.031	-0.578	-0.047	-0.884
		Transit	--	--	-0.123	-0.891	-0.091	-0.653	-0.157	-1.126	-0.108	-0.765
		Ride Share	--	--	0.898	3.710	0.931	3.814	0.975	3.893	1.027	4.065
	Total hours worked in a week: 40-49 hours (reference)		-	-	-	-	-	-	-	-	-	-
	Total hours worked in a week: 50+ hours	Auto	--	--	-0.082	-6.990	-0.067	-5.253	-0.070	-5.912	-0.050	-3.888
		Transit	--	--	-0.138	-4.120	-0.157	-4.527	-0.145	-4.239	-0.179	-4.869
		Ride Share	--	--	-0.199	-2.367	-0.256	-2.907	-0.187	-2.184	-0.246	-2.749
	Log Likelihood at Convergence		-12303.2		-12288.1		-12277.2		-12255.1		-12241.3	
	Number of Cases		19713		19713		19713		19713		19713	

It is recommended to use of all the variables in different models, as a method to test whether the data structure is appropriate and model setup stays consistent. The first phase of estimations consisted of 49 models that incorporated all the variables. Displayed above are only those models with relatively better performing model fit, i.e., the models with a smaller log likelihood value (less negative). The closer the model is to zero, the better it fits the data. This follows from the fact that the log likelihood is a maximization function of choice and probability of choosing an alternative. If a respondent chose a particular alternative and the model accurately assigned a higher probability (closer to one) to that mode, the function $d_i^n \times \ln(P_i)$ would tend closer to zero. For example, between model 1 and model 2, model 2 performed better, owing to a smaller log likelihood at convergence.

Examining one of the models, the coefficients associated with each parameter can be interpreted by relating them to the utility equation associated with each alternative. The first model has a coefficient of – 0.039 for IVTT, - 0.037 for OVTT and – 0.091 for cost. Agreeing with conventional theory, travel cost and travel time have negative coefficients, implying that the alternative with the highest travel time or cost will have the least utility. The Alternative specific constants (ASCs) represent those measures of utility that the explanatory variables in the model fail to capture. The ASCs have been computed keeping eVTOL as the reference alternative, i.e., $ASC_{eVTOL} = 0$. In logit modeling, any of the alternatives can be chosen as the reference alternative – the estimation remains unaffected. Since the study is being conducted to estimate demand for eVTOL, measuring the utilities of the other alternatives against it would be more interpretable. By constraining every coefficient except the ASCs to 0 (equivalent of estimating an ASC only model), the analyst gets a generic, broad picture of how the alternatives can be ranked. The positive ASC for auto and transit imply a higher utility for those two modes while the negative ASC for rideshare implies a lower utility, with respect to eVTOL.

The "days worked outside home" parameter is a categorical variable, where category one is 2-4 days, category two is 5 days, and category three is 6-7 days. The parameter will yield alternative specific coefficients in the estimation, with respect to eVTOL as the reference alternative ($DaysWorkedOutsideHome_{eVTOL}$ = 0). When dealing with categorical variables, one of the categories must also be kept as the reference, and the coefficients obtained will be with respect to that category. Typically, the category with the greatest number of observations (highest frequency) is taken as the reference, making category two the reference for this variable. Given a set of *n* categories and *k* alternatives, the estimation results will contain *(n-1) * (k-1)* coefficients. In the table below, the reference category is category 2 and reference alternative is eVTOL.

Table 6 - Coefficients for categorical variables

	Auto	Transit	eVTOL	RideShare
Category 1	X	X	-	X
Category 2	-	-	-	-
Category 3	X	X	-	X

The coefficient for category three for the auto alternative is -0.145, for transit is 0.101 and for rideshare is -0.025. Keeping in mind that eVTOL has a coefficient of 0, this implies that on an average, if a respondent works more than 5 days a week outside home (reference), their mode choice can simply be ranked on the basis of the magnitude and direction of the coefficients, from most positive to most negative – transit, eVTOL, rideshare and then auto. The odds ratio is a simpler way to interpret individual coefficients – the exponent of the coefficient corresponding to each alternative tells us how much more or less likely (depending on the sign) the individual would select the alternative. Therefore, if a respondent works more than 5 days a week outside home, they are exp(0.101) = 1.11 times more likely to select transit than eVTOL, while they are 1/exp(-0.145) = 1.16 times less likely to choose auto than eVTOL. The other coefficients can be similarly interpreted. The t-stat value is a measure of the significance of the coefficient.

The coefficients sufficiently explain which mode would have a higher utility, thus indicating which mode would have a higher probability of being chosen. Therefore, for each case and its corresponding IVTT, OVTT and other explanatory variables, the probability of choosing the given alternatives can be calculated using Equation 2.

Looking horizontally across all the models presented, there is consistency in the coefficients and t-stats for the five generic variables included in the utility function, which is a solid indication of accurate model specification, data structure and stability in estimation and convergence. The other alternate specific coefficients like hybrid ownership, gender, congestion, etc. that feature into the utility functions of the respective models also influence mode choice, with varying degrees of significance. It is also interesting to note the models which spectacularly failed; for example, the “occupation” categories had no significant coefficients affecting mode choice based on the respondent’s employment sector. This implies that a person’s job type doesn’t contribute much to their decision to use eVTOL as a commuting option.

The next step in model estimation was to filter out the good models from the bad ones, i.e., those that fit better than the rest coupled with mostly significant coefficients. Running on experience and careful research judgement, the second set of models was chosen. The research team was interested in observing the effect of certain demographic variables like age and income on mode choice, while also examining typical commute characteristics like automobile ownership, frequency of rideshare usage and whether the respondent made stops to and from work. Since the project primarily revolves around predicting the potential popularity of an unknown flying service, extraneous variables like air travel frequency were also shortlisted for further estimation. The reasoning behind choosing the final list of variables was to highlight the point corresponding to each explanatory variable (threshold) at which the respondent switched from their everyday commute mode to trying urban air mobility.

The models presented in the following subsection have been estimated as before. Often in discrete choice modeling, the categories for certain variables don't work as expected or fail to achieve significance or convergence. There are many reasons that could be causing such issues – some categories may have too few observations to arrive at statistically significant coefficients, the variable could be irrelevant as a decision-making factor for this dataset or simply because there are too many categories, yielding weak coefficients. In such cases, some of the commonly used workarounds include combining multiple categories into concise, simpler ones, or constraining coefficients which were almost equal in magnitude and direction to be equal. The results in the Table 7 include variables whose coefficients have been constrained to improve model fit.

5.3 Intermediate set of MNLs

New categorical variables based on the interpretations of the first set of estimations were created. ELM has a user-friendly interface to estimate the models, and the output is neatly presented with the models stacked side-by-side, improving readability. When estimating multiple models at once, the presentation of the coefficients from different models next to each other allows for easy comparison and filtering the superior estimations.

The new set of models have similar outputs as the initial runs, and the research team looked out for oddities and inconsistencies. Among the four congestion options provided, only “moderate” and “heavy” were used in the models, owing to their higher significance from the initial set. The rideshare frequency variables were compressed into fewer categories in decreasing order of frequency, so the coefficients could be interpreted with the highest frequency (once a week) as reference. Rideshare as a regular and occasional commute mode to work were used along with rideshare frequency to identify logical trends, especially for those respondents who had the discrete choice between rideshare and eVTOL. The number of kids in the household being treated as a categorical variable in the first set, was converted to a binary variable; 1 if there were any kids at home, 0 for none. This was done because the high frequency of observations with no kids were awkwardly skewing the results. Vehicle ownership was combined with household size to create a variable that represented the vehicles to adults ratio in the household, with the objective of observing the differences between households who share an automobile with others and those with one or more than one car per person.

