CONGESTION MITIGATION AND STUDENT MODE CHOICE: A STATISTICAL ANALYSIS OF THE I-66 HIGH OCCUPANCY TOLL LANES IMPACT ON TRANSIT AND UNIVERSITY STUDENT MODE CHOICE IN THE WASHINGTON D.C. AREA

by

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Congestion Mitigation and Student Mode Choice: A Statistical Analysis of the I-66 High Occupancy Toll Lanes Impact on Transit and University Student Mode Choice in the Washington D.C. Area

A Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at George Mason University

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DEDICATION

For SR, DR, ER, TR, GF, GS, HS, and SJ.
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Tables</td>
<td>x</td>
</tr>
<tr>
<td>List of Figures</td>
<td>xi</td>
</tr>
<tr>
<td>List of Equations</td>
<td>xii</td>
</tr>
<tr>
<td>Abstract</td>
<td>xiii</td>
</tr>
<tr>
<td>Chapter 1: Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Background</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Research Motivation / Study Setting</td>
<td>3</td>
</tr>
<tr>
<td>1.2.1 I-66 Inside the Beltway HOT Lanes</td>
<td>4</td>
</tr>
<tr>
<td>1.2.2 University Setting: George Mason University, Fairfax, VA</td>
<td>7</td>
</tr>
<tr>
<td>Chapter 2: Literature Review</td>
<td>9</td>
</tr>
<tr>
<td>2.1 Impact of Tolling</td>
<td>9</td>
</tr>
<tr>
<td>2.1.1 Alternate Mode Choice</td>
<td>9</td>
</tr>
<tr>
<td>2.1.2 Value of Time and Willingness to Pay</td>
<td>11</td>
</tr>
<tr>
<td>2.1.3 Income</td>
<td>12</td>
</tr>
<tr>
<td>2.1.4 Transit</td>
<td>13</td>
</tr>
<tr>
<td>2.1.5 I-405 HOT Impacts in Seattle, Washington</td>
<td>16</td>
</tr>
<tr>
<td>2.2 Student Mode Choice</td>
<td>20</td>
</tr>
<tr>
<td>2.3 Perceptions of Autonomous Vehicles</td>
<td>28</td>
</tr>
<tr>
<td>2.4 Summary</td>
<td>30</td>
</tr>
<tr>
<td>Chapter 3: Methodology</td>
<td>35</td>
</tr>
<tr>
<td>3.1 I-66 HOT Lane Transit Impacts</td>
<td>35</td>
</tr>
<tr>
<td>3.1.1 Data sources</td>
<td>35</td>
</tr>
<tr>
<td>3.1.2 Analysis</td>
<td>36</td>
</tr>
<tr>
<td>Variables</td>
<td>37</td>
</tr>
<tr>
<td>Precipitation</td>
<td>38</td>
</tr>
<tr>
<td>Temperature</td>
<td>38</td>
</tr>
</tbody>
</table>
Inauguration Day .................................................................................................................. 60
Cherry blossom days ........................................................................................................ 60
Service runs per day .......................................................................................................... 60
Number of bus stops ......................................................................................................... 61

4.1.3 Washington Metropolitan Area Transit Authority (WMATA) ............................. 61
  Trip duration .................................................................................................................... 62
  On time ............................................................................................................................ 62
  Trip late ........................................................................................................................... 63
  Trip on time ..................................................................................................................... 63
  Passenger per hour ....................................................................................................... 63
  Revenue miles ............................................................................................................... 63
  Gas price ......................................................................................................................... 63
  Unemployment rate ..................................................................................................... 63
  Temperature .................................................................................................................. 64
  Total precipitation ......................................................................................................... 64
  Inauguration day ............................................................................................................ 64
  Cherry blossom days ..................................................................................................... 64

4.2 Student survey analysis: Results of GMU student mode choice survey ............... 65
  4.2.1 Descriptive results ............................................................................................... 66
    Safety 1 ....................................................................................................................... 68
    Accessibility 1 ............................................................................................................ 68
    Stability ....................................................................................................................... 68
    Accessibility 2 ............................................................................................................ 68
    Preference/Attitude 1 ............................................................................................... 69
    Safety 2 ....................................................................................................................... 69
    Reliability 1 ............................................................................................................... 69
    Reliability 2 ............................................................................................................... 69
    Toll 1 ............................................................................................................................ 69
    Preference/Attitude 2 ............................................................................................... 70
    Toll 2 ............................................................................................................................ 70
    Early adopter 1 .......................................................................................................... 70
    Early adopter 2 .......................................................................................................... 70
Time Flexibility 1 ........................................................................................................ 70
Time Flexibility 1 ........................................................................................................ 70
Arrival Time .................................................................................................................... 70
4.2.2 Discrete Choice Analysis Results ........................................................................ 71
Scenario 1 – Drive vs Bus .............................................................................................. 71
Scenario 2 – Conditional AV vs Conventional Car ...................................................... 72
Scenario 3 – Full AV vs Conventional Car .................................................................... 72
Chapter 5: Discussion ..................................................................................................... 74
5.1 Impacts of the I-66 HOT Lanes on Transit .............................................................. 74
5.2 University Student Survey ........................................................................................ 75
  5.2.1 Correlation of Variables ...................................................................................... 75
  5.2.2 Scenario 1 ............................................................................................................ 76
     Expense ...................................................................................................................... 76
     Time .......................................................................................................................... 76
     Safety 2 ...................................................................................................................... 77
     Reliability 1 .............................................................................................................. 77
     Accessibility 1 ......................................................................................................... 77
     Preference/Attitude 1 ............................................................................................... 77
  5.2.3 Scenario 2 ............................................................................................................ 78
     Cost per trip ............................................................................................................. 78
     Time .......................................................................................................................... 78
     Preference/Attitude 2 ............................................................................................... 79
  5.2.4 Scenario 3 ............................................................................................................ 79
     Cost per trip ............................................................................................................. 79
     Time .......................................................................................................................... 80
     Income ...................................................................................................................... 80
     Preference/Attitude 2 ............................................................................................... 81
5.3 Limitations ................................................................................................................. 81
  5.3.1 Ridership Data .................................................................................................... 81
  5.3.2 Survey Data ........................................................................................................ 82
5.4 Future Work ............................................................................................................... 86
Chapter 6: Conclusion ...................................................................................................... 88
Appendix: Survey ............................................................................................................. 92
References......................................................................................................................... 103
LIST OF TABLES

Table 1: Presenting transit agency, data type, and bus routes analyzed in this thesis. ..... 36
Table 2: Displaying the variables used in the regression model for each transit agency. 37
Table 3: Displaying AM toll trends for each day of the week for the estimated segment of road that is part of the WMATA 5A’s route. .................................................. 43
Table 4: Displaying PM toll trends for each day of the week for the estimated segment of road that is part of the WMATA 5A’s route. .................................................. 44
Table 5: Presenting the corresponding survey questions with independent variables used in the statistical model. ................................................................. 48
Table 6: Presenting the independent variable with the corresponding scenario. The actual questions can be seen in the Appendix. .......................................................... 49
Table 7: Presenting Results of LCT regression analysis. ................................. 54
Table 8: Presenting results of PRTC regression analysis. ................................. 58
Table 9: Presenting results of WMATA regression analysis. ............................ 62
Table 10: Results of WMATA regression when only statistically significant variables are modeled........................................................................................................ 65
Table 11: Presenting results for Scenario 1. .................................................. 72
Table 12: Presenting results from Scenario 2. .............................................. 72
Table 13: Displaying results for Scenario 3. ................................................. 73
Table 14: Presenting the odds ratios for each variable used in Scenario 2.......... 78
Table 15: Displaying a summary of the odds ratios for each variable in Scenario 3. ..... 79
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1: Displaying gas price trends across the U.S. from July 2016 to September 2018. Source: U.S. Energy Information Administration (EIA), 2018.</td>
<td>40</td>
</tr>
<tr>
<td>Figure 3: Displaying regular gas price trends across the U.S., Virginia, and Washington D.C. from March 2016 to March 2019. Source: GasBuddy.com, 2018.</td>
<td>41</td>
</tr>
<tr>
<td>Figure 4: Displaying plotted data from Table 3.</td>
<td>43</td>
</tr>
<tr>
<td>Figure 5: Displaying plotted data from Table 4.</td>
<td>44</td>
</tr>
</tbody>
</table>
# LIST OF EQUATIONS

<table>
<thead>
<tr>
<th>Equation</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation 1: Linear regression model.</td>
<td>36</td>
</tr>
<tr>
<td>Equation 2: Utility function of a mode.</td>
<td>51</td>
</tr>
<tr>
<td>Equation 3: Utility function in a logit model.</td>
<td>51</td>
</tr>
<tr>
<td>Equation 4: Probability of a logit model when assuming a logit distribution.</td>
<td>52</td>
</tr>
<tr>
<td>Equation 5: LCT linear equation when all variables are modeled.</td>
<td>53</td>
</tr>
<tr>
<td>Equation 6: LCT linear equation when only significant variables are modeled.</td>
<td>57</td>
</tr>
<tr>
<td>Equation 7: PRTC equation when all variables are modeled.</td>
<td>58</td>
</tr>
<tr>
<td>Equation 8: PRTC linear equation when only significant variables are modeled.</td>
<td>61</td>
</tr>
</tbody>
</table>
ABSTRACT

Congestion Mitigation and Student Mode Choice: A Statistical Analysis of the I-66 High Occupancy Toll Lanes Impact on Transit and University Student Mode Choice in the Washington D.C. Area

Melissa L. Rossi, M.S.
George Mason University, 2019
Thesis Director: Dr. Shanjiang Zhu

Today’s university students are tomorrow’s workforce. Transportation infrastructure that is implemented to relieve congestion will be used by these current students in the future when they are in the peaks of their careers. Additionally, in the past decade, there has been a transformational change in personal travel modes and choices due, in large part, to shared mobility services. Students adapt more quickly to changes due to technological revolutions than older generations. Thus, it is paramount to understand students’ perceptions and opinions of transportation modes and congestion mitigation methods. While students’ travel behaviors could change once entering the workforce or undergoing other lifestyle changes, many of their perceptions of public transit and tolling could stay the same. The most recent congestion mitigation project in Northern Virginia is the I-66 HOT Lanes Inside the Beltway, which opened in December 2017. This project has a regional impact and promotes multimodal use along the corridor. In November 2018,
Amazon announced that its second headquarters (HQ2) would be coming to Northern Virginia. With the economic growth Amazon HQ2 will bring to Northern Virginia, more people will be attracted to the region, putting an additional strain on an already congested transportation network. Additionally, the impending arrival of autonomous vehicles in the transportation fleet could change traveler’s mode choice, travel utility, the value of time, and willingness to pay. The purpose of this paper is to investigate the effectiveness of the I-66 HOT lanes in promoting transit use through analysis of aggregated transit ridership data and George Mason University students’ current mode choice, perceptions of transit, opinions of congestion relief strategies, and perceptions of autonomous vehicles by analyzing individual responses in a stated preference survey. By gaining a better understanding of students’ perceptions of different modes and congestion mitigation methods, more strategic investments can be made for projects that include modes that reduce congestion and that travelers want to use.
CHAPTER 1: INTRODUCTION

1.1 Background

Across the country, traffic congestion in urban areas has become an increasing problem, impacting travel times across modes such as transit and single occupancy vehicles. The Washington D.C. Metropolitan area experiences some of the worst traffic in the country. According to Inrix, the Washington D.C. area ranks sixth as the worst traffic in the United States with 11% of driving time spent in congestion and 63 peak hours spent in congestion in 2017 (Inrix, 2017).

On November 13, 2018, Amazon announced the opening of Amazon HQ2 in Crystal City, VA. The news produced relatively mixed feelings from the public. Ultimately, while several groups were happy with the prospect of continued economic development in the region, some have an underlying concern about whether the existing transportation system can handle a surge in population. Amazon’s presence in Seattle not only grew the economy but also increased real estate prices. Economic growth has many advantages, such as raising the standard of living, higher income, and more jobs. For example, since Amazon moved its headquarters to Seattle, the city was transformed through the influx of young, highly paid, and well-educated workers (Day, 2018). Seattle had tremendous economic growth during the Great Recession because of Amazon’s “rapid expansion” (Day, 2018). Transportation infrastructure improved by creating a
multimodal system through streetcars, bus lanes, bike lanes, and private shuttles for Amazon employees (Siddiqui, 2018). However, these benefits from economic development brought about disadvantages, for some, such as higher housing prices and increased traffic (Roberts, 2017). It is possible that this economic success cannot be replicated across the county (Roberts, 2017) since Northern Virginia already experiences some of the worst traffic congestion in the country (Siddiqui, 2018). With the addition of Amazon, the region could feel the negative impacts of economic development before the positive effects become apparent (Roberts, 2017).

Economic growth attracts more people to a region to capitalize on new employment and educational opportunities. More people in an area means more people using the transportation network and increased congestion. Many Amazon employees use public transit in their commutes (Siddiqui, 2018). While the DC region has a variety of public transit options, a sudden surge in ridership may be too much for the system to handle. This could increase traffic congestion on the roads in the region even more. Methods need to be implemented to mitigate existing congestion and prepare to accommodate future congestion.

The Federal Highway Administration (FHWA) within the US Department of Transportation (USDOT) has developed a six-point plan to reduce congestion in urban areas. This is based upon a “4T Strategy”: Tolling, Transit, Telecommuting/Travel Demand Management, and Technology (USDOT, 2007). Tolling, or congestion pricing, is a key part of managing congestion because the price changes depending on the number of travelers using the facility. Charging a toll will discourage some travelers from picking
that route and encourage the travelers to pick alternate routes or modes. Finally, tolling can be used to promote transit ridership, which relieves congestion.

The most recent tolling facility in the region is the I-66 High Occupancy Toll (HOT) Lanes Inside the I-495 Capital Beltway. One of the goals of this project is to promote transit use and other multimodal options along the I-66 corridor during peak hours. Toll revenue is used to help fund the transit agencies that service the corridor. The goal of this tolling facility is to reduce congestion for commuters today and far into the future.

The transportation infrastructure that is being built today to relieve congestion will be utilized by current students when in the peaks of their careers. Because of this, it is important to understand students’ perceptions and opinions of certain modes and congestion mitigation methods. While students’ travel behaviors could change as they enter the workforce, many of their perceptions of public transit and tolling could stay the same due to any preexisting bias. Additionally, as vehicles with higher levels of autonomy enter the market place, travelers will have different mode options that have never previously been examined. This new paradigm of transportation technology could change commuters’ value of time and willingness to pay for certain modes.

1.2 Research Motivation / Study Setting

The purpose of this research is to investigate the effectiveness of the I-66 HOT lanes in promoting transit use and to understand George Mason University students’ mode choice behavior relating to transit, tolls, and autonomous vehicles. By gaining a
better understanding of students’ perceptions of different modes and congestion mitigation methods, more strategic investments can be made in modes that reduce congestion and that travelers want to use.

1.2.1 I-66 Inside the Beltway HOT Lanes

The I-66 HOT Lanes opened on December 4, 2017. The I-66 improvement project is a congestion mitigation project from the Virginia Department of Transportation (VDOT) with the goals of reducing congestions through HOT lanes during peak hours and peak directions. These dynamically priced tolls run from I-495 to U.S. Route 29 in Rosslyn, Virginia. The tolls are operational during peak hours and for the peak directions only. Carpoolers (HOV2), buses, and motorcycles can ride the I-66 Express Lanes for free during tolling operation. In 2022, the HOV requirement will change from HOV2 to HOV3 in conjunction with the opening of the I-66 Express Lanes Outside the Beltway (VDOT, 2019). Single occupancy vehicles (SOV) are required to pay a toll. It is important to emphasize that before the HOT lanes were implemented on I-66 Inside the Beltway, the only vehicles permitted to travel on that portion of the corridor were HOV2+, buses, motorcycles, and certain hybrid vehicles. Hybrid drivers are no longer permitted to use the lanes for free (Siddiqui & Lazo, 2017). The HOT lanes give SOV travelers the option to use I-66 during peak hours for a toll.

Both HOV2 and SOV need to have E-ZPass Flex to pay the toll or to designate HOV mode (VDOT, 2019). In addition to the toll, transit services that use I-66 Inside the Beltway have added additional routes and offer incentives to take transit. The
implementation of these HOT lanes has become an opportunity to promote public transit among I-66 commuters.

In June 2018, the Northern Virginia Transportation Commission (NVTC) published a performance report for transit servicing I-66 Inside the Beltway. The report found that there was a significant increase in ridership on commuter and express bus routes following the implementation of the I-66 toll in December 2017 (NVTC, 2018). Transit operators reported to NVTC that travel times for commuter bus routes also improved since the toll “due to the improved traffic conditions” (NVTC, 2018). The speed on that segment of the corridor improved by 15% between February 2017 and February 2018 (NVTC, 2018). The report looks at all local and express buses that service the corridor from the following transit agencies: Arlington Transit (ART), Fairfax Connector, Loudoun County Transit (LCT), Potomac and Rappahannock Transportation Commission (PRTC), and Washington Metropolitan Area Transit Authority (WMATA). At the time of the performance report, only 4 months of operation data were available, so there was not enough data to analyze the impact of tolling on transit (NCTV, 2018). However, some trends in ridership can be easily seen.

For instance, the average weekday ridership of express buses from Fairfax Connector, Loudoun County Transit, and PRTC increased (NVTC, 2018). Since these are express buses, they only run during peak periods (NVTC, 2018) and tolls are only collected during peak periods. NVTC noted that the increase in ridership may be a result of a combination of tolling and the “new capacity funded by the I-66 Commuter Choice program” (NVTC, 2018). Out of all the transit agencies that service the corridor, only 3
agencies reported its weekday ridership results after the toll began. Fairfax Connector experienced a +32% in average weekday ridership, PRTC experienced a +58% in average weekday ridership, and Loudoun County Transit experienced a -12% in average weekday ridership from February 2017 to February 2018 (NVTC, 2018).

One of the most controversial items surrounding the I-66 HOT lanes implementation is the toll price. Before the tolls were installed, VDOT modeled different toll scenarios and anticipated that the tolls would typically reach a high of $9 during the AM peak eastbound (5:30 AM – 9:30 AM) and $8 during the PM peak westbound (3:00 PM-7:00 PM) (VDOT, 2015). On the first day of tolling, the toll peaked at $34.50 (Siddiqui & Lazo, 2017). VDOT reported that 39 vehicles (approximately 1% of the rush hour SOV commuters) paid this toll (Lazo, 2017). The average price was $10.70 for the AM peak and $3.80 for the PM peak (Lazo, 2017). On December 5, 2017, the second day of tolling, the toll price during the morning peak was $40 to travel 10 miles (Siddiqui & Lazo, 2017). The toll prices frequently make news headlines and in early 2018, when the toll reached $47.25 for a one-way trip, commuters were “outraged” (Lazo, 2018). While transportation officials were prepared to investigate possibilities to adjust the tolling algorithm to satisfy the complaints, they wanted to “give the system time before considering changes” (Lazo, 2018). It is important to stress that SOVs are not forced to pay the toll; there are several toll-free alternate routes for SOV travelers to take instead of I-66 (Routes 7, 50, 123, 193, and the George Washington Memorial Parkway).