Table 7 - Intermediate set of refined MNLs

Category	Parameters	Alternatives	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Generic parameters	In-vehicle travel time		-0.035	-0.033	-0.033	-0.033	-0.034	-0.036	-0.038	-0.038	-0.038	-0.04
	Out of vehicle travel time		-0.051	-0.059	-0.059	-0.059	-0.053	-0.05	-0.036	-0.036	-0.037	-0.037
	Travel cost		-0.094	-0.093	-0.093	-0.093	-0.093	-0.094	-0.091	-0.091	-0.092	-0.092
	Guaranteed Uber/Lyft ride if eVTOL can't takeoff OR transit doesn't arrive (only for eVTOL and Transit)		0.326	0.304	0.304	0.305	0.316	0.329	0.369	0.371	0.371	0.386
	Transfer in the transit ride (applicable only to Transit)		0.341	0.455	0.473	0.473	0.398	0.306	0.224	0.226	0.223	0.216
Alternative specific parameters	eVTOL taken as reference alternative		--	--	--	--	--	--	--	--	--	--
Congestion	Presence of moderate congestion along commute route to or from work	Auto	-0.129	--	--	--	--	--	--	--	--	--
		Transit	0.15	--	--	--	--	--	--	--	--	--
		Ride Share	-0.503	--	--	--	--	--	--	--	--	--
	Presence of heavy congestion along commute route to or from work	Auto	-0.061	--	--	--	--	--	--	--	--	--
		Transit	-0.152	--	--	--	--	--	--	--	--	--
		Ride Share	-0.17	--	--	--	--	--	--	--	--	--
Frequency of rideshare usage (categorical, five categories)	Never use rideshare (reference)		--	--	--	--	--	--	--	--	--	--
	Use rideshare 1-3 times a year	Auto	--	-0.016	-0.015	-0.006	--	--	--	--	--	--
		Transit	--	0.078	0.087	0.068	--	--	--	--	--	--
		Ride Share	--	0.388	0.642	0.456	--	--	--	--	--	--

Category	Parameters	Alternatives	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model 10
Frequency of rideshare usage (categorical, five categories)	Use rideshare 4-12 times a year	Auto		-0.111	-0.109	-0.094						
		Transit	--	-0.049	-0.045	-0.055	--	--	--	--	--	--
		Ride Share	--	-0.636	-0.49	-0.63	--	--	--	--	--	--
	Use rideshare 2-3 times a month	Auto	--	-0.171	-0.162	-0.149	--	--	--	--	--	--
		Transit	--	-0.055	-0.045	-0.067	--	--	--	--	--	--
		Ride Share	--	-0.421	-0.358	-0.41	--	--	--	--	--	--
	Use rideshare once a week	Auto	--	-0.175	-0.159	-0.148	--	--	--	--	--	--
		Transit	--	-0.108	-0.088	-0.119	--	--	--	--	--	--
		Ride Share	--	-0.059	0.011	-0.045	--	--	--	--	--	--
Rideshare purpose	Use rideshare regularly for work	Auto	--	--	-0.334	--	--	--	--	--	--	--
		Transit	--	--	-0.418	--	--	--	--	--	--	--
		Ride Share	--	--	-0.506	--	--	--	--	--	--	--
	Use rideshare occasionally for work	Auto	--	--	--	-0.278	--	--	--	--	--	--
		Transit	--	--	--	0.16	--	--	--	--	--	--
		Ride Share	--	--	--	-0.134	--	--	--	--	--	--
Kids	Presence of kids at home	Auto	--	--	--	--	-0.171	-0.179	--	--	--	--
		Transit	--	--	--	--	-0.062	-0.087	--	--	--	--
		Ride Share	--	--	--	--	-0.396	-0.425	--	--	--	--
Gender	Male as reference	Auto	--	--	--	--	--	0.110	--	--	--	--
		Transit	--	--	--	--	--	0.157	--	--	--	--
		Rideshare	--	--	--	--	--	0.110	--	--	--	

Model Statistics	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model 10
Log Likelihood at Zero	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5	-13780.5
Log Likelihood at Constants	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5	-13667.5
Log Likelihood at Convergence	**-12459.1**	**-12285**	**-12270.2**	**-12260.5**	**-12403.4**	**-12351.9**	**-12450**	**-12426.5**	**-12418.3**	**-12234.6**
Rho Squared w.r.t. Zero	0.0959	0.1085	0.1096	0.1103	0.0999	0.1037	0.0965	0.0983	0.0988	0.1122
Rho Squared w.r.t Constants	0.0884	0.1011	0.1022	0.1029	0.0925	0.0963	0.0891	0.0908	0.0914	0.1048
Adjusted Rho Squared w.r.t. Zero	0.0951	0.1075	0.1084	0.1091	0.0993	0.1029	0.0957	0.0972	0.0976	0.1112
Adjusted Rho Squared w.r.t Constants	0.0878	0.1003	0.1012	0.1019	0.0921	0.0956	0.0885	0.09	0.0904	0.104
Number of Cases	19912	19912	19912	19912	19912	19912	19912	19912	19912	19912

Models 2, 3, 4 and 10 seemed to have performed best, judging only by the smaller log likelihood values. However, log likelihood should be used as a comparison tool only when the number of parameters included in the estimation are the same. It is expected that log likelihood improves with the addition of variables (Train, 2003) and thus, pointless to compare a model with 14 parameters against one with 8. Having said this, the model with air frequency categories performed the best among those with more parameters, implying that frequency of air travel significantly impacts a respondent's choice to choose eVTOL. Of the models with 11 or fewer parameters, the model with kids and gender performed the best, indicating that eVTOL demand could differ between the sexes, subject to the presence of children in the house.

The generic variables (IVTT, OVTT, cost, transfer and ride guarantee) were inevitably consistent. Looking at the significance of the other coefficients obtained, Heavy Congestion stayed completely insignificant. Among certain variables, entire categories (like rideshare frequency category 2, i.e., frequency of rideshare usage being less than 4 times a year) were rendered insignificant. A recurring trend observed was that coefficients associated with the rideshare alternative reported higher instances of insignificance. Such behavior was expected, owing to its proportionately small sample size compared to those who used auto or transit as their daily commute mode. This observation led the research to rerun the models after completely excluding rideshare as an alternative.

On first look, the auto and transit coefficients for rideshare frequency category 5 (those who use rideshare once a week or more) are almost the same (-0.1481 and –0.1189 respectively). These two coefficients can be constrained to be equal – this would imply that the research team is explicitly instructing the model to assign equal importance to both auto and transit for those who belong to category 5 of rideshare frequency.

The factor analysis conducted in SPSS created a weighted score from the responses to the personality-based questions. The author wasn't involved in the part of the research involving the factor analysis – additional details on the detailed methodology adopted to conduct the factor analysis can be found in (Garrow, Mokhtarian, German, & Glodek, 2019). Six distinct factors were obtained from the analysis – "pro collective modes" (in favor of transit, rideshare and other non-single occupancy modes of transportation), "stressful commute" (agree to having a daily stressful commute), "control" (likes to be in control of the vehicle they're in, or isn't comfortable with someone else driving the vehicle), "pro car and technology" (are open to trying new technology), "fear technology" (afraid of trying new technology) and "pro-environment" (would prefer a non-polluting mode of commute). These factors are values assigned to each respondent, a non-mean centered score explaining the extent to which they conform to the said factor. The factors were included in the MNL models as explanatory variables, to observe their effect on mode choice. Two other factors, "eVTOL enthusiasm" and "eVTOL concern" were also computed; as their names suggest, the two factors represented the level of excitement and skepticism towards eVTOL respectively.

Table 8 - MNL model with factors

Category	Parameters	Alternative	Coefficient	T-stat
Generic parameters	In-vehicle travel time		-0.044	-38.439
	Out of vehicle travel time		-0.042	-13.561
	Travel cost		-0.102	-34.214
	Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and Transit)		0.416	13.474
	If there's a transfer in the transit ride (applicable only for Transit)		0.263	2.788
Alternative specific parameters	**eVTOL taken as reference alternative**			
ASCs	Alternative specific constants	Auto	0.965	14.807
		Transit	0.841	7.652
		Rideshare	0.209	0.592
Factors obtained from factor analysis in SPSS	I am for using collective modes (transit, rideshare or carpool)	Auto	-0.271	-15.508
		Transit	-0.138	-2.404
		Rideshare	0.436	2.800
	I like to be in control (driving) while in a car	Auto	-0.053	-3.007
		Transit	-0.037	-0.714
		Rideshare	0.110	0.993
	My commute generally to work is stressful	Auto	-0.004	-0.270
		Transit	-0.044	-0.937
		Rideshare	-0.077	-0.724
	I am interested in new technology	Auto	-0.079	-5.039
		Transit	-0.042	-1.022
		Rideshare	-0.395	-4.210
	I am concerned about the impacts of travel on the environment	Auto	-0.003	-0.216
		Transit	0.268	5.678
		Rideshare	0.321	3.011

	Parameters	Alternative	Coefficient	T-stat
	I am afraid of technology	Auto	0.108	7.138
		Transit	0.083	2.027
		Rideshare	-0.085	-0.716
eVTOL appeal	I am concerned about the possibility of commuting by eVTOL taxis	Auto	0.271	12.880
		Transit	0.102	1.618
		Rideshare	0.329	2.607
	I am enthusiastic about the possibility of commuting by eVTOL taxis	Auto	-0.458	-22.774
		Transit	-0.576	-9.830
		Rideshare	-0.641	-3.675
	Log likelihood at convergence		-11160.368	
	Number of cases		19713	

The coefficients for most of the factors seem to explain mode choice as expected – "pro environment" had positive coefficients for rideshare and transit, and "Fear of Technology" was leaning towards auto or transit as their choice of transportation. Unsurprisingly, those who showed eVTOL enthusiasm ranked eVTOL as their first choice, while the eVTOL concern folks ranked eVTOL below the other three alternatives. What's counter-intuitive is that the "control" factor reported negative coefficients for Auto. This could be due in part to multi-collinearity among factors or, as described below, the fact that we have some individuals in the dataset who never chose eVTOL that could be biasing coefficients.

5.4 Final MNLs

As discussed in the previous section, a cluster analysis was conducted in SPSS by the research team to identify specific groups of people within the given dataset, determined by their responses to the eVTOL appeal and usage questions. These groups were categorized based on their likelihood of using eVTOL and ranked on their level of enthusiasm versus their level of concern for eVTOL. The responses were plotted to visually arrive at six mutually exclusive clusters within the dataset (Garrow, Mokhtarian, German, & Glodek, 2019) as shown in figure 6. The author wasn't involved in the part of the research involving the cluster analysis – additional details on the detailed methodology adopted can be found in (Garrow, Mokhtarian, German, & Glodek, 2019).

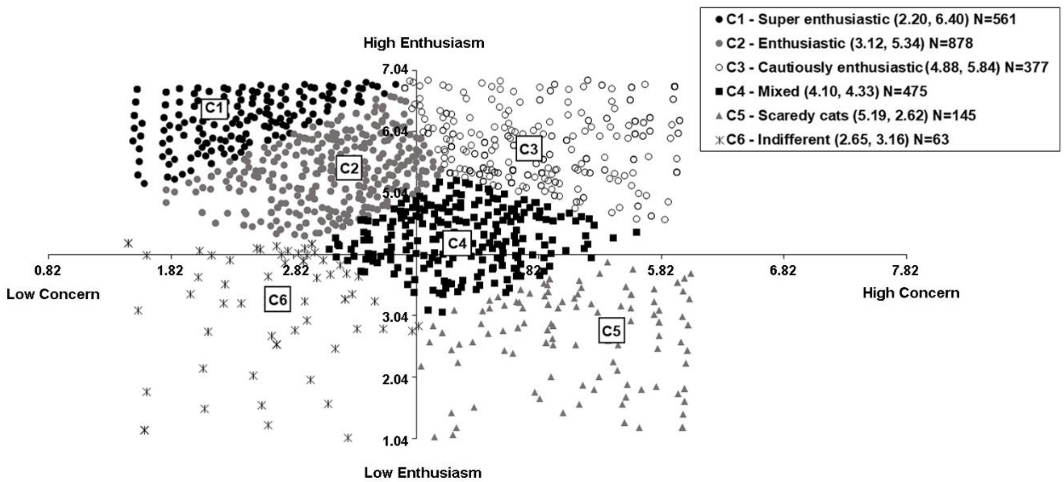


Figure 6 - Six clusters identified by their non-mean scores

As the names suggest, the "super enthusiastic" cluster defines those respondents who ranked high on the level of enthusiasm and low on the level of concern, theoretically placing them on top of the target audience. The opposite end of the spectrum is the "scaredy cats" cluster, ranking low on enthusiasm and high on concern. A total of six clusters were identified.

In order to observe variation in taste preference among the individuals, the clusters were used as segmentation tools. It was assumed that respondents belonging to each cluster would have different values of time and exhibit unique travel behavior. To observe this hypothesis, a one model per cluster was estimated. Rideshare was omitted as an alternative, as clustering rendered too few observations for each segment, leading to inconsistencies. The models from the previous section were estimated separately for responses corresponding to each cluster number (i.e., 1 = Super

Enthusiastic, 4 = Mixed). The “indifferent" cluster was ignored, owing to a small sample size. The pooled model (all clusters together, without indifferent) was then compared against the models corresponding to each cluster.

Table 9 - Segmentation results

Category	Parameter	Alternative	Pooled Model	Super Enthusiastic	Enthusiastic	Cautiously Enthusiastic	Mixed	Scaredy Cats
			value	value	value	value	value	value
Generic parameters	In-vehicle travel time		-0.043	-0.060	-0.058	-0.035	-0.034	-0.030
	Out of vehicle travel time		-0.041	-0.052	-0.052	-0.045	-0.030	-0.033
	Travel cost		-0.095	-0.149	-0.116	-0.087	-0.069	-0.024
	Guaranteed Uber/Lyft ride incase eVTOL can’t takeoff due to bad weather OR transit doesn’t arrive (only for eVTOL and Transit)		0.405	0.564	0.370	0.440	0.445	0.479
	If there’s a transfer in the transit ride (applicable only for Transit)		0.272	0.079	0.260	0.270	0.335	1.860
Alternative specific parameters		eVTOL taken as reference alternative						
Income	Household income (midpoint of categories/1000)	Auto	0.031	-0.180	0.194	-0.149	0.172	-0.124
		Transit	-0.024	-0.112	-0.012	1.095	-0.665	15.378
Vehicles to adults ratio (three categories)	Number of vehicles is 0 (reference)							
	Vehicles to adults ratio between 0 and 1	Auto	0.058	-0.289	0.018	0.146	0.191	1.730
		Transit	-0.158	-0.242	0.072	-2.298	0.736	12.662
	Vehicles to adults ratio > 1	Auto	-0.011	-0.095	-0.076	0.153	0.011	1.702
		Transit	-0.272	0.422	-0.389	-1.813	0.941	7.935
Kids	Presence of kids at home	Auto	-0.287	-0.141	-0.230	-0.479	-0.322	-0.324
		Transit	-0.156	0.154	-0.097	-0.842	0.109	0.267
Hybrid ownership	Do you own a hybrid vehicle?	Auto	-0.038	0.281	-0.132	0.065	-0.144	-0.013
		Transit	0.386	0.490	0.676	0.419	0.102	-18.608
Gender	Male is reference	Auto	0.174	0.125	0.067	0.079	-0.025	-0.933

		Transit	0.127	-0.012	0.001	1.060	0.316	-1.745
Category	**Parameter**	**Alternative**	**Pooled Model**	**Super Enthusiastic**	**Enthusiastic**	**Cautiously Enthusiastic**	**Mixed**	**Scaredy Cats**
Congestion	Presence of heavy congestion	Auto	0.045	0.295	-0.293	0.332	0.068	1.126
		Transit	-0.135	-0.403	-0.313	2.570	-1.551	21.137
	Presence of moderate congestion	Auto	-0.060	-0.054	-0.066	-0.283	0.182	0.663
		Transit	0.113	-0.431	-0.364	-0.455	1.116	2.885
Factors from SPSS	I am for using collective modes (transit, rideshare or carpool)	Auto	-0.281	-0.209	-0.247	-0.222	-0.348	-0.344
		Transit	-0.250	0.181	0.348	0.341	-0.412	-16.280
	I like to be in control (driving) while in a car	Auto	0.106	-0.230	-0.111	0.102	-0.089	0.027
		Transit	0.105	-0.019	-0.102	0.717	-0.247	0.212
	My commute generally to work is stressful	Auto	0.006	-0.031	-0.036	0.005	0.111	0.466
		Transit	0.055	-0.144	-0.168	0.086	0.112	-0.598
	I am interested in new technology	Auto	-0.083	-0.186	-0.025	-0.062	-0.008	-0.718
		Transit	-0.127	-0.163	-0.053	-0.962	0.123	-9.213
	I am concerned about the impacts of travel on the environment	Auto	-0.065	-0.091	0.022	0.003	-0.090	-0.045
		Transit	0.116	0.612	-0.024	-0.562	0.291	-7.033
	I am afraid of technology	Auto	0.196	0.100	0.141	0.102	0.138	0.220
		Transit	0.127	0.162	0.097	0.106	0.102	4.073
Air frequency (four categories)	One roundtrip per week or more (reference)							
	7-36 roundtrips per year	Auto	-0.028	-0.100	0.033	0.055	0.055	-0.605
		Transit	-0.041	-0.434	-0.203	0.450	-0.390	-13.229
	1-6 roundtrips per year	Auto	0.034	0.007	0.109	-0.042	0.116	-0.219
		Transit	-0.019	-0.173	-0.129	0.526	-0.267	-12.342
	Less than 1 roundtrip per year	Auto	0.105	0.091	0.133	0.066	0.138	-0.046
		Transit	0.092	0.281	-0.021	0.423	-0.199	-11.772
ASCs	Alternative specific constants	Auto	0.025	-0.176	-0.016	0.124	0.099	1.432
		Transit	-0.170	0.019	-0.094	-1.753	0.682	8.976
	Converged		-11030.18	-2192.601	-3903.445	-1576.223	-2165.427	-238.6081
	No. of cases		18560	4288	6832	2632	3656	1152
	VOT ($/hour)		26.82	24.19	29.73	23.85	29.17	75.62
	IVTT/OVTT		1.045	1.150	1.102	0.766	1.107	0.904