In July 2018, the VDOT published a 6-month performance report of the HOT lanes. This reported cited that the average toll price for a round trip was $13.09 (Office
of the Secretary of Transportation, 2018). In August 2018, VDOT published another performance report of the lanes. The average toll price for a round trip dropped to $10.90, though the average toll price from December 2017 to August 2018 was $12.54 (VDOT, 2018). While the toll occasionally can be $40 or more, this is a rare occurrence.

Approximately 0.02% of all trips on the I-66 HOT lanes are $40 or more (117 trips out of 744,395 trips) (VDOT, 2018). Around 46.2% of travelers used the E-ZPass Flex in toll mode, while 41.3% of drivers were in HOV (free) mode, and the remaining 12.5% did not have an E-ZPass Flex (VDOT, 2018). In August 2017, the average speed on the corridor before tolling was 52.7 mph and travel time was 12 minutes during the eastbound peak and 46.1 mph and 13.8 minutes during the evening peak (VDOT, 2018). In August 2018, the average speed and travel time had improved to 56.2 mph and 11.3 minutes during the eastbound peak and 57.3 mph and 11.1 minutes during the westbound peak (VDOT, 2018). The speed and travel times on the neighboring parallel arterials also improved, apart from the George Washington Memorial Parkway which experienced decreased speeds and decreased travel times due to bridge repair on the arterial (VDOT, 2018).

1.2.2 University Setting: George Mason University, Fairfax, VA

George Mason University (GMU) is a public research university in Fairfax, Virginia. As of the Spring 2019 semester, there were 35,929 students enrolled in the U.S. campuses. The main Fairfax Campus is located approximately 20 miles outside of Washington, D.C., but there are other campuses located in Virginia: Arlington Campus
(Arlington, VA) and SciTech Campus (Manassas, VA). There are various transportation options for GMU students. Free shuttles are available to take students to different parts of the Fairfax Campus, to other campuses, or local Metro Stations. The university also has a partnership with the Fairfax City “City-University-Energysaver” (CUE) bus system, in which GMU students can ride for free. There are carpooling services organized through the university and also available through Zimride (a ridesharing program that connects drivers and passengers).

The university student population has continued to grow as time has gone on. However, the increases in student population have not translated to an increase in student transit use. During the 2017 fiscal year, a total of 589,581 total trips were taken using GMU’s free shuttle service. This is 39,284 fewer trips than the 2016 fiscal year. Even though in 2018 around 37.2% of the Fairfax City CUE ridership was comprised of GMU students, the number of students using this service has decreased steadily since the 2015 fiscal year. Parking permit sales have remained fairly constant. It is important to understand why there is a steady decrease in transit ridership. This study seeks to understand students’ transportation preferences on a broader scope outside of the university setting.
CHAPTER 2: LITERATURE REVIEW

A literature review was conducted in order to better understand the current research of tolling, student mode choice, and autonomous vehicle preferences. For the papers included that regarded tolling, studies were selected based on road facility, location within the United States, the identification of significant and non-significant statistical variables, and findings related to carpooling or transit. There is a transit subsection which includes an international study. Studies about student mode choice were selected to understand what factors influenced student mode choice around the world and to research survey techniques. Finally, there is a section describing papers regarding public perceptions of autonomous vehicles. The current research on the topics is summarized below.

2.1 Impact of Tolling

2.1.1 Alternate Mode Choice

On several corridors across the United States, existing HOV lanes have been converted to HOT lanes. Introducing tolling to a roadway can impact users’ choices to drive solo, carpool, or use transit. In one study (Burris, Alemazkoor, Benz, & Wood, 2014), the researchers analyzed how changing existing HOV lanes to HOT lanes could impact carpooling. The study looked at SR-91 in Southern California, I-15 in San Diego, I-394 in Minnesota, SR 167 near Seattle, I-95 near Miami, the Houston HOT Lanes in
Texas, and I-85 in Atlanta. All of these facilities were previously HOV lanes, with the exception of SR-91 (Burris et al., 2014). The results showed that, overall, carpooling is negatively impacted by the introduction of HOT lanes. However, due to many exogenous factors, such as additional lane capacity and fluctuations in gas price, the researchers concluded that there was not enough information to exclusively say that carpooling decreased because the attractiveness of driving alone outweighed the toll cost (Burris et al., 2014).

Introducing HOT lanes can also change mode choice on a corridor. In (Goel & Burris, 2012), the researchers compared the impacts of an asset of HOT lanes that shared similar “design and operational” characteristics through a pairwise comparison. The study focused on corridor ridership and mode choice data. Through the analysis, it was found the corridors studied responded differently to the implementation of HOT lanes. On I-95 in Miami and SR-91 in San Diego, less than 30% of the total corridor HOV2 vehicles used the express lanes (Goel & Burris, 2012). There was almost no change in transit ridership due to the implementation of HOT lanes (Goel & Burris, 2012). External factors like gas prices and the 2008 economic recession were related to the usage of the HOT lanes (Goel & Burris, 2012). As the gas price went up, carpool trends went up. On SR-167, as gas prices declined, fewer people rode transit or carpools and more people preferred to pay the toll while traveling in an SOV (Goel & Burris, 2012). Finally, on I-25, as the unemployment rate increased, the number of toll-paying travelers decreased (Goel & Burris, 2012).
In a 2003 assessment of implementing HOT lanes in Northern Virginia, it was found that converting HOV lanes to HOT lanes would help alleviate congestion, but also potentially compromise the DC slug line (Safirova, Gillingham, Nelson, & Harrington, 2003). Before HOV lanes were implemented in Chicago, people were concerned that HOV lanes would negatively impact transit (Schofer & Czepiel, 2000). These lanes would constitute as a failure if they were not utilized (Schofer & Czepiel, 2000). There never was a follow-up study to assess the performance of the later constructed I-95, I-495, or I-66 HOV and, later for some, HOT lanes.

When dynamic tolls were first introduced on SR 91 in San Diego, 324 users were interviewed to understand and characterize the travel behavior of commuters (Mastako, Rillet, & Sullivan, 1998). The commuters were interviewed in 1996, one year after the HOT lanes had opened (Mastako et al., 1998). HOV3+ vehicles and motorcycles traveled for free on the corridor (Mastako et al., 1998). After the HOT lanes opened, ridesharing among users increased as more people opted to use higher occupancy vehicles (Mastako et al., 1998). Later studies believed that dynamic tolling is important in managing travel demand and in avoiding HOT lane breakdown (Liu, Zhang, Wu, & Wang, 2011). This study found that speed, traffic volume, and travel time were all significant in assessing the toll lanes effectiveness (Liu et al., 2011).

2.1.2 Value of Time and Willingness to Pay

Tolling can influence travelers’ value of time. In a study by (Burris, Nelson, Kelly, Gupta, & Cho, 2012), surveys, loop detectors, and tolling data were used to
determine which factors contributed to users’ decision making regarding the usage of I-394 in Minnesota and I-15 in San Diego (Burris et al., 2012). The results showed that people were willing to pay a toll, even if the travel time benefits were very small (Burris et al., 2012). Customers using I-394 were willing to pay an average of $73/hr in the morning $116/hr in the afternoon (Burris et al., 2012). The willingness to pay can also vary depending on the facility. For instance, customers using I-15 had a lower willingness to pay than I-394 users (Burris et al., 2012). (Finkleman, Casello, & Fu, 2011) found that users’ willingness to pay was related to income and trip urgency.

A study by (Janson & Levinson, 2014) also looked at how tolls can influence travelers’ behavior on the I-394 HOT lanes in Minnesota. A field experiment was conducted to determine a driver’s sensitivity for toll prices along I-394 and I-35W (Janson & Levinson, 2014). Over the duration of the study (October 2012 to January 2013), the pricing plan was adjusted slightly (Janson & Levinson, 2014). When drivers saw a higher toll price, they were more likely to choose to use the HOT lanes because of the that higher toll prices indicated downstream congestion (Janson & Levinson, 2014). Ultimately, drivers were willing to pay between $60/hr to $124/hr for travel time savings (Janson & Levinson, 2014). Travelers used the HOT lanes, not only for travel time savings but also for travel reliability (Janson & Levinson, 2014).

2.1.3 Income

Income also played a role in frequent express lane use on SR-91 in San Diego (Mastako et al., 1998). Travelers with higher incomes were more likely to use the express
lanes than lower income travelers (Mastako et al., 1998). Therefore, “lower income commuters choose HOV2 to reduce travel costs and that more income commuters choose HOV2 to reduce travel time” (Mastako et al., 1998). Another study found that users with lower incomes were more likely to consider alternative modes than users with higher incomes (Finkleman et al., 2011). However, both low- and high-income users were likely to use the HOT lanes if road conditions were extremely congested (Finkleman et al., 2011).

2.1.4 Transit

Case studies focused on HOT lanes in San Diego, Minneapolis, and Denver looked at how the conversion from HOV to HOT lanes impacts public transportation services and ridership levels (Turnbull, 2008). Bus use before and after the implementation of HOT levels remained fairly constant on all corridors (Turnbull, 2008). Additionally, the bus fares in all three locations are similar to the tolls to ride on the HOT lanes (though these prices are subject to change are certain times due to the dynamic pricing) (Turnbull, 2008). Ultimately, the author concluded that the impact between bus fare and toll price on mode choice is not clear (Turnbull, 2008). In some cases, converting HOV lanes to HOT lanes can negatively impact transit ridership (Chum & Burris, 2008). (Chum & Burris, 2008) developed a choice model based on surveys distributed to park-and-ride bus passengers in Houston, Texas. The research focused on choice riders, who were defined as people who own a car but choose “to take transit”
Bus riders were unlikely to switch modes with the HOT implementation (Chum & Burris, 2008).

HOT lanes can also impact bus performance. (Pessaro, Turnbull, & Zimmerman, 2013) examined the impact of HOT lanes on bus performance in Miami, Minneapolis, and Atlanta through longitudinal comparison among the different bus systems in the respective cities over several years using pre- and post- HOT era data. The researchers found that the conversion to HOT lanes did not negatively impact bus performance or ridership (ridership increased). In every city in the study, buses experienced travel time savings (Pessaro et al., 2013). All of the cities “enhanced their transit service in advance of the tolling” (Pessaro & Songchitruksa, 2014). Bus riders generally perceived the HOT lanes positively, with 53% of new riders in Miami, 23% of new riders in Minneapolis, and 45% of new riders in Atlanta saying that the HOT lanes incentivized them to take transit (Pessaro et al., 2013).

The bus riders also had a positive perception of the tolls, with the exception of those surveyed in Atlanta (Pessaro et al., 2013). Even though conditions improved, people from Atlanta believed that their travel times increased since the toll implementation and also believed that the HOT lanes were not good for the Atlanta region (Pessaro et al., 2013). Most of the people who commented this also believed that tolling was unfair to people with low incomes (Pessaro et al., 2013). Upon reflection, the researchers believed that Atlanta's negative response to the HOT lanes was a result of their disapproval for the HOT lanes before implementation, but this assumption has yet to
be confirmed. From this, the authors concluded that even if congestion pricing provides benefits, it can still be a hard sell to the public.

In Israel, transit ridership and travel behavior were evaluated when the fare was adjusted (Sharaby & Shiftan, 2012). While this study does not include toll facilities, it is still important to include to understand transit ridership behavior under different conditions. In this study, farebox data and onboard surveys were collected on transit riders in Haifa, Israel (Sharaby & Shiftan, 2012). A multinomial logit model was used to model the data. The researchers found that reduction in transit fare was significant in attracting transit users (Sharaby & Shiftan, 2012). Also, they found that there were three factors in "public transport reform: it encourages travelers to shift from private cars or taxi to buses; it created new trips, offering more opportunities for activity participation; it increased travel options by allowing travelers to choose a better route" (Sharaby & Shiftan, 2012). These are all important factors to consider when promoting transit ridership.

Travelers’ attitudes about transit can affect their decisions to use a certain mode. A study in south Los Angeles investigated how attitudes, perceptions, and norms impact people’s choice to use public transportation (Spears, Houston, & Boarnet, 2013). Data was collected through a survey of 279 residents and analyzed in a regression model. From their analysis, the researchers determined that attitudes about public transportation service and concerns for personal safety were important indicators of transit use "independent of the built environment" (Spears et al., 2013). A similar question was asked in a study investigating the relationship between people’s attitudes towards
transportation and their travel behavior in the Netherlands. (Kroesen, Handy, & Chorus, 2017) examined if these were consistent over time. A two-wave mobility survey was used to estimate “cross-lagged panel models and latent transition models”. The researchers found that the use and attitude of certain modes influence each other over time.

BRT lanes have the potential of reducing congestion on a corridor. (Barker & Polzin, 2004)’s study modeled a combination of premium transit services and pricing strategies in Northern Virginia. They determined that including a BRT lane in a HOT facility was cost-effective (Barker & Polzin, 2004). Ultimately, for transit to be effective in reducing congestion, it is necessary for incentives that make transit more attractive than other modes. (Chakrabarti, 2017) examined effective strategies to increase transit competitiveness with cars in Los Angeles County. Through a descriptive analysis of geographical characteristics and a multinomial logistic regression model, factors such as speed, frequency, and reliability of the transit service were all of value to bus riders (Chakrabarti, 2017). In order for transit services to attract discretionary riders, they must provide exceptional service (Chakrabarti, 2017). The results of this study show that good quality transit service during the home-to-work journey specifically is important to attract bus riders (Chakrabarti, 2017). Transit agencies need to invest in the right things to attract and retain riders (Chakrabarti, 2017).

2.1.5 I-405 HOT Impacts in Seattle, Washington

In Seattle, Washington, congestion pricing has the potential of promoting transit use (Pessaro & Songchitraksa, 2014). Variable tolling was introduced on the SR-520
bridge in December 2011 (Pessaro & Songchitruksa, 2014). Approximately 11 months before tolling was implemented on the SR-520 bridge, transit agencies enhanced the frequency of their service. The enhanced service drew a 10% ridership increase before the toll and another 14% ridership increase after the toll (Pessaro & Songchitruksa, 2014). The gas price and the unemployment rate were both significant factors in transit use (Pessaro & Songchitruksa, 2014). Additionally, the researchers conducted a survey of riders before and after tolling (Pessaro & Songchitruksa, 2014). The results showed that 19% of bus riders “were influenced to take transit because of the enhanced transit service” before the toll and 55% of bus riders “were influenced to take transit because of the toll” (Pessaro & Songchitruksa, 2014). Because of this response from bus riders, the researchers concluded that HOT encourage transit use.

The SR-520 toll bridge connects with I-405, a dynamically priced tolling facility. HOT lanes were implemented on I-405 on September 27, 2015 (WSDOT, 2018a). HOV3+ could use the express lanes for free; HOV2+ had to pay a toll during weekday peak periods; and, on weekday evenings, weekends, and major federal holidays, the lanes are open toll-free to all traffic (WSDOT, 2018a). In their 24-month operational report, WSDOT reiterated the goals of the I-405 Express Toll Lanes: to “provide a choice for drivers”, to “provide a faster and more predictable trip”, and to “fund future improvements” (WSDOT, 2018a). These lanes use dynamic tolling, with the price fluctuating from $0.75 to $10 (WSDOT, 2018a). The toll rate does not exceed $10 (WSDOT, 2018a). While in surveys, customers across all ages, genders, and incomes showed consistent positive support for the express toll lanes, “most I-405 drivers” did not
“think express toll lanes benefited low-income people” (WSDOT, 2018a). Support for the lanes has gradually increased over time.

During the time of the I-405 Express Lanes implementation, the region experienced an increase in population and economic growth. The population of the region grew by 4%, with over 168,000 additional “people between March 2015 and March 2017” (WSDOT, 2018a). Additionally, since tolling began, near “175,000 new drivers licenses were issued” in the surrounding counties (WSDOT, 2018a). Because of this growth, the traffic volume increased (WSDOT, 2018a). Transit has along the corridor has increased by 5% since the express lanes opened (WSDOT, 2018a). Since the HOV3+ limits the number of vehicles allowed to use the toll lanes, transit “travel times are more reliable in both directions on I-405” (WSDOT, 2018a). However, the transit travel times for routes along neighboring arterials experienced increased variability and, for some transit agencies, decreased reliability (WSDOT, 2018a). In the 30-month report, travel time decreased for all transit agencies whose routes were on the corridor, except for one route which experienced over a minute of increased travel time (WSDOT, 2018b).

The Washington Joint Transportation Committee conducted a study of the I-405 Express Toll Lanes to assess the performance of the corridor. The researchers used data from loop detectors, toll transaction, and HERE/INRIX data from cell phones (Washington Joint Transportation Committee, 2018). The I-405 performance measures were outlined by Washington State statute RCW 47.56.880, of which, the researchers selected the following three: “Whether the express toll lanes generate sufficient revenue to pay for all I-405 express toll lane-related operating costs; Whether express toll lanes
maintain speeds of 45 miles per hour at least 90% of the time during peak periods; and
Whether the average traffic speed changed in the general purpose lanes” (Washington Joint Transportation Committee, 2018). In the WSDOT 24-month operational study, it was reported that the funds generated from the toll lanes ($44.5 million) more than enough covered the operation and maintenance costs of the lanes ($15.7) (Washington Joint Transportation Committee, 2018). The Washington Joint Transportation Committee confirms that the lanes are “financially self-sufficient” (Washington Joint Transportation Committee, 2018). However, the FHWA speed performance metric (that the traffic in the toll lanes must move at 45 mph 90% of the time) is not met. WSDOT reported that the northbound lanes meet the speed requirement “94% of peak periods but the southbound direction only reaches the metric 76% of peak periods” (WSDOT, 2018). The Washington Joint Transportation Committee study found that, on average, speeds on the express lanes are above 45 mph during the peak period 85% of the time northbound and 78% southbound between January 2017 to June 2017 (Washington Joint Transportation Committee, 2018). However, the express lanes are servicing “more vehicles” than the previous HOV facility with 59.2% more northbound and 94.5% more southbound (Washington Joint Transportation Committee, 2018). Finally, there was no significant change in the speeds of the general-purpose lanes during the peak period (Washington Joint Transportation Committee, 2018). While there was an initial speed improvement when the newly paved general-purpose lanes were opened, the speed returned to “pre-” tolling amounts over time (Washington Joint Transportation Committee, 2018).
2.2 Student Mode Choice

There have already been many studies attempting to capture the mode choice of university students. Understanding the mode choice of students can help model the travel demands of a university. One study in Canada examined the daily travel behavior of commuting students, faculty, and staff at a large university in order to understand the travel demands of the university population (Daisy, Hafezi, Liu, & Millward, 2018). The researchers used a travel diary survey to collect data from the participants. They used a zero-based negative binomial (ZINB) model to model the data. The researchers found that the most used mode of travel for home to work/school-based trips for undergraduate and graduate students was walking since they lived fairly close to campus, and the most used mode for faculty and staff was driving (Daisy et al., 2018). As the purpose of the trip changed, the mode choice changed. For example, if the purpose of the trip was entertainment related, the main mode used for students, faculty, and staff was driving (Daisy et al., 2018). Across students, faculty, and staff, transit use was lower than car use (Daisy et al., 2018). From their findings, the researchers recommended that transportation planning should be done to provide more multi-modal options to the university population to help manage travel demand.