The values of time for each cluster were calculated, using the formula

$$VOT = \frac{\beta_{IVTT}}{\beta_{Cost}} * 60\ \$/hour \tag{5}$$

Intuitively, the VOT for the super enthusiastic cluster should be the highest, followed by the enthusiastic cluster and lastly, the scaredy cats. This is based on the assumption that those who are excited to try eVTOL would be more willing to pay extra to reduce their travel time. However, as seen in the table above, the VOT calculations are fluctuating across the clusters, with no visible trend. Therefore, our VOT calculations aren't the most reliable interpretation of demand model coefficients. It could also point to the limitations posed by survey responses, in that respondents leaning towards eVTOL enthusiasm need not necessarily afford it, or actually use the service, and are being swayed by the excitement of a new, “cool" transportation mode. Keeping aside the VOT calculations, a quick look at the betas and their t-stats shows high degrees of insignificance and instability. This led the research team to further refine the existing model by highlighting other tradeoff reasons / including more explanatory variables.

Each of the five cities surveyed are different – different people, economies, prices and incomes. It is important to scale the cost and income variables to account for the differences in standard of living in the different cities, thereby normalizing the financial component of the demand model to a standard scale. The consumer price index (CPI), is a measure that is commonly as a proxy to quantify the cost of living in each city. The CPI is a weighted average of the change in prices over time for everyday consumer goods, thus establishing a prevalent trend in consumption patterns for individuals in that geographic region (Chen, 2019). CPI is a measure that is calculated by the Bureau of Labor Statistics (BLS) on a monthly basis. Among the five CSAs surveyed, San Francisco and Los Angeles have a much higher CPI than Atlanta and Dallas. Therefore, the income ranges reported in California cannot be directly compared to those in Georgia. The CPI value for each CSA was taken as the mean of the previous 12 months reported by BLS. The cost and income variables were adjusted to incorporate the CPI component, and estimations were conducted by including the newly created variables. The inclusion of CPI adjusted income as an explanatory variable gave more significance to the model, along with a better model fit. Their importance in demand model estimation prompted the research team to include the CPI adjusted variables in the models that followed.

From the above discussion, it is clear that discrete choice modeling is a highly iterative process, involving a lot of back and forth between output and estimation. Dropping rideshare as an alternative in the logit model estimation is logical as auto and transit are primarily the two modes used to and from work. The results thus obtained from the following estimation would be more representative of the average commuter. The final results have been estimated on a dataset with the rideshare observations filtered out.

To recap the models so far, all the explanatory variables were thrown into different combinations to estimate an initial set of 50 models. The better performing of those were then refined, categories were changed, coefficients were constrained and a more consolidated set of 10 models were estimated. Observing that the betas for the rideshare alternative were repeatedly turning up inconsistent, the same set of models was estimated by dropping rideshare as an alternative, leading to slight improvement in model fit. Recognizing the fact that each person's decision rule would be different, model segmentation was conducted based on the clusters identified in the cluster analysis, albeit with inconclusive results.

As mentioned before, discrete choice modeling works on the underlying theory of highest marginal utility, which is a function of travel time, travel cost and other explanatory variables associated with determining mode choice. The biggest determinants of which alternative is chosen for commute being time and cost, it is natural that high cost or high travel time would dissuade respondents from choosing that particular alternative. However, around 14% of the respondents never chose eVTOL, while another 14% always chose eVTOL. Therefore, about 30% of the data is straightlined in either direction, skewing the results away from the true nature of the time-cost tradeoff. Since they always chose the same alternative, the coefficients obtained on the explanatory variables don't apply to these respondents – the models are unable to account for their bias towards or against eVTOL. Keeping this in mind, the dataset was further filtered, to estimate demand for eVTOL on only the mixed responses, i.e., without the straightlining. This was the final straw in the logit modeling, giving the research team a clear picture of which variables and on what datasets worked best for estimating demand. The final set of refined MNLs are presented in the table below.

Table 10 - Final models (without factors)

		Mode	**All data**		**No Rideshare**		**No always and never eVTOL**		**No rideshare AND always and never eVTOL**	
			Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
			Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Category	**Parameter**									
ASCs	Alternative specific constant	Auto	0.070	0.274	0.074	0.278	0.383	0.432	0.385	0.434
		Ride share	-0.254	0.429			1.110	1.355		
		Transit	0.207	0.416	0.217	0.426	0.603	0.832	0.612	0.842
Generic	Travel cost		-0.092	-0.092	-0.093	-0.093	-0.136	-0.135	-0.137	-0.137
	In-vehicle travel time		-0.039	-0.039	-0.039	-0.039	-0.061	-0.061	-0.062	-0.062
	Out of vehicle travel time		-0.037	-0.037	-0.038	-0.038	-0.055	-0.055	-0.056	-0.056
	Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and Transit)		0.376	0.376	0.379	0.379	0.567	0.567	0.573	0.573
	If there's a transfer in the transit ride (applicable only for Transit)		0.231	0.232	0.233	0.233	0.268	0.268	0.269	0.269
Air travel frequency (four categories, only significant one included)	One roundtrip per week or more (reference)		-	-	-	-	-	-	-	-
	1-6 roundtrips per year	Auto	0.180	0.171	0.181	0.172	0.087	0.084	0.088	0.08
		Ride share	0.187	0.173			-0.159	-0.168		
		Transit	0.128	0.129	0.128	0.129	0.061	0.061	0.062	0.061
Congestion (coefficient only for significant alternative included)	Presence of moderate congestion along commute route to or from work	Auto	-0.159	-0.161	-0.160	-0.161	-0.051	-0.053	-0.052	-0.053
Household income (three categories, only significant one included)	Household Income (75 – 149K per year) (reference)		-	-	-	-	-	-	-	-
	Household Income (150 – 199K per year)	Auto	0.012		0.012		0.014		0.014	
		Ride share	-0.234				-0.204			
		Transit	-0.074		-0.074		-0.067		-0.067	
Consumer price index (CPI)	CPI for each CSA normalized with the midpoint value	Auto		-0.252		-0.253		-0.031		-0.032
		Ride share		-1.563				-0.846		
		Transit		-0.513		-0.513		-0.521		-0.523

adjusted income	of category ranges									
Log likelihood	Converged		-12173.3	-12170.7	-11838.6	-11836.1	-7992.27	-7994.02	-7775.22	-7775.57
No. of Cases			19713	19713	19064	19064	14098	14098	13744	13744

Table 11 - Final models (with factors)

		Mode	**All data**		**No Rideshare**		**No always and never eVTOL**		**No rideshare AND always and never eVTOL**	
			Model 9	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**
			Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Co-efficient
Category	**Parameter**									
ASCs	Alternative specific constant	Auto	0.803	0.891	0.808	0.897	0.658	0.679	0.662	0.682
		Ride share	0.715	1.103			1.230	1.446		
		Transit	0.885	1.136	0.897	1.149	0.886	1.119	0.896	1.130
Generic	Travel cost		-0.104	-0.104	-0.105	-0.104	-0.139	-0.139	-0.140	-0.140
	In-vehicle travel time		-0.043	-0.043	-0.043	-0.043	-0.062	-0.062	-0.062	-0.062
	Out of vehicle travel time		-0.041	-0.041	-0.042	-0.042	-0.056	-0.055	-0.056	-0.056
	Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and transit)		0.413	0.413	0.417	0.417	0.574	0.574	0.579	0.579
	If there's a transfer in the transit ride (applicable only for transit)		0.260	0.261	0.261	0.262	0.269	0.270	0.270	0.271
Air travel frequency (four categories, only significant one included)	One roundtrip per week or more (reference)		-	-	-	-	-	-	-	-
	1-6 roundtrips per year	Auto	0.137	0.130	0.137	0.130	0.083	0.081	0.084	0.081
		Ride share	0.247	0.237			-0.140	-0.150		
		Transit	0.055	0.056	0.056	0.056	0.038	0.037	0.038	0.037
Congestion (coefficient only for significant alternative included)	Presence of moderate congestion along commute route to or from work	Auto	-0.090	-0.092	-0.090	-0.092	-0.044	-0.045	-0.044	-0.046