Another study in Canada sought to analyze the home to work/school patterns of individuals, with a focus in transit route choice (Eluru, Chakour, & El-Geneidy, 2012). Surveys were used to collect traveler choice data. Multinomial, mixed, and binary logit models were used to analyze and model the data. The results of the study showed that respondents found travel time on a bus “the most onerous” with the travel time by metro
and train as close seconds (Eluru et al., 2012). Decreasing bus travel time increased the likelihood that people would choose to take the bus (Eluru et al., 2012).

(Danaf, Abou-Zeid, & Kaysi, 2014) compared the mode choice for home-to-school trips of university students in Beirut, Lebanon, with the mode choices of the general population of the Greater Beirut Area. The researchers used discrete choice models to forecast students’ mode choice under different scenarios. However, they did not model non-motorized modes, assuming that most students who live within walking distance to the university “commute on foot” (Danaf et al., 2014). Travel time, cost, income, car ownership, gender, family net worth, and residence location all were significant factors in the mode choice of students. Students from wealthier families had a higher value of time than the general public (Danaf et al., 2014). The researchers noted that transportation policies that may be successful to the general public may not be successful for university students since the university student travel behavior is so complex. In order for transportation policies that focus on shifting student mode choice from cars to more sustainable modes of transportation to be successful, policymakers need to tailor policies specifically towards university students and their preferences (Danaf et al., 2014).

At the University of Trieste in Italy, researchers analyzed the mode choice decisions of students, faculty, and staff to see how these decisions would be impacted by 8 different transportation management policies (Rotaris & Danielis, 2014). The data were modeled using a pivoted Bayesian experimental design, a mixed logit model with error components, and a calibrated scenario analysis on the individual level specific to the
revealed preference data. Data was also collected from interviews. The results showed changing parking regulations at the university (e.g., the price of the permit, the number of spaces, etc.) impacted mode choice in the factor of bus use (Rotaris & Danielis, 2014). However, students would only be impacted if an “hourly parking tariff” was introduced (Rotaris & Danielis, 2014). Overall, subsidizing bus services would positively affect bus ridership (Rotaris & Danielis, 2014).

The same researchers published a study in 2015 to fill the gap between existing literature by estimating the effectiveness and efficiency of 9 different hypothetical transportation policies aimed at reducing car use. Mode choice data was collected through 372 in-person interviews at different locations at the university (Rotaris & Danielis, 2015). Through their analysis, the researchers found that 8 of 9 policies were effective in reducing car use, but only 6 were efficient. Fully subsidizing bus fares were found to be most effective in reducing car use in commuting to school (Rotaris & Danielis, 2015). However, the researchers do not believe that this is financially sustainable and recommend a combination between partial bus subsidy and parking restrictions where the parking revenue goes back into the bus system to help subsidize the fare.

Incentives can be useful in promoting sustainable transportation options, like non-motorized modes and public transportation. In a study by (Delmelle & Delmelle, 2012), students at the University of Idaho were surveyed to assess their mode choice. The researchers used various statistical methods and ArcGIS to analyze and display the data. Non-motorized transportation options were already accessible among students and
became popular choices during good weather (Delmelle & Delmelle, 2012). This study found that in order to reduce commuting by car, disincentives against driving could be introduced by raising the minimum parking permit cost (Delmelle & Delmelle, 2012). However, the researchers stress that increasing the minimum parking permit cost should not place a large financial burden on those students “forced to commute by car due to family or employment commitments” (Delmelle & Delmelle, 2012). Additionally, this study shows how gender, parental status, and temporal differences can impact mode choice. For instance, the survey results show that females surveyed were less likely to use non-motorized forms of transportation because of safety concerns, such as poor infrastructure for walking or biking (Delmelle & Delmelle, 2012). Students who had children were more likely to drive to campus (Delmelle & Delmelle, 2012).

Similarly, in Barcelona, Spain, researchers examined how spatial location, socioeconomics, and social behavior influence travel demand by car in a university setting (Soria-Lara, Marquet, & Miralles-Guasch, 2017). A travel demand survey was used to collect data which was analyzed through chi-squared Automatic Interaction Detection and non-parametric tests (Soria-Lara et al., 2017). The researchers concluded (from both models used) that spatial location factors have less influence than socioeconomic and social behavior factors in choosing a car as the main mode of transportation. They confirmed the conclusion reached by (Delmelle & Delmelle, 2012).

In some study areas, there is a strong social relationship between students that dictate their preferences and behaviors. Survey data from 12 universities in Shiraz, Iran, showed that Iranian students preferred to use less active modes of transportation
(Etminani-Ghasrodashti, Paydar, & Hamidi, 2018). While students mainly used public transportation for their home to work/school trips, they preferred to use private cars (Etminani-Ghasrodashti et al., 2018). The researchers suspect that this is because of Iran’s restriction on inter-gender public interaction of young adults in public place or on public transportation. Additionally, public transportation did not support the respondents “friendship orient[ed] lifestyle” (Etminani-Ghasrodashti et al., 2018).

A study of university students in rural Thailand found that male and female students had similar social travel behavior. The survey data was collected at Suranaree University of Technology, which is a unique campus since it was not planned to “encourage non-motorized transport on campus” (Limanond, Butsingkorn, & Chermkhunthod, 2011). This made walking and bicycling the “least popular modes of travel” (Limanond et al., 2011). Whether or not a student-owned a personal vehicle (typically a two-stroke motorcycle instead of a car) impacted mode choice (Limanond et al., 2011). The students who did not own a personal vehicle relied on 3 modes of transportation: riding with a friend, driving a friend’s car, or taking the free bus service offered on campus (Limanond et al., 2011). The free bus was not a popular mode because it had infrequent headways and traveled on an indirect route (Limanond et al., 2011). The researchers concluded that the results of the study show a “high social interdependency” among the students to travel to their desired destinations (Limanond et al., 2011). The researchers decided that this is a perfect example of how it is important to design a university campus for sustainable transportation.
There can be other factors that influence a student’s mode choice. (Ewing, Schroeer, & Greene, 2004) conducted a study to analyze the factors that contribute to students’ mode choice. It is important to note that the students surveyed were grade levels K-12 and therefore do not have as many mode options as university students. The researchers collected the data through a travel diary survey and modeled the data through a nested logit choice model and a multinomial model (Ewing et al., 2004). Certain factors such as residential location, employment, and decisions regarding car ownership were exogenous to the travel choice model. The study found that students who traveled through areas with sidewalks on major roads were more likely to walk (Ewing et al., 2004). Factors relating to the built environment were not significant in this study (Ewing et al., 2004). However, in a study by (Whalen, Páez, & Carrasco, 2013), factors relating to the built environment were significant. In this study, the mode choices of students were determined by a combination of cost, individual attitudes, and environmental factors relating to the built environment, like street and sidewalk density (Whalen et al., 2013).

A study by (Zhan, Yan, Zhu, & Wang, 2016) examined which factors influenced student mode choice and travel frequency. The researchers used online travel surveys to obtain data. The data was then analyzed using a nonparametric statistical hierarchical tree-based regression model. When students at universities in Beijing, Nanjing, and Shanghai were surveyed, factors that influenced mode choice were travel distance, bicycle ownership, and gender (Zhan et al., 2016). Student travel frequency was influenced by family income and student grade (i.e., undergraduate level, graduate level).
(Zhan et al., 2016). Both school location and public transit station coverage ratio were factors that influence student mode choice and travel frequency (Zhan et al., 2016).

Environmental and psychosocial factors may also contribute to student mode choice. (Molina-García, Castillo, & Sallis, 2010) argues that these factors determine students’ active mode choice when commuting to school. The researchers conducted a survey with a 518 sample of students from two universities in Valencia, Spain. An SEM model was used to analyze the data. Some of the variables considered were socioeconomic status, self-efficacy, barriers to active transport, walking and cycling facilities, and the distance to the university. The results of the study showed that active commuting was inversely related to access to a personal car. Both the psychological and environmental variables analyzed were significant. The most important motivation for students to use active transportation was to save money (Molina-García et al., 2010). The researcher suggests that improving public transportation can promote active transportation among students (Molina-García et al., 2010).

One study examined if the decline in driving among millennials was associated with an increase in millennial transit use (Brown, Blumenberg, Taylor, Ralph, & Voulgaris, 2016). The travel behavior data and transit use levels of millennial adults (assumed to be 16+ years) were taken from the 2001 and 2009 NHTS, the EPA’s SLD, and the U.S. Census (Brown et al., 2016). The researchers concluded that their results did not show that millennials were embracing transit for the long term. Instead, millennials were using transit to support lifestyle factors (i.e., being a student, lower income, and not having any children), demographic factors (race or ethnicity), and locational factors (i.e.,
living in a densely populated area) (Brown et al., 2016). Transit use among this age group was also not directly related to the time periods analyzed (Brown et al., 2016).

(Zhou, 2012) looked at student mode choice in the car-dependent/dominant region of Los Angeles. The data was modeled using spatial analysis and a multinomial logit model. The researcher found that having a parking permit reduces the odds of using alternative modes to driving. Having a discounted transit pass increased the odds of choosing different travel modes (Zhou, 2012). Gender, student status (undergraduate vs graduate), and age were significant to biking, walking, or using public transit (Zhou, 2012). If students lived near friends or classmates, they were more likely to take public transit while students who lived alone were more likely to travel alone (Zhou, 2012). Finally, the researchers found the most students commute during off-peak travel times.

Policies can help to encourage multimodal transportation. (Zhou, 2014) examined what needed to be done in the realm of public policy to encourage the university to relinquish their dependence on cars. Data was collected through an online survey from students at the University of California, Los Angeles. A series of chi-squared tests were used to test the statistical significance of the data. Survey questions were different depending on if the student lived on or off campus. The results of the study found that university students are more likely to focus on the affordability of a mode or living conditions than the general population (Zhou, 2014). Whether or not a student lived alone or with others also influence their mode choices (Zhou, 2014). For instance, students who lived alone were more likely to drive than those who lived with other people (Zhou, 2014). Transit pass subsidies influenced students’ mode choice (Zhou, 2014). Gender and
student status (graduate vs undergraduate) also were important factors in predicting mode choice (Zhou, 2014). Female and graduate students were “less likely to use alternative transportation” than their male and undergraduate peers (Zhou, 2014). Females were less likely to choose biking as a mode due to safety concerns (Zhou, 2014). Finally, graduate students who were enrolled 1-1.5 year degree programs were less likely to own a bike or commute by bike (Zhou, 2014).

2.3 Perceptions of Autonomous Vehicles

Autonomous vehicles have been an increasingly hot topic. This new mode, like any new mode, has the potential of altering peoples’ travel behavior. Some studies anticipate that AVs can increase the capacity of roadways and reduce congestion by removing human error from driving (Guerra, 2016), (Malik, 2017). Currently, vehicles with Level 3 autonomy are already commercially available. While fully autonomous vehicles are the next to become available commercially, it could be many years until these products reach the mainstream market. (Litman, 2019) predicts an AV market penetration rate between 20-40% for 2030 and 40-60% for 2040. (Bagloee, Tavana, Asadi, & Oliver, 2016) predicts 50% market penetration for 2040. Both (Lavasani, Jin, & Du, 2016) and (Litman, 2019) agree that the AV market penetration rate will not reach between 80-100% until 2050. The success of the adoption of these modes depends on the choices of consumers.

The consumers’ perception of a product is important for its success. Multiple studies have looked at peoples’ perceptions of autonomous vehicles. (Bansal,
Kockelman, & Singh, 2016) conducted a state preference survey of residents in Austin, Texas in 2014. The survey was distributed over email through neighborhood associations. While there were 510 respondents, only 358 completed the survey, and 11 were not residents of Austin (Bansal et al., 2016). This left the reduced the sample size to 347. The results showed that 48% of respondents were willing to be less than $2000 for adding Level 3 automation to their vehicles, 28% were willing to pay between $2000-$5000, and 24% were willing to pay more than $5000 (Bansal et al., 2016). The majority of respondents also reported that they would engage in the following activities while traveling in an AV of higher autonomy: text or talk, sleep, work, and “looking out the window of the vehicle” (Bansal et al., 2016). The respondents had a higher willingness to pay for Level 4 autonomy than Level 3 autonomy (Bansal et al., 2016). The researchers suspect that this is because the travelers would be able to perform recreational or productive activities while in a Level 4 AV but not a Level 3 AV (Bansal et al., 2016).

(Daziano, Sarrias, & Leard, 2017) also did a study to understand consumer’s willingness to pay for different levels of autonomy. Approximately 1,260 individuals completed the survey in 2014 (Daziano et al., 2017). The survey included options for various levels of autonomy and also non-autonomous (conventional) vehicles (Daziano et al., 2017). The results found that the average household was willing to pay more for a fully autonomous vehicle ($4,900) than a partially autonomous vehicle ($3,500) (Daziano et al., 2017). This was slightly different than (Bansal et al., 2016) but followed a similar trend. Ultimately, people are willing to pay more for something if they have a larger perceived benefit of the service.
2.4 Summary

Throughout existing literature, researchers have analyzed the impact of tolling on corridors, identified significant factors that drive university student’s mode choices, and conducted surveys on the public’s perceptions and willingness to pay for autonomous vehicles. In the articles summarized above, when HOT lanes are implemented in a facility, the transit ridership either remains constant or increases. While incorporating HOT lanes on corridors has the potential to sway travelers to use alternate modes of transportation besides driving, it changes depending on the facility, the quality of service of alternate modes, and users’ willingness to pay.

Overall, there is a consensus among researchers that people will choose to use HOT lanes for the reliability and travel time savings. Researchers predominantly agree that gas price, unemployment rate, income, and attitudes are also drivers for HOT and alternate mode choice. Some studies found that when gas prices increased, people were less likely to use the tolls because they were less likely to drive. Other studies agreed that higher unemployment rates decreased travel since these members of the population would not be traveling on their normal commuting routes. Income also can be a factor in choosing to use the HOT lanes as an SOV (paying the toll) or through carpooling (HOV+), transit, or by choosing a different route to avoid the toll. If the income is impacted by an economic recession, then the inclinations to take the HOT lanes drops.

Researchers also agree that a traveler’s attitude of and perception of certain modes determine mode choice. In one case, even though the HOT lanes were successful in
reducing travel times since the public was opposed to the construction before the congestion relief implementation, they did not have a good attitude towards the lanes. Also, if the public perceives a mode as “unsafe” they will be less likely to choose that mode. Many of the researchers agreed that travelers would be more inclined to take transit if the bus performance was stellar and the riders had a good attitude about public transportation.

Even with these agreements, there is no general consensus on whether or not tolling promotes transit use. The success of a transit performance on a HOT facility varied from corridor to corridor. Transit ridership along these corridors either remained static (predominantly the same as pre-tolling conditions) or ridership increased. However, the ridership increase may not be directly related to the toll but related indirectly, especially if the transit agencies enhanced its service before tolling was implemented. Finally, there are limited studies on tolling in Northern Virginia and little to no studies regarding transit performance on the I-66 HOT Lanes Inside the Beltway. This alone makes studying the impacts of tolling on transit lines servicing the I-66 corridor necessary.

The literature on student mode choice comes to many of the same conclusions and researchers generally agree. Throughout these studies, researchers agree that travel time, mode cost, car ownership, gender, family net worth, residential location, parental status, employment, student status, income, age, and the presences of transit subsidies are all important factors in predicting student mode choice. Researchers also found that student mode choice is related to access to a mode (car, bus stop, etc.), the price of mode, the age
of the student, being an undergraduate vs graduate, and safety of a mode. Additionally, there is a unique social accept to student mode choice. If students lived near classmates or lived with other people, they would be more likely to travel with other people, whether that be carpooling or taking transit together. Female students were found to be more concerned with safety than male students.

Across most studies, money (i.e., income and transportation cost) was a very important factor. In general, students want to save money to supplement the cost of their education, so they will be more inclined to take cheaper modes. However, this could be different if the student does not financially support themselves. For example, many undergraduates are supported financially in some way by their parents, guardians, or spouse, though there are exceptions. On the other hand, many graduate students work full-time or part-time and primarily support themselves financially. They are either completely financially independent or partially dependent on their parents, guardians, or spouse, though, once again, there are exceptions. However, in both cases, money would be a factor. Students could potentially sacrifice factors such as travel time savings or trip reliability for the benefit of saving money. They could be influenced to take a mode they normally would not choose simply because it is cheaper. Still, this distinction is not clear in the studies conducted so far.

Most if not all of these studies look at student travel behavior while students are students without any consideration for what choice they will make in the future when they are no longer students. Studies like this are great to identify important factors that drive student decisions to select certain modes and how to serve future students better at
the university level. However, what these studies do not address is what current student’s transportation preferences are now and how these preferences will influence future transportation choices when the student’s lifestyle changes (i.e., entering the workforce).

This finding is important because students will not be students forever. Those who have low incomes now will not necessarily have these same low incomes when they start their careers. With the increase of income expected from getting a job after completing their education, students could have a greater willingness to pay for transportation mode. With the newfound monetary resource or even increased mode access (i.e., car accessibility, moving to live in proximity to a bus route, etc.), today’s student could make travel behavior decisions based on their transportation preferences besides the constraint of money. Because of this, it is necessary to understand what factors are statistically significant to students’ mode choice.