		Mode	All data		No Rideshare		No always and never eVTOL		No rideshare AND always and never eVTOL	
Category	**Parameter**		**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**
Household income (three categories, only significant one included)	Household income (75 – 149K per year) (reference)		-	-	-	-	-	-	-	-
	Household income (150 – 199K per year)	Auto	0.026		0.026		0.017		0.017	
		Ride share	-0.130				-0.164			
		Transit	-0.075		-0.075		-0.056		-0.056	
Consumer price index (CPI) adjusted income	CPI for each CSA (mean of 12 recorded months) normalized with the midpoint value of category ranges	Auto		-0.057		-0.058		0.016		0.016
		Ride share		-0.880				-0.666		
		Transit		-0.576		-0.577		-0.495		-0.497
Factors (coefficient only for significant alternatives included)	I am afraid of technology	Auto	0.091	0.092	0.091	0.093	0.081	0.082	0.081	0.082
	I am concerned about the impacts of travel on the environment	Auto	-0.008	-0.009	-0.008	-0.009	0.016	0.016	0.017	0.016
		Ride share	0.297	0.293			0.212	0.207		
		Transit	0.262	0.261	0.263	0.262	0.048	0.047	0.048	0.047
	I am for using collective modes (transit, rideshare or carpool)	Ride share	0.343	0.329			-0.015	-0.011		
eVTOL perception	I am concerned about the possibility of commuting by eVTOL	Auto	0.182	0.181	0.182	0.181	0.091	0.091	0.092	0.091
		Ride share	0.039	0.053			0.401	0.408		
		Transit	0.103	0.108	0.103	0.109	0.070	0.080	0.070	0.081
	I am enthusiastic about the possibility of commuting by eVTOL	Auto	-0.527	-0.525	-0.528	-0.526	-0.174	-0.174	-0.175	-0.174
		Ride share	-0.948	-0.938			-0.129	-0.146		
		Transit	-0.605	-0.603	-0.606	-0.604	-0.201	-0.196	-0.201	-0.197
Log Likelihood	Converged		-11241.3	-11243.1	-10927.5	-10929.3	-7906.78	-7907.97	-7700.33	-7700.7
No. of Cases			19713	19713	19064	19064	14098	14098	13744	13744

5.5 Latent class and mixed logit

The above presented MNLs speak of a clear picture on the factors that are influencing mode choice for the respondents from the survey conducted. Although the impact of the explanatory variables may have largely accounted for all the tradeoff decisions made, there exist hidden decision rules that only a subset of the entire sample follows. A simple MNL cannot explicitly explain this phenomenon, because it only captures the average effect of the parameters chosen. A latent class model is designed to address this limitation of the MNL model – it can be used to classify decision rules into multiple “class membership" models and assigns a probability of belonging to the above said class. A simple latent class model retrieves class membership likelihoods implicitly from the dataset, and it can be made richer by introducing parameters of our choice. Latent class models take much longer than MNLs to converge. It is good practice to start off first by just estimating two classes, progress to three, four and so on. It’s like an iterative experiment, to observe how well the models behave until their breaking point. The models can be stretched until they fail to converge, and a close look at the betas for each class can give us a better understanding of which configuration works best for the study. The Larch package in Python was used to estimate the latent class models.

Typical decision rules that latent class models identify include always choosing the cheapest alternative or the fastest alternative (Hess, Stathopoulos, & Daly, 2011). Our dataset has 1.9% choosing the cheapest and 4.4% choosing the fastest, thus making it unlikely that the latent class model can define membership based on the same. As pointed out above, an initial analysis of the data highlighted a significant portion of the dataset always (or never) choosing eVTOL as their commute mode. The first latent class models run which included just the five generic variables as parameters with a simple constant defining class membership, reiterated the above finding. In the experiment with three classes, one class exhibited extreme positive utility towards eVTOL, while the other class showed extreme negative utility towards eVTOL, appropriately identifying the two groups from our preliminary assessment. Since the model already confirmed something already known, and the fact that four latent classes were unsuitable in pointing at anything new, the filtered dataset after removing the straightlined observations (both who always selected eVTOL and never selected eVTOL) was used to estimate a model with two classes.

After removing both ends of the choice spectrum, the more heterogeneous dataset gave more promising results, as shown below.

Table 12 - Latent class model (with 2 classes)

		Class 1	Class 2
Parameters	**Alternative**	**Coefficient**	**Coefficient**
Alternative specific constants	Auto	0.781	0.128
	Rideshare	-0.824	-0.550
	Transit	1.614	-0.131
Travel cost		-0.089	-0.136
In-vehicle travel time		-0.112	-0.022
Out of vehicle travel time		-0.083	-0.026
Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and Transit)		0.187	0.456
If there's a transfer in the transit ride (applicable only for Transit)		-0.263	0.371
Class membership constant		0	0.587
Value of time (VOT) in $/hour		75.5	9.7
Number of Cases		19713	
Log Likelihood at Convergence		-12277	
Log Likelihood at Null Parameters		-13664	

The class membership constant is calculated keeping one of the classes as the reference. In this case, class 1 is kept as the reference (equal to 0). The class membership constant for class 2 is 0.587, and it can be interpreted the same way as probability between alternatives is calculated in an MNL:

$$P_{Class2} = \frac{\exp(0.587)}{\exp(0.587) + \exp(0)} = 0.6416$$

64.16% of the dataset has a probability of belonging to class 2, automatically placing the other 35.84% in class 1. The VOT for class one is significantly higher than the VOT for class 2, implying that class 1 is the group that prioritized low travel time over high travel cost. The two classes missing from this analysis, i.e., those who always selected eVTOL and never selected eVTOL, can be plugged back into class membership to create a more comprehensive model with four latent classes. The next step towards refining the latent class model would be to include more explanatory variables, both in the individual MNL models and in the class membership model. This can provide a richer definition of what each class represents.

Latent class models take time to converge because of their inherent complexity in estimating a discrete choice model to determine class allocation. Latent class models also pose the additional problem of often stumbling upon local optima, making them sensitive to the starting values and throwing up convergence issues. Estimating latent class models in Larch gave quick results; however, its high sensitivity to initial values were worrying. Latent class models, although partly overcome the average effect, still don't possess the flexibility to fully explain the variation in betas. In the most ideal scenario, a latent class model with the right parameters is usually sufficient to explain mode choice. With over 19000 cases and not very conclusive latent class results, the research team's next logical step was to estimate a mixed logit model.

A mixed logit model, instead of calculating the mean of the coefficients for each respondent, assigns a distribution to the specified parameter. The distribution could either be normal, log normal, or random. By assigning a distribution to the betas, the model is allowing an additional degree of freedom for the parameters to vary over, improving the explanatory power of the logit model. Latent class models are usually estimated along with a mixed logit model (Hess, Stathopoulos, & Daly, 2011) – if the model fit improves by a lot, then the mixed logit specification is further explored. If there is only marginal improvement in log likelihood, then the results from the latent class are retained, and the process is terminated. Since Larch doesn't have mixed logit capabilities, the estimation was moved to Stata 15. The results shown below have been obtained by assigning a normal distribution on the cost parameter.

Table 13 - Mixed logit model

Category	**Parameter**	**Alternative**	**Coefficient**	**T-stat**
Generic	In-vehicle travel time		-0.0434	-35.86
	Out of vehicle travel time		-0.04157	-13.1
	Guaranteed Uber/Lyft ride incase eVTOL can't takeoff due to bad weather OR transit doesn't arrive (only for eVTOL and Transit)		0.420537	13.08
	If there's a transfer in the transit ride (applicable only for Transit)		0.225743	2.3
	Travel cost		-0.11618	-24.22
	Normal sd(cost)		0.077369	0.061306
Alternative specific parameters	**Parameter**	eVTOL taken as reference	Coefficient	T-stat
ASCs	Alternative specific constants	Auto	0.399807	4.54
		Transit	0.299339	1.52
		Rideshare	-0.62138	-1.31
Frequency of air travel (four categories)	One roundtrip per week or more (reference)			
	1-6 roundtrips per year	Auto	0.083469	6.29
		Transit	0.022519	0.61
		Rideshare	0.073792	0.66
Congestion	Presence of congestion on the commute to or from work	Auto	-0.12087	-2.65
		Transit	0.027989	0.23
		Rideshare	0.550483	1.37
Vehicles to adults ratio	Number of vehicles to adults in the household	Auto	-0.22331	-4.63
		Transit	-0.11846	-1.08

		Rideshare	-0.22631	-0.92
Stops	Stops made on the commute to or from work	Auto	-0.10764	-2.78
		Transit	0.349975	2.97
		Rideshare	0.15128	0.63
Category	**Parameter**	**Alternative**	**Coefficient**	**T-stat**
Hybrid ownership	Hybrid vehicles owned	Auto	0.036932	0.74
		Transit	-0.62619	-4.12
		Rideshare	0.677541	2.56
Household income (categories)	75-149K per year (reference)			
	150-199K per year	Auto	0.049799	2.2
		Transit	-0.1654	-2.44
		Rideshare	-0.27025	-1.76
	200K+ year	Auto	-0.01428	-0.98
		Transit	-0.01969	-0.49
		Rideshare	-0.19659	-1.97
Log simulated likelihood			**-11034.26**	

The extra coefficient obtained from the mixed logit estimation is the standard deviation for the normal distribution applied on cost. The mean and standard deviation together helps calculate the percentage of the population that place a positive value and the percent that places a negative value on the variable (Train, 2003). The estimated mean on cost is -0.1162, and standard deviation is 0.0774; using the normal distribution function, it can be said that about 93% of the population places cost as a negative influence on mode choice, and that cost is a positive influence for the remaining 7%.

While attempting to include the other alternate specific variables in the model and assigning distributions to each of them, Stata ran into convergence issues. A limitation of Stata 15 mixed logit modeling is that alternate specific variables can’t be implicitly assigned a distribution in the command line. The workaround to that was to create three new columns per parameter, unique to each alternative (except eVTOL; kept as reference). However, this adjustment led to the creation of many zeroes in the dataset, further causing correlation problems and thus not allowing the models to converge. Changing the starting values, number of draws, integration sequence or maximization technique didn't work either. The modeling aspect of this study was thus terminated, with a refined set of MNL models and a partially complete latent class model.

CHAPTER 6. DISCUSSION

6.1 Survey results

As outlined in the sections above, the eVTOL index was a method used to funnel down the broad demographic dataset, into a workable subset of potential eVTOL users, who may exhibit higher likelihoods of using the service. The index was developed to assign a theoretical weight to each demographic characteristic that defines travel behavior, and then aggregate these weights into factored scores which would translate into a rank for all the CSAs included in the case study. Although the index remained incomplete at the moment this document was written, the data collection process initiated a conversation around the kind of questions that would need to be asked in the state choice survey. It also provided the research team with a logical rationale behind defining categories for the different questions. The index are an immediate, tangible deliverable that could feature in network modeling for the companies interested in UAM. The aggregated trip distances between O-D pairs, weighted with the number of trips forms an important piece of information that can translate into creating demand corridors in the CSAs. The CSA with the highest number of such corridors could then be chosen as the area most feasible to launch eVTOL as a service.

The survey being circulated across five CSAs helped arrive at a more representative sample of various demographics across the U.S. The objective of choosing five vastly different types of metro areas was to include an inherent normalization process for differences in commute patterns across cities. Similar to adjusting income variables with CPI, by estimating models on data which encompasses five CSAs, the research team aimed to capture demand over a spectrum of travel times, mode splits and city sprawls. For example, San Francisco and Boston have significantly higher transit ridership than Atlanta and Dallas, thus automatically skewing the mode split in favor of transit even before the introduction of eVTOL. The demand models estimate potential changes in market share, on an average of the alternative choices over these cities.

As mentioned above, close to 15% of the respondents always chose eVTOL in the stated preference section of the survey. This implies an extremely high inclination towards trying the new service, no matter what the associated travel time versus cost tradeoffs are. This subset of the sample must be the most attractive in terms of marketability for the service. There was also a subset of around 14% of the sample who never chose eVTOL. It's interesting to observe the demographic characteristics of both subgroups and compare if they align well with our initial assumptions regarding the market segment most likely to use eVTOL. A quick scan for the sample set showed the following results:

Table 14 - Characteristics of "always eVTOL" versus "never eVTOL" respondents

	Mean age (in years)	Mean commute distance (in miles)	Mean income (in 100K)	Mean number of vehicles	Mean air travel frequency	% of respondents who were male
Always selected eVTOL	43	15	171	2	1-6 roundtrips a year	59%
Never selected eVTOL	50	19	167	2	Less than 1 roundtrip a year	50%

The segment of people who would never switch from their current mode are older, about the same income category, report lower air travel frequency and have more women than those who always chose eVTOL. It is worth mentioning that the survey results such as these cannot be taken completely at face value. Since eVTOL is an unheard-of concept, it is possible that those who always chose to take the flying taxi service today may be reluctant to actually use it, once operational. It’s similar to how five years back, an autonomous vehicle survey would’ve recorded more positive observations, while the same survey today would be received with skepticism – simply because five years back AVs were just a utopian idea, stuff seen before only in sci-fi movies. Today, we stand in the middle of at least eight major auto manufacturers conducting pilot tests using AVs; we observe repeated failure and even in extreme cases, casualties. eVTOL today appears “cool" and “game changing” and more people would respond positively about using it, but once the service is ready, the comfort of traveling in a confined space with three strangers at an altitude just above the tallest skyscrapers with a potential of rainfall may not sound as appealing. Therefore, it’s wise to analyze these observations with caution.

Observing the “never eVTOL” group also highlights the deficiencies in the service that could be drawing them away from eVTOL. Since they would be the least likely to switch modes, there exist some definitive reasons prompting them to behave so, which opens up room for improvement and change. As discussed above, a follow-up question was asked to those who never chose eVTOL, about the changes that can be made to the service that may incentivize them to consider taking eVTOL more often. Of all the reasons, lower cost and higher time savings were cited most often. This implies that the proposed aircraft performance metrics aren’t worth the price being charged. Either the flights need to travel faster, or the time spent outside the cabin (OVTT) must be reduced, or the cost per mile must be lowered. Another frequently recurring reason cited was that the service is too new, and that these respondents would wait for others to try it out first and then consider it based on the reviews. Expectedly, the lack of safety metrics and historic crash data is dissuading commuters for choosing it as a feasible travel option. We may observe more conclusive results in subsequent surveys, after a couple of test runs are conducted and the service is sufficiently publicized.

6.2 Demand model

The final set of MNL models, as seen in **Error! Reference source not found.** and **Error! Reference source not found.** record the influence of those explanatory variables which had significant coefficients. Of those, the generic variables were all significant and yielded expected directionality in terms of their effect on utility. The other important parameters like congestion and air frequency didn’t deviate heavily from expectations. Respondents who were frequent flyers exhibited higher inclination towards experimenting with eVTOL. This could imply that frequent flyer data from multiple airlines can be purchased and targeted marketing strategies aimed specifically at this segment can be created. Presence of congestion inevitably dissuaded respondents away from auto and rideshare modes, directing mode splits in favor of eVTOL and transit. Cities ranking high on national congestion indexes could be looked at to implement the flying taxi service.

The differences between the coefficients for the four datasets used indicate more streamlined and consistent results. Removing rideshare as an alternative only displays market share between auto and transit, which are the more conventional commute modes to and from work. The models run without rideshare present a more realistic picture of the travel patterns that exist today and thus, are also more reliable in predicting eVTOL demand. The next set of models are those not including observations who always and never selected eVTOL. These models capture the tradeoff decisions that are made by the mid-segment, i.e., the swing respondents. These coefficients can provide more accurate prediction, conditional on a heterogeneous dataset that can choose either alternative.