With any new technology or transportation disruptor, peoples’ travel choices could change with this introduction of this new mode. Additionally, the disutility surrounding travel could decrease or even become a utility depending on the situations surrounding the mode. The increasing autonomy of vehicles introduces new modes into the transportation fleet and will provide even more choices to commuters. Currently, from previously stated literature, autonomous vehicles are not predicted to be at an 80-100% market share until 2050. If this prediction is correct, it is likely that fully autonomous vehicles could be introduced into the vehicle fleet when today’s university students are in the middle of their careers. There is a gap in the literature since there are no studies researching university students’ perceptions of autonomous vehicles. Since
students will be the individuals taking advantage of the new transportation technologies for commuting purposes, it is important to investigate students’ bias towards certain mode choices in autonomous vs non-autonomous scenarios given different levels of autonomy, price, and travel time options.

Overall, there is a gap in the literature relating university students’ perception of alternate mode choices to congestion brought about by increased economic development. There are also no scholarly studies on mode choice of students in the Washington D.C. Metropolitan Area, specifically George Mason University. Because of this, it is necessary to examine students’ perceptions of certain modes in this urban/suburban region, to identify how strongly students’ choices take cost into consideration, to assess the impacts of local tolling facilities on students’ choices, and to understand students’ perceptions of autonomous vehicles in relation to non-autonomous vehicles.
CHAPTER 3: METHODOLOGY

3.1 I-66 HOT Lane Transit Impacts

To understand the impacts of tolling on bus ridership, the bus ridership data from approximately one year before tolling and one year after tolling along I-66 Inside the Beltway was analyzed using a multi-linear regression model to assess the impact selected variables had on transit ridership. All local transit agencies that service I-66 were contacted to request data. Ultimately, ridership data was provided by three local transit agencies and by a transit funding organization in the region. Only bus routes that traveled along I-66 Inside the Beltway were included in the analysis.

3.1.1 Data sources

The data was provided by local transit agencies that service the corridor and the Northern Virginia Transportation Commission (NVTC), which provides funding for transit services in the region. All the ridership data was formatted as .xlsx files. The transit agency and route are shown in Table 1 below:
Table 1: Presenting transit agency, data type, and bus routes analyzed in this thesis.

<table>
<thead>
<tr>
<th>Transit Agency</th>
<th>Route(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potomac and Rappahannock Transportation Commission (PRTC) and NVTC</td>
<td>M100, M200, G100, and G200</td>
</tr>
<tr>
<td>Washington Metropolitan Area Transit Authority (WMATA)</td>
<td>5A</td>
</tr>
</tbody>
</table>

3.1.2 Analysis

The bus ridership data was analyzed using a multi-linear regression model. The model is described below:

\[ y = \beta_1 x_1 + \cdots + \beta_n x_n + \beta_0, \forall n \]

Equation 1: Linear regression model.

Where \( y \) equals the ridership, \( x \) is a dependent variable, \( \beta \) is a dependent coefficient, and \( \beta_0 \) is the intercept. Depending on the transit service analyzed, \( y \) can equal ridership
during a month, time of day (i.e., Peak AM, Peak PM), weekday average, or schedule (i.e., quarterly).

**Variables.** Variables were selected that could externally impact ridership. Not all the regression models contain the same variables. This is because not all transit agencies had the same types of data available. This is outlined in Table 2 below:

<table>
<thead>
<tr>
<th>Transit Agency</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loudoun County Transit (LCT)</td>
<td>• Total boarding’s per revenue hour</td>
</tr>
<tr>
<td></td>
<td>• Incentive [$]</td>
</tr>
<tr>
<td></td>
<td>• Precipitation (monthly average) [in]</td>
</tr>
<tr>
<td></td>
<td>• Temperature (monthly average) [°F]</td>
</tr>
<tr>
<td></td>
<td>• Toll price (monthly average) [$]</td>
</tr>
<tr>
<td></td>
<td>• Gas price (monthly average) [$/gal]</td>
</tr>
<tr>
<td></td>
<td>• Unemployment rate (monthly average) [%]</td>
</tr>
<tr>
<td></td>
<td>• All-round Monthly Fare (SmarTrip) [$]</td>
</tr>
<tr>
<td></td>
<td>• Inauguration Day</td>
</tr>
<tr>
<td></td>
<td>• Cherry Blossom Days</td>
</tr>
<tr>
<td></td>
<td>• Route Headways (monthly average) [minutes]</td>
</tr>
<tr>
<td></td>
<td>• Number of Stops</td>
</tr>
<tr>
<td></td>
<td>• Service Runs per Day</td>
</tr>
<tr>
<td>Potomac and Rappahannock Transportation Commission (PRTC)</td>
<td>• Precipitation (monthly average) [in]</td>
</tr>
<tr>
<td></td>
<td>• Temperature (monthly average) [°F]</td>
</tr>
<tr>
<td></td>
<td>• Toll price (monthly average) [$]</td>
</tr>
<tr>
<td></td>
<td>• Gas price (monthly average) [$/gal]</td>
</tr>
<tr>
<td></td>
<td>• Unemployment rate (monthly average) [%]</td>
</tr>
<tr>
<td></td>
<td>• All-round trip fare [$]</td>
</tr>
<tr>
<td></td>
<td>• Inauguration Day</td>
</tr>
<tr>
<td></td>
<td>• Cherry Blossom Days</td>
</tr>
</tbody>
</table>

Table 2: Displaying the variables used in the regression model for each transit agency.
<table>
<thead>
<tr>
<th>Transit Agency</th>
<th>Variables</th>
</tr>
</thead>
</table>
|                | • Route Headways (monthly average) [minutes]  
|                | • Service Runs  
|                | • Number of Bus Stops  
| Washington Metropolitan Area Transit Authority (WMATA) | • Precipitation (schedule average) [in]  
|                | • Temperature (schedule average) [°F]  
|                | • Toll price (schedule average) [$]  
|                | • Gas price (schedule average) [$/gal]  
|                | • Unemployment rate (schedule average) [%]  
|                | • Trip end time [hr:min:sec]  
|                | • Trip on time [%]  
|                | • On time [%]  
|                | • Trip late [%]  
|                | • Passenger per hour  
|                | • Revenue miles [miles] |

**Precipitation.** Precipitation data was obtained from the Ronald Reagan Station near Falls Church, Virginia from [www.wunderground.com](http://www.wunderground.com). This includes both rainfall and snowfall. Precipitation is recorded in inches and the cumulative precipitation for the month is used for the analyses. Please note that for the WMATA analysis, the average precipitation during the bus schedule period (quarterly) is used.

**Temperature.** Temperature data was obtained from the Ronald Reagan Station near Falls Church Virginia from [www.wunderground.com](http://www.wunderground.com). It is recorded in Fahrenheit and the average temperature for the month is used for the analyses. Please note that for the WMATA analysis, the average temperature over the bus schedule period (quarterly) is used.
Gas Price. Gas price trends were obtained from the U.S. Energy Information Administration (EIA) and www.gasbuddy.com. The EIA provided the price trends for U.S. regular all formulations of retail gasoline. The trends can be seen in Figure 1. To check to see if the national average was a good metric to use for the analysis, these price trends were compared with historical averages at www.gasbuddy.com. The national average gas price is plotted in blue; the state of Virginia average is plotted in red, and the Washington, D.C. average is plotted in green as seen in Figure 2. Since the U.S. average gas price is between the Washington, D.C. gas price and the Virginia gas price, these values were used for the analysis. Please note that for the WMATA analysis, the average gas price over the bus schedule period (quarterly) is used.
Figure 1: Displaying gas price trends across the U.S. from July 2016 to September 2018. Source: U.S. Energy Information Administration (EIA), 2018.
Figure 2: Displaying regular gas price trends across the U.S., Virginia, and Washington D.C. from March 2016 to March 2019. Source: GasBuddy.com, 2018.

**Unemployment rate.** Unemployment rate trends were obtained the National Conference of State Legislatures (NCSL) for the month is used for the analyses. Please note that for the WMATA analysis, the unemployment rate is averaged over the bus schedule period (quarterly).

**Exclusive LCT Variables.** The exclusive variables included were total boardings per revenue hour, a $100 transit incentive for I-66 commuters impacted by the toll, LCT SmarTrip Fare, the route frequency per month averaged across all routes, the number of stops serviced, and the service runs per day. These can be seen in Table 7 in Chapter 4.

**Exclusive PRTC Variables.** The exclusive variables that were included were the PRTC Fare, route frequency per month (from February 2019 timetables), service runs per day
(from February 2019 timetables), and the number of bus stops (from February 2019 timetables). These can be seen in Table 8 in Chapter 4.

**Exclusive WMATA Variables.** The exclusive WMATA variables included were the trip end time, the trip duration, measured on time trips, the percentage of late trips, the percentage of on time trips, the passengers boarding per mile, revenue miles, and WMATA SmarTrip fare. These can be seen in Table 9 in Chapter 4.

**Toll prices.** VDOT maintains an I-66 historical tolling website which calculates past tolls based certain inputs (i.e., entering point, trip date and time, exiting point, etc.). The historic tolls are presented as 4-week averages across the tolling periods for Monday through Friday.

Since the WMATA ridership data is broken down by average weekday riders per time period, the toll prices used in the analysis is the five-day average every 15 minutes of tolling. Also, the 5A travels along I-66 from the Dulles Rt 267 to approximately Exit 75. Table 3 and Figure 3 shows the eastbound toll trends every 15 minutes. Table 4 and Figure 4 shows the westbound toll trends every 15 minutes. The average toll price for the week for each time is shown in green on both charts. Since the rest of the ridership data is aggregated per quarter, the tolling for both the morning and evening peak periods is averaged into the tolling for the day.
Table 3: Displaying AM toll trends for each day of the week for the estimated segment of road that is part of the WMATA 5A’s route.

<table>
<thead>
<tr>
<th>Time</th>
<th>Monday ($)</th>
<th>Tuesday ($)</th>
<th>Wednesday ($)</th>
<th>Thursday ($)</th>
<th>Friday ($)</th>
<th>AVG ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5:30 AM</td>
<td>2.9</td>
<td>3</td>
<td>4.25</td>
<td>4.25</td>
<td>3.5</td>
<td>3.58</td>
</tr>
<tr>
<td>5:45 AM</td>
<td>1.9</td>
<td>2</td>
<td>2.5</td>
<td>2.4</td>
<td>1.5</td>
<td>2.06</td>
</tr>
<tr>
<td>6:00 AM</td>
<td>3</td>
<td>2.5</td>
<td>3.25</td>
<td>2.5</td>
<td>1.5</td>
<td>2.55</td>
</tr>
<tr>
<td>6:15 AM</td>
<td>2.75</td>
<td>2.75</td>
<td>3.175</td>
<td>2.75</td>
<td>1.7</td>
<td>2.63</td>
</tr>
<tr>
<td>6:30 AM</td>
<td>4.1</td>
<td>6</td>
<td>6</td>
<td>6.25</td>
<td>2.4</td>
<td>4.95</td>
</tr>
<tr>
<td>6:45 AM</td>
<td>5.75</td>
<td>6.75</td>
<td>7</td>
<td>7.5</td>
<td>2.45</td>
<td>5.89</td>
</tr>
<tr>
<td>7:00 AM</td>
<td>5.75</td>
<td>7.25</td>
<td>7.4</td>
<td>7.25</td>
<td>3.1</td>
<td>6.15</td>
</tr>
<tr>
<td>7:15 AM</td>
<td>9.75</td>
<td>9</td>
<td>9.95</td>
<td>11.25</td>
<td>3.25</td>
<td>8.64</td>
</tr>
<tr>
<td>7:30 AM</td>
<td>12.5</td>
<td>15.5</td>
<td>13.75</td>
<td>12.75</td>
<td>5.25</td>
<td>11.95</td>
</tr>
<tr>
<td>7:45 AM</td>
<td>12.55</td>
<td>22</td>
<td>17.5</td>
<td>22.5</td>
<td>5.3</td>
<td>15.97</td>
</tr>
<tr>
<td>8:00 AM</td>
<td>12.1</td>
<td>22.75</td>
<td>19.95</td>
<td>24</td>
<td>6.3</td>
<td>17.02</td>
</tr>
<tr>
<td>8:15 AM</td>
<td>11.75</td>
<td>22</td>
<td>23.75</td>
<td>25</td>
<td>6.3</td>
<td>17.76</td>
</tr>
<tr>
<td>8:30 AM</td>
<td>14.25</td>
<td>28</td>
<td>23.75</td>
<td>27.5</td>
<td>7.9</td>
<td>20.28</td>
</tr>
<tr>
<td>8:45 AM</td>
<td>13</td>
<td>32</td>
<td>21.75</td>
<td>30</td>
<td>7.6</td>
<td>20.87</td>
</tr>
<tr>
<td>9:00 AM</td>
<td>12.9</td>
<td>26</td>
<td>23.75</td>
<td>22.5</td>
<td>6</td>
<td>18.23</td>
</tr>
<tr>
<td>9:15 AM</td>
<td>10.9</td>
<td>11</td>
<td>19</td>
<td>17.75</td>
<td>4.4</td>
<td>12.61</td>
</tr>
</tbody>
</table>

Figure 3: Displaying plotted data from Table 3.
Table 4: Displaying PM toll trends for each day of the week for the estimated segment of road that is part of the WMATA 5A’s route.

<table>
<thead>
<tr>
<th>Westbound from Exit 75 to Dulles Rt 267</th>
<th>Monday [$]</th>
<th>Tuesday [$]</th>
<th>Wednesday [$]</th>
<th>Thursday [$]</th>
<th>Friday [$]</th>
<th>AVG [$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>3:00 PM</td>
<td>6</td>
<td>12</td>
<td>7</td>
<td>9</td>
<td>9.1</td>
<td>8.62</td>
</tr>
<tr>
<td>3:15 PM</td>
<td>3.5</td>
<td>9</td>
<td>4.5</td>
<td>4.75</td>
<td>4.9</td>
<td>5.33</td>
</tr>
<tr>
<td>3:30 PM</td>
<td>4.4</td>
<td>10.25</td>
<td>4.75</td>
<td>5.25</td>
<td>6.8</td>
<td>6.29</td>
</tr>
<tr>
<td>3:45 PM</td>
<td>4.1</td>
<td>8</td>
<td>5.25</td>
<td>5.8</td>
<td>5.45</td>
<td>5.72</td>
</tr>
<tr>
<td>4:00 PM</td>
<td>4.5</td>
<td>7.2</td>
<td>5</td>
<td>5.75</td>
<td>6.9</td>
<td>5.87</td>
</tr>
<tr>
<td>4:15 PM</td>
<td>4.1</td>
<td>7.25</td>
<td>6</td>
<td>6.25</td>
<td>5.45</td>
<td>5.81</td>
</tr>
<tr>
<td>4:30 PM</td>
<td>7.5</td>
<td>8.95</td>
<td>6.5</td>
<td>8.25</td>
<td>6.9</td>
<td>7.62</td>
</tr>
<tr>
<td>4:45 PM</td>
<td>5.5</td>
<td>6.75</td>
<td>6.1</td>
<td>7</td>
<td>6</td>
<td>6.27</td>
</tr>
<tr>
<td>5:00 PM</td>
<td>6.98</td>
<td>5.8</td>
<td>6.5</td>
<td>7.5</td>
<td>6.5</td>
<td>6.66</td>
</tr>
<tr>
<td>5:15 PM</td>
<td>6.25</td>
<td>6.75</td>
<td>6.6</td>
<td>7</td>
<td>6.75</td>
<td>6.67</td>
</tr>
<tr>
<td>5:30 PM</td>
<td>9.5</td>
<td>7</td>
<td>7</td>
<td>12</td>
<td>8.45</td>
<td>8.79</td>
</tr>
<tr>
<td>5:45 PM</td>
<td>6.25</td>
<td>6.75</td>
<td>9.6</td>
<td>9</td>
<td>7.1</td>
<td>7.74</td>
</tr>
<tr>
<td>6:00 PM</td>
<td>5.75</td>
<td>8.5</td>
<td>6.75</td>
<td>7.25</td>
<td>6.6</td>
<td>6.97</td>
</tr>
<tr>
<td>6:15 PM</td>
<td>5.25</td>
<td>6</td>
<td>6.6</td>
<td>6.75</td>
<td>6.4</td>
<td>6.20</td>
</tr>
<tr>
<td>6:30 PM</td>
<td>4.75</td>
<td>5.25</td>
<td>4.9</td>
<td>6.5</td>
<td>4.7</td>
<td>5.22</td>
</tr>
<tr>
<td>6:45 PM</td>
<td>5.05</td>
<td>5</td>
<td>4.9</td>
<td>5.75</td>
<td>6.5</td>
<td>5.44</td>
</tr>
</tbody>
</table>

Figure 4: Displaying plotted data from Table 4.
VDOT published a 6-month performance report about the HOT lanes. This report cited that the average toll cost for round trips was $13.09 (Office of the Secretary of Transportation, 2018). Because of the large number of routes analyzed in LCT and PRTC, the average toll price used was $13.09.

### 3.2 GMU student survey

#### 3.2.1 Survey solicitation and data collection

An online anonymous survey was administered to the George Mason University students through Qualtrics, a software which collects and analyzes survey data. An IRB application was submitted and approved before conducting the survey. The survey was solicited from mid-March to early April 2019 through in email, social media, in-person solicitation at lectures, and paper fliers posted around the Fairfax Campus. An email with the solicitation was sent out to undergraduate and graduate students in the Civil, Environmental, and Infrastructure Engineering (CEIE) department, the Information Technology Department, the Cyber Security Engineering Department, and to graduate students in the Department of Statistics. The survey was advertised to graduate engineering students in the Graduate Student Affairs Newsletter. Mason Parking and other organizations at the university promoted the survey to the student body through its social media accounts. If students were interested in participating in a raffle to win a $20 Starbucks gift card, they were given the option to provide their contact information at the end of the survey. Five students were selected randomly at the end of the semester as
winners of the raffle. Their contact information was deleted after the study was complete. The survey questionnaire can be seen in the Appendix.