The value of time calculation gives an indication of the “willingness to pay" quotient of the sample set. VOT becomes interesting when computed over subsets within the same data. We may have some assumptions regarding each group’s willingness to pay, and the VOT helps quantify this variable. The clusters used to perform segmentation in the MNLs is an example of how VOT can confirm our assumption that those who are most enthusiastic about eVTOL would have a higher VOT. VOT calculations tend to be unstable and aren’t an accurate representation of mode choice. This is especially true in the current study because most of the respondents and potential eVTOL users belong to a higher income category. It is likely that they all clusters identified, from super enthusiastic to scaredy cats report identical VOTs. The reasons for a group of individuals to exhibit high concern and low enthusiasm levels (i.e., scaredy cats) may not be associated with cost at all – as seen, safety and uncertainty have also been pointed out as reasons for not choosing eVTOL. VOT calculations have more serious implications when calculating mode choice between auto and transit alone, as transit users fall under a wide income range. Air travel on the other hand identifies itself with a more homogenous, high income category. This is likely why income as an explanatory variable failed to arrive at significant coefficients, since most of the respondents belonged to higher income categories and any movement above or below in this already exclusive social bracket wouldn’t significantly influence mode choice.

The factors derived from the factor analysis were helpful in trying to measure personality differences within the dataset and how a person’s attitude could influence travel behavior. Although this angle may be interesting to approach, the results obtained from these models must be interpreted carefully. Firstly, personalities aren’t constant – people change all the time, and to pin a personality on a particular individual is in itself a risky proposition. Furthermore, quantifying these subjective characteristics and estimating demand models off of them creates room for unreliability. Having said that, the personality traits open up the possibilities for expanding the unknown, unobservable portion of the theoretical function – the error term. Since the deterministic component of utility can't account for all the variables that affect mode choice, the factors obtained can help resolve the uncertainty over the error term. Keeping in mind the nature of the factors, their coefficients stayed mostly in expected directions.

It is likely that an individual's personality shapes their travel choices, and the factors analysis is the closest we can assign a mathematical argument to them. The Likert scale may be insufficient in describing personalities – a more comprehensive look at people's behavior and its effect on transportation would require a detailed psychometric experiment, where subjects are made to respond to external stimuli, multiple scenarios and simulations, followed-by a discrete choice question. All of this is beyond the scope of this study; this report cannot conclusively argue for demand variations subject to the qualitative behavioral factors.

The clusters separate respondents into categories defined by their excitement or skepticism regarding eVTOL. Although the VOT calculations fluctuate across the clusters, the sample distribution makes a compelling argument. Going by what the clusters say, about 58 % are sure to at least look forward towards trying an eVTOL taxi. 8% of the survey respondents are most likely to reject the service no matter what. The middle 34 %, i.e., cautiously enthusiastic and mixed clusters, are the moldable segment. It can be said that they are eager to see what's in store for the future but have their reservations about the same. Since they can be swung either way, efforts can be made in identifying markets which respond similarly and service providers can implement strategies of appealing to this segment by improving those aspects of the service which are holding them back.

DCM is an experimental study, involving the addition and removal of parameters until satisfactory results are obtained. It is impossible to estimate the perfect model, by including all the explanatory variables that would've gone into a person's decision. Primarily, this is because every individual's priorities are different and the factors each person considered may not have been part of the survey. Finally, discrete choice modeling is applicable to rational decision makers. It is highly possible that the decision to drive versus taking the train on a particular day could be driven by irrational, illogical and unexpected reasons – because that's who we are as human beings! Therefore, the predictive capabilities of even the best models may lead to errors. This sets up a good precedent for the potential market share changes that could occur with the introduction of eVTOL as a viable transportation service.

6.3 Policy implications

The policy implications of this study are manifold. Discussions currently revolve around the flight capabilities, manufacturing challenges, pricing strategy and local government's involvement.

6.3.1 AVs and eVTOL

Autonomous vehicles are right around the corner, ready to own and operate in the foreseeable future. It won't be long before AVs will be available on the market and ownership starts increasing. With more firms entering into the contest of being the pioneers in deploying the first AVs at every instance, rideshare companies like Uber and Lyft have taken notice. The shared economy business model that such companies follow works on the principle of privately-owned vehicles being used in the firm's service, driven by the car owners themselves. The introduction of AVs into the transportation system can allow for purchase and operation of the driverless by the firm and thus reduce the labor involved. This could drastically cut costs for the company and make their point-to-point transportation service more efficient. Uber and Lyft could each be running their own fleet of AVs that can pool, match and drop riders off quicker than it does today. It is interesting to speculate the impacts of an AV rideshare system and even privately owned AVs on eVTOL taxis.

If the latter scenario where the same firm owns the AVs and a flying taxi pans out, eVTOL can be combined with the AV rideshare to create a seamless, synergetic travel experience. The last mile concerns associated with eVTOL can be addressed by including an AV ride from the destination vertiport to the final destination. Ground and air transportation can be packaged into one, through detachable pods scattered across the city (Lambert, 2018). Those who would not be willing to pay for AV ownership would prefer to share an AV or eVTOL ride (Richardson & Davies, 2018). As a demographic, the younger generation isn't as concerned about AV safety, which could pave the way for implementation of eVTOL – they are more inclined towards the positive reception of new technology (Richardson & Davies, 2018). On the other hand, private ownership of autonomous vehicles can acclimatize the owners to a level of comfort within a private, confined space that they may be unwilling to share space with strangers in eVTOL (Zia & Mackenzie, 2015). People can work on their commute to work in an AV – the value of time wouldn't matter anymore. AVs bring with them the promise of congestion reduction and thus, shorter travel times; this further reduces the value of the shorter commute eVTOL offers (Schrank & Eisele, 2012). AVs also improve the safety of road travel, and allow people without driving licenses, the elderly, disabled and children to commute effortlessly in a comfortable space – this could completely discount the benefits that eVTOL offers (Zia & Mackenzie, 2015).

6.3.2 Transit and eVTOL

Transit ridership in the US is on the decline (Graehler & Mucci, 2019). Various factors like the rapid growth of automobiles, well maintained roads, cheap fuel and cultural incentives in favor of automobile ownership contributed to poorly designed and operated transit systems in most American cities. Over the past decade, thanks to a millennial wave promoting transit, increased gas prices and a change in perception, ridership has seen sudden spikes, and agencies are also increasing their efforts to incentivize commuters to switch modes (Pyzyk, 2019). eVTOL's introduction may disrupt the rising interest in public transportation, and this also beg the question to be asked – is eVTOL transit?

eVTOL bears similarities to transit in that both have fixed routes, fixed schedules and the fact that you share space with strangers. Vertiport design could mirror the way transit stations are designed today. Better transit oriented development (TOD) practices include increasing the residential footprint around a transit station, which would prompt the residents in those houses to use the service (Cervero, 2007). A mixed land-use plan would always allow for a constant frequency of ridership during the day (Loutzenheiser, 1997). As we noted above, OVTT is a significant deterrent to public transportation – attractions like restaurants, entertainment centers and retail can distract riders from feeling the extreme disutility of OVTT. eVTOL differs from transit in its cost, number of people that can be ferried in one trip, stops along the way between origin and destination and ownership. A conversation about competition or synergy between the two alternatives is necessary, and metropolitan planning organizations (MPOs) are including eVTOL in their regional transportation plans (RToP), even if it's just a passing comment.

6.3.3 Engineering perspective

eVTOL taxis are slated to revolutionize the way we travel. It could completely change the dynamics of ground transportation. Depending on the draw of market share that eVTOL pulls from automobiles, congestion on our expressways could reduce, as there would simply be lesser cars choking up the road network. However, inefficient vertiport design could create congestion circulation patterns around them, thereby not alleviating congestion, just dispersing it. As a system, there would be lesser vehicle miles travelled (VMT), thanks to lesser automobile trips being made (Richardson & Davies, 2018). If the reality where eVTOL and AVs are deployed in tandem comes true, VMT may actually increase – AV rideshare allow the possibility of extra dead trips (trips made with the vehicle going empty) made looking for passengers.

6.3.4 Planning perspective

From a planning perspective, it is clear that the fact that long distance commutes can be made in such a short time on an eVTOL taxi can lead to urban sprawl. Sprawl is a measure of urban expansion that is characterized with single-family households living on large plot sizes, almost no street activity and a heavy dependence on automobiles, i.e., the suburbs. Not only does the long distance from city center compel a higher time spent inside the vehicle, it also puts a strain on the city's resources. The only drawback that suburbia faces in this setup is a stressful, high travel time driving commute; eVTOL eliminates that, and sprawl could intensify (Zia &

Mackenzie, 2015). On the social side, an eVTOL taxi isn't affordable to most people, at least in the short-term. The equity distribution would lean increasingly on the wealthier class, thereby providing no social benefits to the general public.

6.4 Limitations and future study

6.4.1 Limitations

Each respondent was presented with eight stated choice questions, i.e., eight cases per person. The software used (ELM and Larch) treat each case as a separate individual person, thus unable to capture the variation in decision rules among cases for each respondent. Such data is known as panel data, and it must be estimated in a way that eight cases can be grouped together and assigned to one person; this will provide us with more rounded coefficients that explain the individual's preference, not the case's. A major limitation of using the survey responses from this survey is that since the possibility of a flying taxi is still a couple of years away, there is a preliminary bias associated with how it could be, what the next few years hold in store and its anticipated success rate. This means that since the responses could be based on speculation and other external influences not accounted for in the survey, the results must be interpreted with a slight hint of skepticism.

6.4.2 Future study

In order to satisfactorily account for the previous limitation, it is imperative to observe public perception at periodic intervals and note any changes in trends and choices. A second survey was launched in March, 2019, with similar questions as asked in the first survey. For the stated choice part, a third alternative was added into the mix – the autonomous vehicle. Respondents were asked to choose between their traditional commute mode, an AV, or an eVTOL taxi. The results from the survey are not only interesting from the perspective of how and where AVs stand in the world of disruptive transportation modes, but also on comparing the eVTOL choices with the first survey. The MNL models will be run on both datasets, and the results would be representative of expected changes in eVTOL demand. Panel data can be accounted for in Biogeme, a more powerful logit modeling software. The research team will continue to run the above models in Biogeme, as a quality control measure. The latent and mixed logit models can further be refined and specified in Biogeme, thus arriving at a larger set of comprehensive models.

CHAPTER 7. CONCLUSION

From the survey conducted, a set of explanatory variables that influence an average commuter's mode choice were identified. Introducing a new mode into the mix of existing, competing alternatives changes the dynamic of travel behavior decisions. Travel time and cost were found to be expected deterrents to the utility of a particular alternative; air travel frequency affects the comfort with which one may choose to travel in an eVTOL aircraft; income was found to be negligible in influencing an individual's decision to choose a flying taxi. A significant takeaway from the study is the extreme level of straightlining that occurred both in favor and against eVTOL, thus spelling a future where there exists a highly polarized commuter base, with a sufficiently large swayable middle-ground constituting the demand for flying taxis.

With test runs scheduled to be conducted in less than a year from now, it's not long before we see eVTOLs frequenting the rooftops of tall buildings. Its benefits to the environment, potential reduction in congestion and the social impact of bringing strangers to share space with each other are very attractive. However, the cost of travel is travel will still be higher than most traditional modes. There needs to be more information circulated, sample demonstrations, a lot of positive reviews, and generally just a presence in the skies for a while before flying taxis can profitably "take-off". Until then, it is exciting to watch, observe, study and discuss the direction in which transportation is heading, the primary objective being travel safety and travel comfort.

CHAPTER 8. REFERENCES

A Vision for the Future of Urban Air Mobility. (n.d.). Retrieved July 17, 2019, from LockheedMartin: https://www.lockheedmartin.com/en-us/news/features/2019-features/a-vision-for-the-future-of-urban-air-mobility.html

ACS Estimates Population by CSA. (2017). (Social Explorer) Retrieved March 2018, from https://www.socialexplorer.com/

Aerial Ridesharing at Scale. (2019). Retrieved July 02, 2019, from Uber Elevate: https://www.uber.com/us/en/elevate/uberair/

Atasoy, B., Glerum, A., & Bierlaire, M. (2011). Mode choice with attitudinal latent class: a Swiss case-study. *Second International Choice Modeling Conference.* Leeds.

Bansal, P., Kockelman, K., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. *Transportation Research Part C*, 1-14.

Cervero, R. (2007). Transit-Oriented Developments Ridership Bonus: A Product of Self-Selection and Public Policies . *Environment and Planning , 39*(9), 2068-2085.

Chen, J. (2019, May 17). *Consumer Price Index (CPI)*. (Investopedia) Retrieved July 05, 2019, from https://www.investopedia.com/terms/c/consumerpriceindex.asp

Fagnant, D. J., & Kockelman, K. (2015). Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations. *Transportation Research Part A: Policy and Practice*, 99-106.

Fu, M., Rothfeld, R., & Antoniou, C. (2019). Exploring Preferences for Transportation Modes in an Urban Air Mobility Environment: Munich Case Study. *Transportation Research Record*, 3-12.

Garrow, L., Binder, R., & German, B. (2018). If You Fly It, Will Commuters Come? Predicting Demand for eVTOL Urban Air Trips. *American Institute of Aeronautics and Astronautics*, 7-9.

Garrow, L., Mokhtarian, P., German, B., & Glodek, J. (2019). Market Segmentation of an Electric Vertical Take-Off and Landing (eVTOL) Air Taxi commutin service in 5 large U.S. cities. *Transport Research Part B*.

Graehler, J. M., & Mucci, R. (2019). Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or emerging modes? *Transportation Research Record*.

Hess, S., Stathopoulos, A., & Daly, A. (2011). Allowing for heterogeneous decision rules in discrete choice models: an approach and four case studies. *Institute for Transport Studies*, 3-15.

Howard, D., & Dai, D. (2014). Public Perceptions of Self-Driving Cars: The Case of Berkeley, California. *Transportation Research Board*.

Ingraham, C. (2017, February 22). *The American commute is worse today than it's ever been*. (The Washington Post) Retrieved July 8, 2019, from https://www.washingtonpost.com/news/wonk/wp/2017/02/22/the-american-commute-is-worse-today-than-its-ever-been/?noredirect=on&utm_term=.4831bb30d0c5

Koppelman, F. S., & Bhat, C. (2006). *A Self-Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models.* US DoT.

Lambert, F. (2018, November 27). *Audi is starting to test its 'all-electric flying and self-driving car'*. (Electrek) Retrieved October 16, 2018, from https://electrek.co/2018/11/27/audi-all-electric-flying-self-driving-car-test/

Lineberger, R., Hussain, A., Mehra, S., & Pankratz, D. M. (2018, January 18). *Elevating the Future of Mobility*. Retrieved July 17, 2019, from Deloitte Insights: https://www2.deloitte.com/insights/us/en/focus/future-of-mobility/passenger-drones-flying-cars.html

Loutzenheiser, D. (1997). Pedestrian Access to Transit: Model of Walk Trips and Their Design and Urban Form Determinants around Bay Area Rapid Transit Stations. *Transportation Research Record, 1604*(1), 40-49.

Madrigal, A. (2019, May 10). *The Future According to Uber*. (The Atlantic) Retrieved July 15, 2019, from https://www.theatlantic.com/technology/archive/2019/05/how-uber-justifies-its-ipo-valuation/588979/

Piven, M. (2018, October 9). *Six fun facts about Combined Statistical Areas*. (Compliance Tech) Retrieved July 11, 2019, from https://compliancetech.com/six-fun-facts-about-combined-statistical-areas/

Pyzyk, K. (2019, February 15). *Transit Ridership declining, but riders could be won back*. (Smart Cities Dive) Retrieved July 12, 2019, from https://www.smartcitiesdive.com/news/transit-ridership-decline-riders-could-be-won-back/548517/

Richardson, E., & Davies, P. (2018). The Changing Public's Perception of Self-Driving Cars. *Research Gate*.

Schrank, D., & Eisele, B. (2012). *Urban Mobility Report.* College Station: Texas A&M Transportation Institute.

Thomsen, M. (2018). Airbus Urban (Air) Mobility. *Transformative Vertical Flight Technical Meeting and Workshop* (pp. 2-17). San Francisco: Vertical Flight Technical Society.

Train, K. E. (2003). *Discrete Choice Methods with Simulation.* Cambridge: Press Syndicate of the University of the Cambridge.

Urban Air Mobility (UAM) Market Study. (2018). (pp. 34-41). Booz Allen Hamilton.

Urban Air Mobility. (2019). Retrieved July 15, 2019, from Airbus: https://www.airbus.com/innovation/urban-air-mobility.html

Urban Air Mobility Adds a New Dimension to Travel. (2018, July). (Mitre) Retrieved July 15, 2019, from https://www.mitre.org/publications/project-stories/urban-air-mobility-adds-a-new-dimension-to-travel

Using Chi-Square Statistic in Research. (n.d.). (Statistics Solutions) Retrieved July 07, 2019

Yedavalli, P., & Mooberry, J. (2019). *An Assessment of Public Perception of Urban Air Mobility (UAM).* Airbus.

Zia, W., & Mackenzie, D. (2015). Help or hindrance? The travel, energy and carbon impactsof highly automated vehicles. *Transportation Research Record*, 1-18.