3.2.2 GMU Spring 2019 Demographics

According to the George Mason University Office of Institutional Research and Effectiveness, as of Spring 2019, there are approximately 35,929 students enrolled at the university on the U.S. campuses. Of these 35,929 students, 25,073 students are undergraduates, 10,268 students are graduates, and 588 are First Professional Law students. For this survey, students from the law school are categorized as “graduate”, putting the total number of graduate students at 10,856. There are more female students than male at the university with 18,908 female students, 16,881 male students, and 140 not reported. The Volgenau School of Engineering (VSE) has approximately 7,621 total students with 1,844 total female students and 1,795 graduate students. The CEIE department has 422 total students and 120 total graduate students with 118 total female students, 81 female undergrads, and 37 female graduate students. While this survey was advertised to all students on the Fairfax Campus through paper fliers, most of the sample will most likely be from the engineering school and be male. However, since the survey does not ask for any information regarding a student’s major, this conclusion is only a reasonable assumption.
3.2.3 Survey design

The survey was designed as a stated preference survey with 32 questions in total which included three different transportation scenarios. In the first part of the survey, participants were asked to agree or disagree with statements in a Likert-style which corresponded to different independent variables used in the analysis. Then, questions were asked to assess the participants' range of time flexibility given different situations. The next section presented three different transportation scenarios: driving with a toll vs bus, conditional AV (Level 3 autonomy) vs conventional car, and full AV (Level 5 autonomy) vs conventional car. The conditionally autonomous vehicle is defined based on the Society of Automotive Engineers International standards and relieves the driver from the task of driving but requires them to be alert to take over control of the vehicle if necessary (SAE International, 2018). Level 5 autonomy is fully autonomous and does not require the driver to take over driving at any point (SAE International, 2018). The purpose of these questions was to gauge the participants’ time and cost sensitivity as well as their willingness to pay for two different AV options. When presented with two different transportation options, participants were asked to select which option they preferred. Each option displayed the cost of the trip, travel time, walking distance, and (when applicable) features associated with the level of autonomy.

There were three sets of questions per transportation scenario. Depending on which option the participant picked in one round impacted the options shown to them in the second round. For example, if a participant picked Option 1 over Option 2 in round one, the cost of Option 1 would increase, and all attributes of Option 2 would remain the
same. Overall, there were eight possible choice combinations per scenario. Variables like walking distance and autonomy were included for the sake of completion, but these were not considered as variables in the overall model because these variables were static among respondents.

**Variables.** Many of the questions in the student corresponded to an independent variable. A breakdown of the variables associated with the questions are in Table 5. Different scenarios were created to assess students’ sensitivity to Travel Time, Cost, Walking Distance, and Automation Level. The breakdown of the corresponding question to scenario option can be seen in Table 6.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safety</td>
<td>• I feel safe taking the bus at night.</td>
</tr>
<tr>
<td></td>
<td>• I do not like to travel with strangers on transit.</td>
</tr>
<tr>
<td>Accessibility</td>
<td>• I have access to a car for my commuting.</td>
</tr>
<tr>
<td></td>
<td>• I take the bus because I do not have access to a car.</td>
</tr>
<tr>
<td></td>
<td>• Do you have a valid driver’s license?</td>
</tr>
<tr>
<td>Stability</td>
<td>• I often take commuting trips with little to no planning.</td>
</tr>
<tr>
<td>Preference/Attitude</td>
<td>• Even if taking the bus is faster, I still prefer driving.</td>
</tr>
<tr>
<td></td>
<td>• If I have a bad experience with something, I am not likely to give it a second chance.</td>
</tr>
<tr>
<td>Reliability</td>
<td>• I believe the bus arrives on schedule.</td>
</tr>
<tr>
<td></td>
<td>• I like to depend on my own driving instead of a transit service to meet my transportation needs.</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Variable</th>
<th>Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toll</td>
<td>• I think the I-66 tolls have improved travel time on the corridor.</td>
</tr>
<tr>
<td></td>
<td>• I think the tolls on I-66 are too high.</td>
</tr>
<tr>
<td>Early Adopter</td>
<td>• When Autonomous Vehicles become available for commercial use, I want to</td>
</tr>
<tr>
<td></td>
<td>try them out.</td>
</tr>
<tr>
<td></td>
<td>• I have tried using an electric vehicle when it first became commercially</td>
</tr>
<tr>
<td></td>
<td>available.</td>
</tr>
<tr>
<td>Time Flexibility</td>
<td>• How late are you willing to be? What is the range of flexibility for your</td>
</tr>
<tr>
<td></td>
<td>arrival at your destination?</td>
</tr>
<tr>
<td></td>
<td>• On a normal day traveling to campus, do you arrive when you expect to</td>
</tr>
<tr>
<td></td>
<td>arrive?</td>
</tr>
<tr>
<td>Student Status</td>
<td>• What is your student level status?</td>
</tr>
<tr>
<td>Finance</td>
<td>• Are you supported financially in some way by a parent(s), guardian(s),</td>
</tr>
<tr>
<td></td>
<td>or significant other?</td>
</tr>
<tr>
<td></td>
<td>• Please select your annual household income range.</td>
</tr>
<tr>
<td>Age</td>
<td>• What is your age?</td>
</tr>
<tr>
<td>Gender</td>
<td>• What is your gender?</td>
</tr>
<tr>
<td>Distance</td>
<td>• How far away do you live from the Fairfax Campus?</td>
</tr>
</tbody>
</table>

Table 6: Presenting the independent variable with the corresponding scenario. The actual questions can be seen in the Appendix.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel Time</td>
<td>• Scenario 1 Questions (see Appendix)</td>
</tr>
<tr>
<td></td>
<td>o Selecting Option 1 corresponds to a higher value of time</td>
</tr>
<tr>
<td></td>
<td>o Selecting Option 2 corresponds to a lower value of time</td>
</tr>
<tr>
<td>Cost</td>
<td>• Scenario 1 Questions (see Appendix)</td>
</tr>
<tr>
<td></td>
<td>o Selecting Option 1 corresponds to a lower value of cost</td>
</tr>
<tr>
<td></td>
<td>o Selecting Option 2 corresponds to a higher value of cost</td>
</tr>
<tr>
<td></td>
<td>• Scenario 2 Questions (see Appendix)</td>
</tr>
<tr>
<td></td>
<td>o Selecting Option 1 corresponds to a lower value of cost</td>
</tr>
<tr>
<td></td>
<td>Cost</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a higher value of cost</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a lower value of cost</td>
<td></td>
</tr>
<tr>
<td>Scenario 3 Questions (see Appendix)</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a higher value of cost</td>
<td></td>
</tr>
<tr>
<td>Walking Distance</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of walking distance</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of walking distance</td>
<td></td>
</tr>
<tr>
<td>Scenario 2 Questions (see Appendix)</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of walking distance</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of walking distance</td>
<td></td>
</tr>
<tr>
<td>Scenario 3 Questions (see Appendix)</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of walking distance</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of walking distance</td>
<td></td>
</tr>
<tr>
<td>Autonomy Level</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of automation</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of automation</td>
<td></td>
</tr>
<tr>
<td>Scenario 2 Questions (see Appendix)</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of automation</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of automation</td>
<td></td>
</tr>
<tr>
<td>Scenario 3 Questions (see Appendix)</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 1 corresponds to a higher value of automation</td>
<td></td>
</tr>
<tr>
<td>o Selecting Option 2 corresponds to a lower value of automation</td>
<td></td>
</tr>
</tbody>
</table>

### 3.2.4 Analysis

Qualtrics stores the data within its online database. However, for the purposes of this study, a more sophisticated method was needed to analyze the data. The data was exported as a .cvs file for use in a descriptive analysis. Additionally, the data was analyzed using McFadden’s choice model (McFadden, 1973) in STATA 15.1.

Discrete choice models are great ways to understand behavioral decisions by looking at observed and unobserved factors. Discrete choice models are different from regression models in several ways. Regression models use a continuous variable (y) and
work well with linear variables where the principle is to draw a straight line. Discrete choice models are modeling a decision or categorical variable that must show three characteristics: mutually exclusive, each category must be a finite number, and exhaustive. In short, regression models ask, “How much?” while discrete choice models ask, “Which?” (Train, 2009). When analyzing student mode choice, discrete choice models are the best alternative to determine the relationship between the decision makers and the alternatives. Most decisions are individual decisions associated with a utility, $U_{ij}$, where $i$ is an individual and $j$ is a certain option (or in this case mode like bus, driving, etc.). For example, the utility equation of a certain mode might possess the following form:

$$U_{ij} = \beta_{1j}T_{ij} + \beta_{2j}C_{ij} + \varepsilon_{ij}$$

Equation 2: Utility function of a mode.

Where $\beta_{1j}$ is a coefficient relating how important this option is to person 1, $\beta_{2j}$ is a coefficient relating how important this option is to person 2, $T_{ij}$ is the travel time, $C_{ij}$ is the cost, and $\varepsilon_{ij}$ is the residual (or unobserved factors).

This study uses a binary logit model. A logit model is a helpful tool because it is closed form, interpretable, and utilizes that Property of Independence from Irrelevant Alternatives (IIA). The utility now becomes:

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \forall j$$

Equation 3: Utility function in a logit model.
Where $V_{nj}$ is the known portion of the utility, $\varepsilon_{nj}$ is the unknown portion (or residual) treated as a random variable, $n$ is the decision maker, and $j$ is the alternative. The residual is assumed to be an independently, identically distributed extreme value that follows the Gumbel distribution (Train, 2009). Assuming this logit distribution and through simplification, the probability becomes:

$$P_r(i) = \frac{e^{V_i}}{e^{V_i} + e^{V_2}}$$

Equation 4: Probability of a logit model when assuming a logit distribution.

Where $V_i$ is the known (aka fixed) portion of the utility.

Ultimately, through a multinomial logit model, the goal is to quantify the decision makers value system, get the $\beta$, and use this to predict future choices. This model will help answer the question, “What will happen in the future given consistent behavior?”

This study analyzes the survey data using a binary choice model, which is the same as a multinominal model, except there are only two alternatives.
CHAPTER 4: RESULTS

4.1 Transit Analysis: Impacts of the I-66 HOT Lanes on Transit

4.1.1 Loudoun County Transit (LCT)

LCT provides numerous bus routes along I-66. Aggregate ridership data per route was available from FY2017-FY2019, which includes one year before and one year after tolling. The ridership data was reported monthly. The F statistic is 20.21 and the Significance F is 1.68E-06. The intercept is -448,823.9512. The $R^2$ is 95.3% and the adjusted $R^2$ is 90.6%. The linear equation with significant variables can be seen below in Equation 5.

$$y = 3165.41TRH + 2324.46NS - 448,823.95$$

Equation 5: LCT linear equation when all variables are modeled.

Where $y$ equals the ridership, $TRH$ is the total boardings per revenue, and $NS$ is the number of stops. The tabular summary of the complete results of the analysis is presented in Table 7.
Table 7: Presenting Results of LCT regression analysis.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>S.E.</th>
<th>t Stats</th>
<th>P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Boardings per Revenue Hour</td>
<td>3165.4109</td>
<td>377.1178</td>
<td>8.3937</td>
<td>1.317E-06</td>
</tr>
<tr>
<td>Incentive [§]</td>
<td>105.0329</td>
<td>147.9612</td>
<td>0.7099</td>
<td>0.4903</td>
</tr>
<tr>
<td>Toll [§]</td>
<td>-50.8318</td>
<td>54.7291</td>
<td>-0.9288</td>
<td>0.3699</td>
</tr>
<tr>
<td>Temperature [°F]</td>
<td>-65.8521</td>
<td>51.1584</td>
<td>-1.2872</td>
<td>0.2205</td>
</tr>
<tr>
<td>Total Precipitation [in]</td>
<td>-58.4444</td>
<td>221.5751</td>
<td>-0.2638</td>
<td>0.7961</td>
</tr>
<tr>
<td>Gas Price [$/gal]</td>
<td>4661.0561</td>
<td>5651.3101</td>
<td>0.8248</td>
<td>0.4244</td>
</tr>
<tr>
<td>Unemployment Rate [%]</td>
<td>1355.2774</td>
<td>3384.9712</td>
<td>0.4004</td>
<td>0.6954</td>
</tr>
<tr>
<td>All-round Monthly Fare (SmarTrip) [§]</td>
<td>1146.4617</td>
<td>1173.1132</td>
<td>0.9773</td>
<td>0.3463</td>
</tr>
<tr>
<td>Inauguration Day</td>
<td>-1639.1076</td>
<td>2537.1128</td>
<td>-0.6461</td>
<td>0.5295</td>
</tr>
<tr>
<td>Cherry Blossom Days</td>
<td>-36.2563</td>
<td>150.4811</td>
<td>-0.2409</td>
<td>0.8134</td>
</tr>
<tr>
<td>Route Headway per Month [minutes]</td>
<td>-1204522.245</td>
<td>1527937.4958</td>
<td>-0.7883</td>
<td>0.4446</td>
</tr>
<tr>
<td>Number of Stops</td>
<td>2324.4684</td>
<td>634.3732</td>
<td>3.6642</td>
<td>0.0029</td>
</tr>
<tr>
<td>Service Runs per Day</td>
<td>628.0045</td>
<td>871.4534</td>
<td>0.7206</td>
<td>0.4839</td>
</tr>
</tbody>
</table>

**Total Boardings per Revenue Hour.** The total boardings per revenue hour are the number of passengers who board the bus per hour when revenue is being collected. This variable positively impacts transit ridership and is statistically significant.

**Incentive.** LCT provides a $100 incentive to cover bus fares for riders whose commutes were impacted by the tolls. This incentive has positively impacted ridership, but it is not significant.

**Toll.** The toll is the average toll price for an all-round trip based on the VDOT 6 month I-66 Inside the Beltway performance report. The toll has negatively impacted transit ridership but is not statistically significant to the analysis. This toll has provided riders with a new commuting option: traveling as an SOV.
Temperature. The temperature is a monthly average corresponding to the month of ridership. The coefficient is negative, and the variable is not statistically significant.

Total Precipitation. The total precipitation is the sum of precipitation during the month, including combined rainfall and snowfall. While this negatively impacts transit ridership, it is not statistically significant to the model.

Gas Price. The gas price is the monthly average per gallon in the region. A higher case price correlates to an increase in transit ridership but is not statistically significant to the model.

Unemployment Rate. The unemployment rate is the monthly average for the country. For this model, a higher unemployment rate positively impacts transit ridership. This indicates that riders do not use the transit system exclusively for commuting purposes.

All-round Monthly Fare (SmarTrip). The all-round monthly fare is the cost per month for a round trip paying with a SmarTrip card as opposed to cash. The fare is $10 per ride for SmarTrip users and $11 per ride for those who pay in cash. The model only looks at the impact of the SmarTrip fare since it is the lower cost. The cost for the entire month was calculated from the operation days. For example, in July 2016, there were 20 operation days, so the cost to take the roundtrip bus rides for the entire month would be:

\[
\frac{\$10}{trip} \times \frac{2 \text{ trips}}{day} \times \frac{20 \text{ operation days}}{month} = \$400/month
\]

Inauguration Day. The 2017 Inauguration day is simulated as a dummy variable in the analysis to capture any unique ridership during January 2017. Ridership was negatively impacted by the Inauguration day. This is most likely because these are commuter routes and, since Inauguration day is a federal holiday for many government workers in
Washington, D.C. and the surrounding area, many commuters would not be going to work.

**Cherry Blossom Days.** The Cherry Blossom Days are meant to capture any ridership change due to the blossoming cherry trees at the tidal basin in Washington, D.C. and the surrounding area. This is a dummy variable that assumes the cherry trees are in bloom for 14 days. In 2017, the cherry blossoms bloomed early, so the dummy variable is put completely in March 2017. In 2018, the cherry blossoms bloomed in late March, so the dummy variable is split into 9 days and 5 days for March 2018 and April 2018 respectively. This natural event negatively impacts transit ridership. Loudoun County is close to 50 miles away from the Tidal Basin. Since viewing the Cherry Blossoms is a recreational trip, travelers would either not be interested in seeing the blossoms because of the distance or would be taking alternate modes of transportation, such as carpooling with family or friends.

**Route Headway per Month.** The route headway is average headway across all commuter routes based on the May 2016, August 2016, July 2017, and July 2018 historic timetables provided by LCT. The average headway across all stops and routes is approximately 21 minutes, but the seconds vary slightly for each schedule. Over time, LCT has decreased its service headway. The average headway for July 2018 was faster than the July 2017 frequency by 1 second. To calculate the route headway per month, the average headway for the schedule was multiplied by the operation days in the month. The negative coefficient shows that this variable negatively impacts ridership. LCT has decreased its service by 2 bus stops and gradually decreased the headway to stops slightly and
therefore is no longer attracting users at those stops. Either the decrease in service is negatively impacting ridership or the service that is currently being provided is not enough to accommodate the influx of riders.

**Number of Bus Stops.** This is the number of bus stops serviced by each line. The number of stops positively impacts ridership and is statistically significant. As bus service is enhanced, more riders are attracted to the mode. LCT has gradually increased the number of stops serviced to 122, until July 2018 where the stops were decreased to 120.

**Service Runs per Day.** The service runs per day represents the number for lines on a bus route per day. The ridership is positively impacted by this variable, but it is not statistically significant.

When only the statistically significant variables are included in the model, the R$^2$ becomes 28.4% and the adjusted R$^2$ becomes 22.4%. The F statistic is 4.75 and the significance F is 0.0181. The intercept is -141,519. The linear equation for LCT becomes

**Equation 6.**

\[ y = 2594.61TRH + 141164NS - 141,519 \]

Equation 6: LCT linear equation when only significant variables are modeled.

Where y equals the ridership, TRH is the total boardings per revenue, and NS is the number of stops. However, due to the lower R$^2$, the predictive power of this model is low.
4.1.2 Potomac and Rappahannock Transportation Commission (PRTC)

PRTC offers several different bus options on I-66. The commuter buses travel on I-66 during tolling hours. The ridership data was reported monthly. The F statistic is 53.77 and the Significance F is 5.25E-10. The intercept is –12,449.15. The $R^2$ is 97.5% and the adjusted $R^2$ is 95.7%. All the variables in Table 8 were modeled but only Route Headway per Month was significant. The linear equation can be seen below in Equation 7.

$$y = 30491.83RH - 12,449.15$$

Equation 7: PRTC equation when all variables are modeled.

Where $y$ equals the ridership and $RH$ is the average route headway per month. The tabular summary of the complete results of the analysis is presented in Table 8.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>S.E.</th>
<th>t Stats</th>
<th>P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toll [$]</td>
<td>1.0854</td>
<td>3.9884</td>
<td>0.272129</td>
<td>0.7892</td>
</tr>
<tr>
<td>Temperature [°F]</td>
<td>46.4230</td>
<td>31.8244</td>
<td>1.458725</td>
<td>0.1653</td>
</tr>
<tr>
<td>Total Precipitation [in]</td>
<td>-214.6958</td>
<td>157.3819</td>
<td>-1.36417</td>
<td>0.1926</td>
</tr>
<tr>
<td>Gas Price [$/gal]</td>
<td>1539.3886</td>
<td>4109.8433</td>
<td>0.374561</td>
<td>0.7132</td>
</tr>
<tr>
<td>Unemployment Rate [%]</td>
<td>-1472.4132</td>
<td>2405.4275</td>
<td>-0.61212</td>
<td>0.5496</td>
</tr>
<tr>
<td>Fare (All-round trip) [$]</td>
<td>-295.3077</td>
<td>214.1589</td>
<td>-1.37892</td>
<td>0.1881</td>
</tr>
<tr>
<td>Route Headway per Month [minutes]</td>
<td>30491.8482</td>
<td>9193.9754</td>
<td>3.316503</td>
<td>0.0047</td>
</tr>
<tr>
<td>Inauguration Day</td>
<td>-2543.3157</td>
<td>1966.7416</td>
<td>-1.29316</td>
<td>0.2155</td>
</tr>
<tr>
<td>Cherry Blossom Days</td>
<td>129.9076</td>
<td>87.7384</td>
<td>1.480625</td>
<td>0.1594</td>
</tr>
<tr>
<td>Service Runs per Day</td>
<td>1837.3551</td>
<td>1117.1869</td>
<td>1.644626</td>
<td>0.1208</td>
</tr>
<tr>
<td>Number of Bus Stops</td>
<td>-2344.7887</td>
<td>2570.3192</td>
<td>-0.91226</td>
<td>0.3761</td>
</tr>
</tbody>
</table>
**Toll.** The toll is the average toll price for an all-round trip based on the VDOT 6 month I-66 Inside the Beltway performance report. The coefficient of the toll is 1.0854. Since it is positive, the toll is positively impacting transit ridership. However, this positive impact is not statistically significant, as seen in the P-value of 0.7892.

**Temperature.** The temperature is a monthly average corresponding to the month of ridership. The coefficient is positive, and the variable is not statistically significant.

**Total Precipitation.** The total precipitation is the sum of precipitation during the month. While this negatively impacts transit ridership, it is not statistically significant to the model. This makes sense since precipitation in the Northern Virginia area is extremely unlikely to deter workers from embarking on their commutes.

**Gas Price.** The gas price is the monthly average per gallon in the region. A higher case price correlates to an increase in transit ridership but is not statistically significant to the model.

**Unemployment Rate.** The unemployment rate is the monthly average for the country. The coefficient is negative, which is understandable since its unemployment rates are higher, previously regular commuters would no longer be taking those routes.

**Fare.** The all-round fare negatively impacts ridership. PRTC normal SmarTrip fare for commuter express buses is $13.80 for the all-round trip. In May 2018, PRTC halved their fare across all commuter services. Since there, the all-round SmarTrip fare has been $6.90.

**Route Headway per Month.** The route headway is average headway across all commuter routes based on the February 2019 bus time tables. Historic bus timetables from PRTC
were unavailable. Because of this, the result may be more liberal than accurate, since, over time, PRTC has enhanced the service of its transit system by incorporating more bus lines, routes, and stops. The coefficient shows that ridership is positively impacted by decreased headway. This makes sense since rational riders would be attracted to good quality service.

**Inauguration Day.** The 2017 Inauguration day is simulated as a dummy variable in the analysis to capture any unique ridership during January 2017. Ridership was negatively impacted by the Inauguration day. This is most likely because these are commuter routes and, since Inauguration day is a federal holiday for many government workers in Washington, D.C. and the surrounding area, many commuters would not be going to work.

**Cherry Blossom Days.** The Cherry Blossom Days are meant to capture any ridership change due to the blossoming cherry trees at the tidal basin in Washington, D.C. and the surrounding area. This is a dummy variable that assumes the cherry trees are in bloom for 14 days. In 2017, the cherry blossoms bloomed early, so the dummy variable is put completely in March 2017. In 2018, the cherry blossoms bloomed in late March, so the dummy variable is split into 9 days and 5 days for March 2018 and April 2018 respectively. This natural event positively impacts transit ridership, though is not statistically significant.

**Service Runs per Day.** The service runs per day represents the number for lines on a bus route per day. The ridership is positively impacted by this since more bus lines on a route enhance the service.
Number of Bus Stops. This is the number of bus stops serviced by each line. In December 2016, with the introduction of a new bus route and a split route, PRTC increased its number of bus stops from 27 to 31. The results show that the number of bus stops negatively impact ridership.

When only the statistically significant variables are included in the model, the $R^2$ becomes 69.4% and the adjusted $R^2$ becomes 68.1%. The F statistic is 56.64 and the significance F is 7.02E-08. The intercept in -25,306.97. The linear equation for PRTC becomes Equation 8.

$$y = 83,085.39RH - 25,306.97$$

Equation 8: PRTC linear equation when only significant variables are modeled.

Where $y$ equals the ridership and $RH$ is the average route headway in minutes.

4.1.3 Washington Metropolitan Area Transit Authority (WMATA)

WMATA has one route that travels along the I-66 corridor. The 5A is an express airport bus. Because of the sophistication of WMATA’s data collection, more variables were able to be provided and used to aid the analysis. The $R^2$ is 89.6% and the adjusted $R^2$ is 89.3%. All the variables that were tested are summarized in Table 9. The significant variables are designated in red.
Table 9: Presenting results of WMATA regression analysis.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>S.E.</th>
<th>t Stats</th>
<th>P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip End Time [hr:min:sec]</td>
<td>235.0484</td>
<td>102.2880</td>
<td>2.2979</td>
<td>0.0221</td>
</tr>
<tr>
<td>Trip Duration [min]</td>
<td>59991.5895</td>
<td>4657.1532</td>
<td>12.8816</td>
<td>5.143E-32</td>
</tr>
<tr>
<td>On time</td>
<td>-69.1775</td>
<td>567.3887</td>
<td>-0.1219</td>
<td>0.9030</td>
</tr>
<tr>
<td>Trip Late [%]</td>
<td>-43.8529</td>
<td>139.7680</td>
<td>-0.3138</td>
<td>0.7539</td>
</tr>
<tr>
<td>Trip On time [%]</td>
<td>-12.8924</td>
<td>183.2817</td>
<td>-0.0703</td>
<td>0.9440</td>
</tr>
<tr>
<td>Passengers per mile</td>
<td>126.6938</td>
<td>3.1846</td>
<td>39.7828</td>
<td>2.73E-141</td>
</tr>
<tr>
<td>Revenue miles [miles]</td>
<td>-23.9146</td>
<td>35.2409</td>
<td>-0.6786</td>
<td>0.4978</td>
</tr>
<tr>
<td>Toll [$]</td>
<td>49.7165</td>
<td>7.6907</td>
<td>6.4645</td>
<td>2.96E-10</td>
</tr>
<tr>
<td>Gas Price [$/gal]</td>
<td>3548.9871</td>
<td>1540.6398</td>
<td>2.3036</td>
<td>0.0218</td>
</tr>
<tr>
<td>Unemployment rate [%]</td>
<td>-943.9208</td>
<td>785.7967</td>
<td>-1.2012</td>
<td>0.2304</td>
</tr>
<tr>
<td>Temperature [°F]</td>
<td>-18.5978</td>
<td>7.8874</td>
<td>-2.3579</td>
<td>0.0189</td>
</tr>
<tr>
<td>Total Precipitation [in]</td>
<td>429.2907</td>
<td>69.3798</td>
<td>6.1875</td>
<td>1.51E-09</td>
</tr>
<tr>
<td>Inauguration Day</td>
<td>-73891.995</td>
<td>8648.7635</td>
<td>-8.5436</td>
<td>2.75E-16</td>
</tr>
<tr>
<td>Cherry Blossom Days</td>
<td>-9239.0312</td>
<td>1160.6847</td>
<td>-7.9600</td>
<td>1.79E-14</td>
</tr>
<tr>
<td>Fare [$]</td>
<td>-4964.4971</td>
<td>1278.5815</td>
<td>-3.8828</td>
<td>1.21E-04</td>
</tr>
</tbody>
</table>

**Trip End Time.** This is the time the scheduled trip ends. The positive coefficient shows that this variable attracts riders and is statistically significant to the analysis.

**Trip Duration.** The trip duration is the trip end time minus the trip start time. This positively impacts transit ridership and is statistically significant.

**On time.** This variable is measured at specific locations in the public schedules called time points. WMATA defines being on time between arriving 2 minutes early to 7 minutes late to the timepoint. This variable negatively impacts transit ridership and is not statistically significant.
**Trip Late.** This is the percentage of late trips for timepoints. Late is defined as any trip more than 7 minutes past the scheduled time. This variable negatively impacts transit ridership and is not statistically significant.

**Trip On time.** This is the percentage of on time trips for timepoints. On time is defined by WMATA as being between 2 minutes early and 7 minutes late to the timepoint. This variable negatively impacts transit ridership and is not statistically significant.

**Passenger per Hour.** The passengers per hour are the number of passengers on the bus per hour. This variable has a positive coefficient and is extremely statistically significant. This makes sense since ridership is a function of the number of passengers who are on the bus.

**Revenue Miles.** The revenue miles are calculated by multiplying the fare paid by each passenger by the miles traveled. This variable has a negative coefficient and is not statistically significant.

**Toll.** The toll price is the average per quarter per time period. Tolling variables are only included for AM Peak eastbound and PM Peak westbound trips. The toll has positively impacted transit ridership and is statistically significant to model.

**Gas Price.** The gas price is the quarterly average per gallon in the region. A higher case price correlates to an increase in transit ridership and is statistically significant to the model.

**Unemployment Rate.** The unemployment rate is the quarterly average for the country. A higher unemployment rate corresponds to a decrease in transit ridership. This is probably because people will not be taking work trips when they are unemployed.
Temperature. The temperature is a quarterly average corresponding to the quarterly schedule of ridership. The average shows mild temperature changes in the region. This variable negatively impacts transit ridership and is statistically significant. Since the average temperatures are not veering towards any extreme, people may choose to take alternate modes depending on the temperature or season.

Total Precipitation. The total precipitation is the sum of precipitation during the quarterly schedule. This includes both rainfall and snowfall. More precipitation promotes transit ridership. During bad weather, people seem to rather take transit than deal with other modes.

Inauguration Day. The 2017 Inauguration day is simulated as a dummy variable in the analysis to capture any unique ridership during January 2017. Ridership was negatively impacted by the Inauguration day and was statistically significant. This is most likely because these are commuter routes and, since Inauguration day is a federal holiday for many government workers in Washington, D.C. and the surrounding area, many commuters would not be going to work.

Cherry Blossom Days. The Cherry Blossom Days are meant to capture any ridership change due to the blossoming cherry trees at the tidal basin in Washington, D.C. and the surrounding area. This is a dummy variable that assumes the cherry trees are in bloom for 14 days. In 2017, the cherry blossoms bloomed early, so the dummy variable is put completely in March 2017. In 2018, the cherry blossoms bloomed in late March, so the dummy variable is split into 9 days and 5 days for March 2018 and April 2018.
respectively. This natural event negatively impacts transit ridership and is statistically significant.

**Fare (SmarTrip)**. The 5A is an airport express route. The fare was $7.00 per trip until the June 2017 schedule began, when the fare was increased to $7.50. This variable has negatively impacted transit ridership and is statistically significant.

When only significant variables are modeled, the $R^2$ becomes 83.6% and the adjusted $R^2$ is 83.3%. The intercept is 1,628.57. The F statistic is 259.65 and the Significant F is 7.123E-155. The results of the regression analysis are in Table 10.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>S.E.</th>
<th>t Stats</th>
<th>P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip End Time [hr:min:sec]</td>
<td>298.543</td>
<td>121.6973</td>
<td>2.453</td>
<td>0.0145</td>
</tr>
<tr>
<td>Trip Duration [min]</td>
<td>58633.788</td>
<td>5032.414</td>
<td>11.651</td>
<td>2.802E-27</td>
</tr>
<tr>
<td>Passengers per hour</td>
<td>127.703</td>
<td>3.842</td>
<td>33.237</td>
<td>7.317E-118</td>
</tr>
<tr>
<td>Toll [$]</td>
<td>70.119</td>
<td>9.369</td>
<td>7.484</td>
<td>4.467E-13</td>
</tr>
<tr>
<td>Inauguration Day</td>
<td>-26671.276</td>
<td>5855.788</td>
<td>-4.555</td>
<td>6.938E-06</td>
</tr>
<tr>
<td>Cherry Blossom Days</td>
<td>-2075.993</td>
<td>390.212</td>
<td>-5.320</td>
<td>1.713E-07</td>
</tr>
<tr>
<td>Fare [$]</td>
<td>-1816.716</td>
<td>244.866</td>
<td>-7.419</td>
<td>6.899E-13</td>
</tr>
</tbody>
</table>

**4.2 Student Survey Analysis: Results of GMU student mode choice survey**

The data was summarized as a descriptive study and analyzed in STATA 15.1 using a binary logit model.
4.2.1 Descriptive Results

There were 268 respondents to the survey. There were 238 complete responses and 30 incomplete responses. Several of these respondent’s data had to be excluded due to insufficient completion or nonresponse. However, some incomplete surveys were still included in the model if the respondent had answered most of the questions. The question that the respondents skipped the most related to gender. These were classified as nonresponses. The ideal sample size for the U.S. campus student population of the university is 35,929 with a 95% confidence level and a 6% margin of error. The number of respondents falls into this category. When only completed surveys are considered, the sample size is ideal with a 95% confidence level and a 7% margin of error. The same sample size metrics are applicable when just the demographics of the engineering school are looked at. Since the majors of the students who took the surveys cannot be determined but the survey was advertised mostly to engineering students, it is reasonable to assume that mostly engineering students took the survey. The sample size is significant for descriptive purposes.

The majority of students on the Fairfax Campus are female and most of the students in the engineering school are male. While the survey was advertised to the entire Fairfax Campus, it was mostly advertised to students in the engineering school. Ultimately, approximately 55% of respondents were male, 41% were female, and 4% were N/A. Additionally, most of the students enrolled at the U.S. campuses are undergraduates. The survey respondents were also mostly undergraduates, with 72%
undergraduates, 22% graduate students, 6% non-degree seeking students, and 0.42% were N/A.

Most undergraduates were financially dependent on a parent, guardian, or significant other while graduate students were mostly financially independent. Consequently, undergraduates had higher incomes than graduate students, probably because they were being financially supported by more than one income. Many respondents’ annual household incomes fell within the $120,000-$199,999 range. Only 10% of respondents had less than $14,999 of annual household income and only 5.6% of respondents had an annual household income more than $200,000. No graduate students had annual household incomes more than $200,000. Nearly 13.4% of respondents did not respond to this question, making it the second most skipped question in the survey. Even though the survey was anonymous, students may have felt uncomfortable disclosing this information.

The respondents mostly lived within 20 miles of the Fairfax Campus. Students who lived on campus accounted for 22.7% of the sample. Only 2.5% of respondents lived more than 30 miles away from the campus. Approximately, 5.8% of respondents did not have a valid driver’s license and 23.8% did not have access to a car for their commuting to campus. Finally, only 28% of all respondents were new to the university within the past year. This number increased to 32% when only completed surveys were looked at.

Overall, because of the sample size and demographics, the data is adequate to describe the university population.
Safety 1. This variable represents the answer to the statement “I feel safe taking the bus at night.” More than half (around 65.6%) of the survey respondents agreed with this statement. However, 57.7% of female respondents reported they did not feel safe taking the bus at night. When just graduate students are examined, only 13.2% disagreed with the statement wherein only 7.5% were female.

Accessibility 1. This variable represents the answer to the statement “I have access to a car for my commuting.” Around 71.2% of respondents reported that they did have access to a car for commuting purposes, while 23.8% did not and 0.05% were N/A.

Stability. This variable represents the answer to the statement “I often take commuting trips with little to no planning.” Out of the 268 respondents, 115 agreed with the statement, 139 disagreed, and 14 were N/A.

Accessibility 2. This variable represents the answer to the statement “I take the bus because I do not have access to a car.” As stated previously, most of the respondents agreed that they had access to a car for their commuting. Because of this, the number of respondents who agreed with Accessibility 2 should be less than or equal to the number of respondents who disagreed with Accessibility 1. Approximately 26.5% of respondents agreed that they took the bus because they did not have access to a car. This is more than the number of 23.9% of respondents who did not have access to a car for their commuting. This discrepancy is most likely explained to an additional respondent not answering this question. In Accessibility 1, 13 respondents answers were N/A while in Accessibility 2, 14 respondents answers were N/A.
**Preference/Attitude 1.** This variable represents the answer to the statement “Even if taking the bus is faster, I still prefer driving.” This statement is purely to gauge respondent’s mode choices regardless of faster travel time. Over half of the respondents (58.2%) agreed that they preferred driving over taking the bus even if the bus was faster, while 36.6% disagreed and 5.2% were N/A.

**Safety 2.** This variable represents the answer to the statement “I do not like to travel with strangers on transit.” Most of the respondents disagreed with this statement (64.6%). Only 38.1% of females agreed that they did not like to travel with strangers on transit.

**Reliability 1.** This variable represents the answer to the statement “I believe the bus arrives on schedule.” 61.6% of respondents agreed with this statement while 32.1% disagreed and 6.3% were unavailable.

**Reliability 2.** This variable represents the answer to the statement “I like to depend on my own driving instead of a transit service to meet my transportation needs.” Surprisingly, only 33.6% of respondents agreed with this statement. Around 57.8% disagreed and were willing to rely on a transit service to meet their transportation needs. However, 8.6% of responses were N/A.

**Toll 1.** This variable represents the answer to the statement “I think the I-66 tolls have improved travel time on the corridor.” This question/statement is important in understanding the students’ perception of the I-66 project. Over half of respondents disagreed that the I-66 tolls had improved the travel time. The remaining 44% agreed and 5.2% of responses were N/A.
**Preference/Attitude 2.** This variable represents the answer to the statement “If I have a bad experience with something, I am not likely to give it a second chance.” 64.2% of respondents agreed with this statement, 30.6% disagreed, and 5.2% were N/A.

**Toll 2.** This variable represents the answer to the statement “I think the tolls on I-66 are too high.” Just over 64% of respondents agreed that the tolls were too high, 30.6% disagreed, and 5.2% were N/A.

**Early Adopter 1.** This variable represents the answer to the statement “When Autonomous Vehicles become available for commercial use, I want to try them out.” While most respondents did agree with this statement, it was only 65.3% which is smaller than expected.

**Early Adopter 2.** This variable represents the answer to the statement “I have tried using an electric vehicle when it first became commercially available.” As expected, the number of respondents who have actually used an electric vehicle when it first became commercially available is very small (14.9%).

**Time Flexibility 1.** This variable quantifies the amount of time respondents are willing to be late for class. On average, respondents were willing to be late to class by 5.62 minutes.

**Time Flexibility 1.** This variable captures the amount of time respondents are willing to be late for a social event. On average, respondents were willing to arrive late to a social event by 16.92 minutes.

**Arrival Time.** This variable captures the amount of time respondents are willing to be late for a social event. On average, respondents were willing to arrive late to a social event by 16.92 minutes. Undergraduates were willing to arrive later to class and social events than
graduate students and non-degree seeking students. Males were willing to arrive later to class and earlier to social events than females.

4.2.2 Discrete Choice Analysis Results

The 268 respondents were asked to complete three different stated preference scenarios. In each scenario (or case), there were two alternatives for the respondent to choose from in three rounds of comparison. Overall, there was a total of 8 different possible combinations of attributes determined by the individual respondent’s choices.

Scenario 1 – Drive vs Bus. The first model in this scenario uses all relevant independent variables: expense, time, gender, Preference/Attitude1, Safety 2, Reliability 1, and Accessibility 1. Expense is a combination of the toll price and the fare combination for each option. There were 1,420 observations with 710 cases. Due to no positive outcome per case, a total of 3 cases (6 observations) were dropped from the model. There were 2 alternatives per case and 3 cases per respondent.

Using these variables, the log-likelihood value increased to -459.34. The Wald chi-squared test was 53.29 with 6 degrees of freedom. Since the P-value was less than 0.05, this model is statistically significant. The summary of the results for Scenario 1 can be seen in Table 11.
Table 11: Presenting results for Scenario 1.

| Variables                  | Coefficients | S.E.  | z     | P > |z| |
|----------------------------|--------------|-------|-------|-----|---|
| Expense                   | -0.0977      | 0.0204| -4.77 | 0.000 |
| Time                      | -0.0207      | 0.0078| -2.66 | 0.008 |
| Preference/Attitude1      | -0.6464      | 0.1790| -3.61 | 0.000 |
| Safety2                   | -0.3900      | 0.1779| -2.19 | 0.028 |
| Reliability1              | 0.3449       | 0.1663| 2.07  | 0.038 |
| Accessibility1            | -0.6580      | 0.1863| -3.53 | 0.000 |

Scenario 2 – Conditional AV vs Conventional Car. There were 1,424 observations and 712 cases. The log likelihood is -309.117 and the Wald chi-squared test with 3 degrees of freedom is 18.60, with the P-value less than 0.05. The results are summarized in Table 12.

Table 12: Presenting results from Scenario 2.

| Variables                  | Coefficients | S.E.  | z     | P > |z| |
|----------------------------|--------------|-------|-------|-----|---|
| Time                      | 0.1042       | 0.0321| 3.25  | 0.001 |
| Cost per Trip             | 0.0785       | 0.0215| 3.64  | 0.000 |
| Preference/Attitude2      | 0.4357       | 0.2138| 2.04  | 0.042 |

Scenario 3 – Full AV vs Conventional Car. There were 1,332 observations and 666 cases for this model. The log-likelihood function of the base model was -278.403. The Wald chi-squared test was 73.62 with 4 degrees of freedom and the P-value was statistically significant. The final model was developed by using all statistically significant variables. Income based on category was used because it provided better results than the median range income. The summary of variables in the model can be seen in Table 13.
Table 13: Displaying results for Scenario 3.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>S.E.</th>
<th>z</th>
<th>P &gt;</th>
<th>z</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>0.2516</td>
<td>0.0341</td>
<td>7.37</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost per trip</td>
<td>0.0803</td>
<td>0.0168</td>
<td>4.78</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>-0.1076</td>
<td>0.0501</td>
<td>-2.15</td>
<td>0.032</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preference/Attitude2</td>
<td>0.7446</td>
<td>0.2300</td>
<td>3.84</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 5: DISCUSSION

5.1 Impacts of the I-66 HOT Lanes on Transit

The ridership of each transit agency reacted differently since the implementation of the tolls. In LCT’s case, the only statistically significant variables were total boardings per revenue hour and the number of stops serviced per day. Both variables positively impacted transit ridership. According to NCTV’s June 2018 report, LCT has experienced increased transit ridership since the opening of the tolls (NVTC, 2018). According to the results of this model, the tolls negatively impact ridership and has a P-value of 0.3699, which is not statistically significant. The conversion of HOV lanes to HOT lanes provides commuters with another option (to travel as an SOV) that they have not had on the route. In this situation, the new mode option could have drawn riders away from LCT. Finally, the route frequency had a negative coefficient.

While LCT has slightly improved its service since 2016, this is only a slight variation from schedule to schedule. According to NVTC, LCT enhanced its commuter bus service by adding two additional bus routes during each peak period (Routes 210, 211, 611, and 612) (NVTC, 2018). Additionally, commuter bus services were extended to “the newly built Dulles South park and ride lot” (NVTC 2018). LCT decreased the number of bus stops serviced in 2018. Obviously, removing stops from a route removes any riders attracted to those stops since the stops no longer exist.
In PRTC’s case, the presence of a toll was also not statistically significant. PRTC enhanced its service in anticipation of the new toll, by adding a new route (G200), splitting an existing route into two (M100 and M200), and increasing the bus frequency. This enhanced service is most likely the cause of increased ridership. Furthermore, this enhanced service explains while the route frequency per month was a positively correlated and statistically significant variable with a P-value of 0.0047. In the model that exclusively analyzed the statistically significant value, the P-value became 7.02E-08.

The toll was statistically significant for WMATA ridership. In this scenario, the presence of the toll positively impacted WMATA ridership on the 5A. Bus riders are encouraged to take the 5A because of the toll. The trip end time, trip duration, passengers per mile, gas price, and total precipitation were also had positive coefficients and were statistically significant. The variables for temperature, Inauguration Day, Cherry Blossom Days, and fare had negative coefficients and were also statistically significant. Since the 5A is an airport express route to Dulles Airport in Sterling, VA, the fare is $7.50, previous $7.00 until the June 2017 schedule.

5.2 University Student Survey

5.2.1 Correlation of Variables

A correlation test was done in order to ensure that the independent variables used the discrete choice analysis were truly independent. All of the variables had the correct signs in relation to each other. All of the variables were independent, except for Preference/Attitude 1 and Early Adopter 1. These share an overlap over 0.5. However,
these two variables have nothing to do with one another. Preference/Attitude 1 exclusively deals with partiality towards driving a conventional car when compared to taking the bus in situations where the bus has a faster travel time. Early Adopter 1 simply asks the respondents if they are interested in trying autonomous vehicles when they become available. These variables were never intended to be used in the same model. Perhaps the reason the correlation test found a relationship between these variables is because of the relatively small data set used in the analysis.

5.2.2 Scenario 1

Scenario 1 compares two modes in a commuting scenario: driving vs taking the bus to attend class at the Fairfax Campus. The students’ willingness to pay is $12.71. This low value is expected since it is assumed students will have a higher sensitivity to cost.

Expense. This variable covers any exogenous cost the commuter may experience. In this scenario, the mode of driving has the additional expense of a toll. Taking the bus requires the traveler to pay the price of the fare. The coefficient is negative, as expected, since higher expense repels a user from a mode. This variable is statistically significant and has a P-value of near zero.

Time. The time is the approximate amount of time it would take the respondents to reach their destination if they selected a certain mode. The coefficient is negative since longer travel times discourage the selection of that mode. This variable is statistically significant with a P-value of 0.008.
**Safety 2.** This variable represents answers to the statement “I do not like to travel with strangers on transit.” It is statistically significant with a P-value of 0.028. The negative coefficient shows that those who agree with this statement are disinclined to select the bus over driving due to these safety concerns.

**Reliability 1.** This variable corresponds to the statement “I believe the bus arrives on schedule.” Those who agreed with this statement believed that the bus was reliable. This variable’s positive coefficient shows that those who held this positive view would pick commuting by bus over commuting by car. It is statistically significant and has a P-value of 0.038.

**Accessibility 1.** This variable denotes the answers to the statement “I have access to a car for my commuting.” Those who have access to a car for commuting purposes are not captive transit riders. This variable is statistically significant and has a P-value of 0.000. Since the first alternative (driving) is the base alternative, the negative coefficient indications that respondents were less likely to choose to take the bus to commute over the car option when they had access to a car.

**Preference/Attitude 1.** This variable captures responses to the statement “Even if taking the bus is faster, I still prefer driving.” It is statistically significant and has a negative coefficient, implying that if someone agrees with this statement, they have an intrinsic bias towards driving regardless of travel time. Safety, reliability, and accessibility are all included in the model and are statistically significant. Because of this, Preference/Attitude 1 can be used as a black box. It represents unobserved factors affecting bias towards driving outside of safety, accessibility, and reliability.
5.2.3 Scenario 2

Scenario 2 compares conditionally autonomous vehicles (level 3) with non-autonomous conventional cars. The odds ratio of each variable was used to better understand the relationship between the individual and their mode choices. A summary can be seen below in Table 14.

Table 14: Presenting the odds ratios for each variable used in Scenario 2.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>1.109</td>
</tr>
<tr>
<td>Cost per Trip</td>
<td>1.082</td>
</tr>
<tr>
<td>Preference/Attitude2</td>
<td>1.546</td>
</tr>
</tbody>
</table>

Cost per trip. This variable represents the hypothetical cost it would take to use a conditional AV or a conventional car for a trip. The cost changed depending on the option the respondent selected. In this model, the cost per trip is significant with a P-value of 0.000. The coefficient is positive, which is the opposite sign than what is typically expected. This sign change can be caused by a couple of things. This is the first scenario that includes a mode with Level 3 autonomy, it is possible that cost is regarded as an indicator of vehicle capacity, thus carrying a positive utility rather than a disutility. This is an unexplored area and further research is recommended to investigate the utility of cost in relation to autonomous vehicles.

Time. The time is the amount of time it will take to travel from the respondent’s origin to their destination using a specified mode. In order to create a reasonable comparison between the autonomous vs non-autonomous modes, each option had the same travel
time when a comparison was made. Depending on the options (or combination of options) that the respondent selected, the travel time increased from 30 minutes to 40 minutes. This variable is significant with a P-value of 0.001. The coefficient is positive, which is expected and indicates that longer travel times attract users towards the autonomous vehicle option for their travel. Since autonomous vehicles provide additional features, the value of time decreases since there are now opportunities to do activities other than driving.

**Preference/Attitude 2.** This variable represents those who agreed with the statement in the questionnaire “If I have a bad experience with something, I am not likely to give it a second chance.” This variable was statistically significant with a P-value of 0.042 and had a positive coefficient. If respondents agreed with this statement, they were less inclined to select the conditionally autonomous option. This variable captures more conservative approaches towards transportation modes.

### 5.2.4 Scenario 3

Scenario 3 compares fully autonomous vehicles (level 5) with non-autonomous conventional cars. The odds ratio of each variable can be seen below in **Table 15**.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>1.286</td>
</tr>
<tr>
<td>Cost per trip</td>
<td>1.083</td>
</tr>
<tr>
<td>Income</td>
<td>0.898</td>
</tr>
<tr>
<td>Preference/Attitude2</td>
<td>2.105</td>
</tr>
</tbody>
</table>

**Table 15**: Displaying a summary of the odds ratios for each variable in Scenario 3.
**Cost per trip.** This variable description is the same as in Scenario 2. The coefficient is positive, and the variable is significant with a P-value of 0.000. While utility of travel is assumed to be negative (or a disutility), the autonomous vehicle option has the potential of creating positive travel utility. For example, in Scenario 3, the survey respondents were provided with a description of the autonomous vehicle, saying that the respondent sleep, study, or relax while traveling. Autonomy has the potential of increasing the productivity of a traveler’s commuting time. Some researchers have noted that travel utility is comprised of three parts: “the utility for the activity at the destination, the utility for activities that can be conducted while traveling, and an enjoyment of the travel itself” (Redmond & Mokhtarian, 2001). The traditional understanding of travel disutility is within the first part, “while the latter two elements are typically ignored” (Redmond & Mokhtarian, 2001). The utilities that the autonomous vehicles provide fall into these two categories. Autonomous vehicles are still an emerging technology. Even though conditionally autonomous vehicles are available commercially, little to no studies have been done to examine the utilities of the consumers that make the choice to use this mode. Because of this, while it is reasonable that the cost per trip has a positive utility, more research needs to be done to further explore the relationship between AV consumers and their choices to assess whether this relationship is consistent.

**Time.** The variable description is the same as in Scenario 2. The coefficient is positive, and the variable is significant with a P-value of 0.000.

**Income.** The income is split into eight different categories, with 1 being the lowest income (less than $14,999) and 8 being the highest income level (more than $200,000).
The coefficient is negative, and the variable is significant with a P-value of 0.032. Individuals were higher incomes begin to gravitate away from the lower cost conventional car to the higher cost fully autonomous vehicle. This is in line with expectations.

*Preference/Attitude 2.* As previously stated in Scenario 2, this variable represents those who agreed with the statement, “If I have a bad experience with something, I am not likely to give it a second chance.” The variable is significant and has a P-value of 0.001. The coefficient is positive, and the results follow the same trend this variable had in Scenario 2.

### 5.3 Limitations

#### 5.3.1 Ridership Data

There are a couple of things to note about the PRTC data and the limitations in the analysis. First, route aggregate ridership was provided by PRTC only for Dec 2016 to Sept 2018. The average monthly ridership for July 2016 to Nov 2016 was calculated from the average weekday ridership from NVTC. Second, NVTC provided information regarding the M100 and M200 route split. However, no ridership for this route prior to the split was available from NVTC or PRTC. Third, NVTC provided service day information. For instance, in Dec 2016, routes M100, M200, and G200 only operated 14 days out of the month. Finally, the average headways across all commuter routes were calculated using the February 2019 bus timetables. Historic bus timetables from PRTC were unavailable. Since the analysis was done using timetables based on the current
conditions, it is possible that the results of the statistical model are more generous than realistic. For example, a news article published when G200 first became a route stated that the route would perform 8 service runs per day (4 per peak period) (InsideNova, 2016). In the February 2019 timetables, G200 performs 10 service runs per day. In the analysis, for Dec 2016, the number of service runs for G200 is recorded as 8 per day, but for the following months, it is recorded as 10 service runs per day because the information was not provided or found discussing when PRTC enhanced the G200 service.

5.3.2 Survey Data

For this study, out of a student population of 30,000+, only 268 individuals responded to the survey and there were 4,034 valid observations for the models. While this sample size is statistically significant with a 95% confidence interval and a 6% margin of error, a relatively small sample size can be potentially problematic to discrete choice modeling. This was seen in the correlation of two unrelated variables (Early Adopter 1 and Preference/Attitude 1). To assess the validity of the results, the methods and results of other surveys were examined.

In (Whalen et al., 2013), the survey was advertised “via email to all students (23,000+) enrolled” at the university for analysis in a multinomial logit model. Out of these 23,000+ students, 1150 responded. (Danaf et al., 2014) sent their survey only via email to all AUB students. There were only 594 observations. The authors acknowledged the limitation of the data set and performed a chi-squared test to determine the
independence of variables. (Eluru et al., 2012) also distributed their survey to all 19,662 surveys to faculty and staff at McGill University. A total of 4,698 respondents were used in the sample, with 2,032 student responses. Similarly, (Etminani-Ghasrodashti et al., 2018) was distributed to 1200 students online and through “paper and pencil advertisement.” Only 770 responses were usable in the analysis. (Molina-García et al., 2010) also used a paper survey to collect samples at two universities in Valencia, Spain. Because the respondents were “recruited via convenience sampling”, all 518 students who received the survey completed it (Molina-García et al., 2010). The total population of the universities is unknown, since the schools were not identified in the study.

In (Zhou, 2012) 10% (3429) of the active students at UCLA “were randomly selected to receive the survey via email.” Out of the 769 respondents, the sample size was 508 (Zhou, 2012). The population of UCLA in 2012 was 36,503. The author compared the number of respondents with the population and performed a chi-squared test. In (Ewing et al., 2004)’s study, two travel diaries were administered under the authority of the Gainesville Metropolitan Transportation Planning Organization through telephone interview and mail-in travel surveys. The first travel survey had 374 responses from a population of 221,570 (Ewing et al., 2004). The second survey had 1766 responses from a population of 218,606 (Ewing et al., 2004). (Finkleman et al., 2011) also used a mail-back survey. The researchers distributed 4000 surveys but only 255 responses were returned and were used to represent the population of the Greater Toronto Area (between 5.7 and 5.9 million at the time of the study) (Finkleman et al., 2011).
In a stated preference study by (Yang, Choudhry, Ben-Akiva, Abreu e Silva, & Carvalho, 2009), a sample size of 150 respondents was used to represent the entire population of the Lisbon Metropolitan Area (2.776 million in 2008). This was a suitable sample size because the 150 respondents were specifically selected to take the survey because they “roughly correspond[ed] to the general socioeconomic characteristics of the Lisbon Metropolitan Area population” (Yang et al., 2009). (Zhan et al., 2016) used an even smaller sample size to complete their analysis. Their survey was distributed online to all students enrolled at eight universities in China (Beijing Jiaotong University, Beihang University, Tsinghua University, Minzu University, Nanjing University, South East University, Fudan University, and Tongji University) for approximately 1 month (Zhan et al., 2016). The combined student population of these universities was approximately 255,156 students at the time of the survey. Only 1343 of the 1523 responses were valid, which makes the sample size of 0.52% of the total student population.

In (Rotaris & Danielis, 2014), 372 samples were collected through in-person interviews. The research targeted student commuters who lived in the province of Trieste, Italy. However, this number is unknown. The researchers guessed that about 40% of the university population in 2010 live in Trieste (approximately 8510 people) (Rotaris & Danielis, 2014). The researchers acknowledged that their sample size was quite small compared to the population it was trying to describe, but “it is usually the case for stated choice studies” (Rotaris & Danielis, 2014). Finally, a survey conducted to residents of Xi’an, China, “were recruited through their employers…”[and] conducted at their
employers’ sites” through web and paper-based surveys (Ye & Titheridge, 2017). There were a total of 1364 responses; 1215 responses were valid.

There are several reasons for listing all these studies. First, most of these studies are distributed online to the entire student population. The survey for this study was not permitted to be advertised to the entire university through email. It was only advertised via email to the engineering students. Even though the survey was not advertised through email to the entire university, a statistically significant sample size was obtained. Second, many of these studies acknowledge the small sample sizes in relation to the total population despite their best data collection efforts. Third, most of these studies model the data in multinomial logit models, as done in this study. All of these studies have still been able to produce significant results that further research. This is predominantly because the data is used for modeling purposes rather than descriptive studies. In his book on survey data and methods, (Groves, 2004) explains that data must be statistically significant for descriptive studies since the sample size seeks to “describe the characteristics of a fixed population.” Data used for modeling purposes, however, depends on the variances of the data set to create good models used for identifying “causes of phenomena” and how these “phenomena affect one another” (Groves, 2004). This kind of data is concerned with correlations and regression coefficients (Groves, 2004). When (Van Acker, Mokhtarian, & Witlox, 2014) experienced a small sample size for their study, they stressed the point that what truly matters for modeling purposes is the “relationship between variables” and a small sample “can still properly capture…the conditional influence” that one variable has on another.
Finally, in their book on discrete choice analysis, (Ben-Akiva & Lerman, 1985)’s only requirement for smaller sample sizes to be adequate to discrete choice models was to make sure that the sample size is unbiased and efficient (relating to the variance of the estimators). As stated previously, the data for this study is not only statistically significant but samples respondents across all demographics. Because of this, even though the sample may be smaller than what is desired, the results of the study are still valid and provide important insights into the relationships between variables relating to student mode choice.

5.4 Future Work

The bus data used for this study was very limited, simply because the I-66 tolling facility is fairly new. While all transit operators that service the I-66 HOT lanes were contacted, only three operators provided data. From these three, only WMATA provided hourly farebox and APC data, though only farebox data was used for the analysis. Additionally, the data for the study was between July 2016 to September 2018, which is a relatively short time period. In the future, doing a long-range study that looks at a larger data set that encompassed several economic cycles could be very insightful for the region. This data could be used to do a time series analysis to do a statistical analysis of the lanes over a long period of time.

Most literature surrounding student surveys only focuses on the student while they are a student. A larger scale survey that follows up with the survey participants after they have entered the workforce could be helpful in predicting long term transportation
behavior. By comparing their transportation opinions in the working world with their transportation opinions as students, an analysis can be done to assess how much the individual’s opinion has changed. This could help transportation policymakers and transit operators in the long term provide the future workforce with transportation that meets their wants and needs.
CHAPTER 6: CONCLUSION

The purpose of this study was to analyze the impact of the I-66 HOT lanes on transit and understand the mode preferences of university students at George Mason University relating to transit, tolls, and autonomous vehicles. Since Northern Virginia is part of the Washington D.C. Metropolitan Area, it has some of the worst congestion in the world. With the impending arrival of Amazon HQ2, the additional workers brought through increased economic development can put further strain on the existing transportation system. Additionally, as new technologies like autonomous vehicles enter the market place, consumers travel behavior could change with the introduction of these new mode choices. HOT lanes and transit are some ways to help mitigate congestion. However, since the future workers are currently university students, a key part of a successful congestion mitigation method is if the users are attracted to that system. Because of that, the transportation preferences, attitudes, and habits of university students are paramount in making future transportation decisions on infrastructure investment.

The regression models of LCT, PRTC, and WMATA showed that each transit agencies reacted differently to the implementation of the toll. The impact of the toll on aggregated ridership of commuter buses along the I-66 corridor was only statistically significant to WMATA. This finding can be explained by several reasons. First, transit ridership has been gradually decreasing for years in the region for many reasons. Many
express bus services along I-66 were new and the short history makes it hard to control confounding factors. Second, the HOT lanes give people who previously could not use I-66 during peak periods without meeting the HOV requirements (or without meeting the green vehicle requirements) the opportunity to travel on the corridor as an SOV. This option may have proven more desirable to the commuters than taking transit. Since the toll was not statistically significant to LCT or PRTC, it cannot conclusively be said that the I-66 tolls have positively or negatively impacted transit ridership. Instead, only the observations can be reported and discussed.

Both PRTC and LCT enhanced its service in anticipation of the tolls. For PRTC, this enhanced service that seems to be attracting riders, not the toll. However, since there was limited availability of the historic PRTC bus schedules, the model is made using February 2019 headway data, which could make the model yield more generous results. The toll negatively impacts LCT ridership, but so does the route headway. This appears to suggest that ridership is directly proportional to the services provided. If an agency provides good service with shorter headways, more riders are likely to be attracted to the system. Future research may address these issues and draw stronger conclusions by using data over a longer period of time.

A total of 268 samples were collected for the survey. While 30 of these responses were incomplete, most responses were able to be used depending on the scenario being analyzed. Descriptive statistics helped to summarize the demographics of the students who took the survey. Males were over-represented when compared to the overall GMU U.S. campus student population. However, this did not come as a surprise since the
survey was advertised most often to students in the engineering school (whose students are predominantly male). Mostly undergraduate students took the survey, which properly represents the U.S. student demographics. Additionally, while all income levels were represented, most respondents fell within the $120,000-$199,999 annual household income range. Undergraduate students had higher annual household incomes than graduate students. They were also mostly financially dependent on a parent, guardian, or significant other. Ultimately, the survey demographics were deemed to adequately represent the overall student population.

Three final multinomial logit models were developed for three different stated preference scenarios asking respondents questions about transit, tolls, and different levels so of vehicle autonomy. Expense and time had negative coefficients, meaning that as these values increased, the attraction to that mode would decrease. The willingness to pay was $12.71, which is unsurprising since the sample set are students. Respondents who reported a preference for driving even if the bus provided faster travel time in the survey section regarding general attitudes towards the transportation system were more likely to pick Option 1 – Drive over Option 2 -Bus. Individuals were more likely to choose the bus option if they perceive it to arrive on schedule. Having car accessibility for commuting purposes make respondents less likely to choose the Option 2 – Bus over Option 1 – Drive. The variable Preference/Attitude 1 captured a bias towards driving outside of accessibility, reliability, and safety. Future research will explore this further.

In Scenario 2 and Scenario 3, travel time and cost per trip had positive utilities. It is assumed that in autonomous scenarios, the travel time will have a positive coefficient
indicated that longer travel times will make the autonomous vehicle option more attractive for the same trip. Since scholars anticipate that autonomy would add time for travelers to be productive, this could produce some positive utility within the user. Only time, cost per trip, and Preference/Attitude 2 were significant variables in determining mode choice in Scenario 2. In Scenario 3, the cost per trip, time, income, and Preference/Attitude 2 were all significant variables.

With the increased population brought to the region through the impending economic development of Amazon HQ2, transit agencies best bet to attracting and retaining riders is by enhancing its service in preparation for the impending strain on the transportation system. Regular surveys should be done of GMU students and perhaps expanded to other local colleges and universities in the Washington D.C. Metro Area to gain a better insight into students’ transportation preferences. The information gained from these surveys can help better understand the transportation preferences of the future workforce.
APPENDIX: SURVEY

Below is the survey distributed to the GMU students. Alternative times and costs are indicated in brackets next to the appropriate variables.

Campus Transportation Study

Consent

<IRB CONSENT FORM IS PASTED HERE FOR THE PARTICIPANT TO READ>

[ ] Yes, I consent
[ ] No, I do not consent

(if no is selected, the subject is directed to the end of the survey)

Transportation Statements
The following are a series of 13 statements about transportation preferences. Please select "Agree" or "Disagree."

I feel safe taking the bus at night.
I have access to a car for my commuting.
I often take commuting trips with little to no planning.
I take the bus because I do not have access to a car.
Even if taking the bus is faster, I still prefer driving.
I do not like to travel with strangers on transit.
I believe the bus arrives on schedule.
I like to depend on my own driving instead of a transit service to meet my transportation needs.
I think the I-66 tolls have improved travel time on the corridor.
If I have a bad experience with something, I am not likely to give it a second chance.
I think the tolls on I-66 are too high.
When Autonomous Vehicles become available for commercial use, I want to try them out.
I have tried using an electric vehicle when it first became commercially available.
**Time**

1. How late are you willing to be? What is the range of flexibility for your arrival at your destination?
   a. For class/meeting *sliding bar from 0 to 50 minutes*
   b. For a social event *sliding bar from 0 to 50 minutes*

2. On a normal day traveling to campus, do you arrive when you expect to arrive?
   a. Yes, I arrive when I expect to arrive.
   b. No, I arrive 5-10 minutes later than I expected.
   c. No, I arrive 10-20 minutes later than I expected.
   d. No, I arrive 20+ minutes later than I expected.

**Options**
The following questions are different transportation scenarios. Please select the option that is most like what you would do in that situation.

It’s 6pm and time to go to the Fairfax Campus to attend your 7:20pm class.

Here are two hypothetical travel plans. Pick the most attractive transportation option for your commute.

  e. **Option 1 – Car (Drive)**
     i. Time = 30 minutes
     ii. Cost (toll) = $6 [$15]
     iii. Total walking distance = 1 minute

   **Round 2 – You Selected Option 1. Pick which option is the most attractive.**

   1. **Option 1 – Car (Drive)**
      a. Time = 30 minutes [40 minutes]
      b. Cost (toll) = $12 [$20]
      c. Total walking distance = 1 minute

   **Round 3 - You selected Option 1. Pick which option is the most attractive.**

     i. **Option 1 – Car (Drive)**
        1. Time = 30 minutes [40 minutes]
        2. Cost (toll) = $20 [$20]
        3. Total walking distance = 1 minute

     ii. **Option 2 – Bus**
        1. Time = 50 minutes [55 minutes]
        2. Cost (bus fare) = $2 [$10]
        3. Total walking distance = 5 minutes

 2. **Option 2 – Bus**
a. Time = 50 minutes
b. Cost (bus fare) = $2 [$5]
c. Total walking distance = 5 minutes

Round 3 - You selected Option 2. Pick which option is the most attractive.

i. Option 1 – Car (Drive)
   1. Time = 30 minutes [45 minutes]
   2. Cost (toll) = $12 [$20]
   3. Total walking distance = 1 minute

ii. Option 2 – Bus
   1. Time = 1hr and 10 minutes [60 minutes]
   2. Cost (bus fare) = $2 [$10]
   3. Total walking distance = 5 minutes

f. Option 2 – Bus
   i. Time = 50 minutes
   ii. Cost (bus fare) = $2 [$5]
   iii. Total walking distance = 5 minutes

Round 2 - You selected Option 2. Pick which option is the most attractive.

1. Option 1 – Car (Drive)
   a. Time = 30 minutes [40 minutes]
   b. Cost (toll) = $6 [$15]
   c. Total walking distance = 1 minute

Round 3 - You selected Option 2. Pick which option is the most attractive.

i. Option 1 – Car (Drive)
   1. Time = 30 minutes [45 minutes]
   2. Cost (toll) = $12 [$20]
   3. Walking distance = 1 minute

ii. Option 2 – Bus
   1. Time = 1hr 10 minutes [60 minutes]
   2. Cost (bus fare) = $2 [$10]
   3. Total walking distance = 5 minutes

2. Option 2 – Bus
d. Time = 1hr and 10 minutes [60 minutes]
e. Cost (bus fare) = $2 [$10]
f. Total walking distance = 5 minutes

Round 3 - You selected Option 2. Pick which option is the most attractive.

i. Option 1 – Car (Drive)
1. Time = 30 minutes [45 minutes]
2. Cost (toll) = $6 [$20]
3. Walking distance = 1 minute

ii. Option 2 – Bus
1. Time = 1hr and 30 minutes [60 minutes]
2. Cost (bus fare) = $2 [$15]
3. Total walking distance = 5 minutes

Conditional Autonomous Vehicles (Conditional AVs) are available commercially and you have access to one. This level of autonomy relieves you from driving the vehicle but requires you to be alert to take over when there are safety hazards. Conventional Cars, where the driver is in full control of the vehicle, are still available.

Here are two hypothetical scenarios. Pick which transportation you would feel most comfortable using for your commute.

g. **Option 1 – Conditional AV**
i. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
ii. Travel time = 30 minutes [30 minutes]
iii. Cost per trip= $20 [$30]
iv. Walking distance = 2 minutes

Round 2 - You selected Option 1. Pick which transportation you would feel most comfortable using for your commute.

1. Option 1 – Conditional AV
a. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
b. Travel time = 30 minutes [30 minutes]
c. Cost per trip = $30 [$35]
d. Walking distance = 2 minutes

Round 3 - You selected Option 1. Pick which transportation you would feel most comfortable using for your commute.

i. **Option 1 – Conditional AV**
1. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
2. Travel time = 30 minutes [40 minutes]
3. Cost per trip = $40 [$35]
4. Walking distance = 2 minutes

ii. Option 2 – Conventional Car
1. Driver in full control of the vehicle
2. Travel time = 30 minutes [40 minutes]
3. Cost per trip = $10 [$20]
4. Walking distance = 3 minutes

Round 2 - You selected Option 2. Pick which transportation you would feel most comfortable using for your commute.

2. Option 2 – Conventional Car
a. Driver in full control of the vehicle
b. Travel time = 30 minutes [30 minutes]
c. Cost per trip = $10 [$20]
d. Walking distance = 3 minutes

Round 3 - You selected Option 2. Pick which transportation you would feel most comfortable using for your commute.

i. Option 1 – Conditional AV
1. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
2. Travel time = 30 minutes [40 minutes]
3. Cost per trip = $30 [$35]
4. Walking distance = 2 minutes

ii. Option 2 – Conventional Car
1. Driver in full control of the vehicle
2. Travel time = 30 minutes [40 minutes]
3. Cost per trip = $10 [$20]
4. Walking distance = 5 minutes

h. Option 2 – Conventional Car
i. Driver in full control of the vehicle
ii. Travel time = 30 minutes [30 minutes]
iii. Cost per trip = $10 [$20]
iv. Walking distance = 3 minutes
Round 2 - You selected Option 2. Pick which transportation you would feel most comfortable using for your commute.

1. **Option 1 – Conditional AV**
   a. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
   b. Travel time = 30 minutes [40 minutes]
   c. Cost per trip = $20 [$20]
   d. Walking distance = 2 minutes

Round 3 - You selected Option 1. Pick which transportation you would feel most comfortable using for your commute.

   i. **Option 1 – Conditional AV**
      1. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
      2. Travel time = 30 minutes [40 minutes]
      3. Cost per trip = $30 [$35]
      4. Walking distance = 2 minutes

   ii. **Option 2 – Conventional Car**
      1. Driver in full control of the vehicle
      2. Travel time = 30 minutes [40 minutes]
      3. Cost per trip = $10 [$20]
      4. Walking distance = 5 minutes

2. **Option 2 – Conventional Car**
   a. Driver in full control of the vehicle
   b. Travel time = 30 minutes [40 minutes]
   c. Cost per trip = $10 [$20]
   d. Walking distance = 5 minutes

Round 3 - You selected Option 2. Pick which transportation you would feel most comfortable using for your commute.

   i. **Option 1 – Conditional AV**
      1. Relieves you from driving and requires you to be alert to take over driving when there are safety hazards
      2. Travel time = 30 minutes [40 minutes]
      3. Cost per trip = $20 [$30]
4. Walking distance = 2 minutes
   
   ii. Option 2 – Conventional Car
   1. Driver in full control of the vehicle
   2. Travel time per trip = 30 minutes [40 minutes]
   3. Cost = $10 [$25]
   4. Walking distance = 7 minutes

Full Automation Vehicles (AVs) are available commercially and you have access to one. This level of autonomy allows you to sleep, study, or relax while traveling.

Here are two hypothetical scenarios. Pick which transportation option you would feel most comfortable using for your commute.

   i. Option 1 – AV
   i. You can sleep/study/relax while traveling
   ii. Travel time = 30 minutes
   iii. Cost per trip= $30
   iv. Walking distance = 1 minute

   Round 2 - You selected Option 1. Pick which transportation option you would feel most comfortable using for your commute.

   1. Option 1 – AV
   a. You can sleep/study/relax while traveling
   b. Travel time = 30 minutes
   c. Cost per trip = $40 [$35]
   d. Walking distance = 1 minute

   Round 3 - You selected Option 1. Pick which transportation option you would feel most comfortable using for your commute.

   i. Option 1 – AV
      1. You can sleep/study/relax while traveling
      2. Travel time = 30 minutes [40 minutes]
      3. Cost per trip = $50 [$35]
      4. Walking distance = 1 minute
   ii. Option 2 – Conventional Car
1. Driver in full control of the vehicle
2. Travel time = 30 minutes [40 minutes]
3. Cost per trip = $10 [$20]
4. Walking distance = 3 minutes

2. **Option 2 – Conventional Car**
   a. Driver in full control of the vehicle
   b. Travel time = 30 minutes
   c. Cost per trip = $10 [$20]
   d. Walking distance = 3 minutes

**Round 3 - You selected Option 2. Pick which transportation option you would feel most comfortable using for your commute.**

i. **Option 1 – AV**
   1. You can sleep/study/relax while traveling
   2. Travel time = 30 minutes [40 minutes]
   3. Cost per trip = $40 [$35]
   4. Walking distance = 1 minute

ii. **Option 2 – Conventional Car**
   1. Driver in full control of the vehicle
   2. Travel time = 30 minutes [40 minutes]
   3. Cost per trip = $10 [$20]
   4. Walking distance = 5 minutes

j. **Option 2 – Conventional Car**
   i. Driver in full control of the vehicle
   ii. Travel time = 30 minutes
   iii. Cost per trip = $10 [$20]
   iv. Walking distance = 3 minutes

**Round 2 - You selected Option 2. Pick which transportation option you would feel most comfortable using for your commute.**

1. **Option 1 – AV**
   a. You can sleep/study/relax while traveling
   b. Travel time = 30 minutes [40 minutes]
   c. Cost per trip = $30
d. Walking distance = 1 minute

Round 3 - You selected Option 1. Pick which transportation option you would feel most comfortable using for your commute.

i. Option 1 – AV
   1. You can sleep/study/relax while traveling
   2. Travel time = 30 minutes [40 minutes]
   3. Cost per trip = $40 [$35]
   4. Walking distance = 1 minute

ii. Option 2 – Conventional Car
   1. Driver in full control of the vehicle
   2. Travel time = 30 minutes [40 minutes]
   3. Cost per trip = $10 [$20]
   4. Walking distance = 5 minutes

2. Option 2 – Conventional Car
   a. You can sleep/study/relax while traveling
   b. Travel time = 30 minutes [40 minutes]
   c. Cost per trip = $10 [$20]
   d. Walking distance = 5 minutes

   Round 3 - You selected Option 2. Pick which transportation option you would feel most comfortable using for your commute.

i. Option 1 – AV
   1. You can sleep/study/relax while traveling
   2. Travel time = 30 minutes [40 minutes]
   3. Cost per trip = $30
   4. Walking distance = 1 minute

ii. Option 2 – Conventional Car
   1. Driver in full control of the vehicle
   2. Travel time per trip = 30 minutes [40 minutes]
   3. Cost = $10 [$25]
   4. Walking distance = 7 minutes
**Demographic Questions**

1. What is your gender?
   a. Male
   b. Female

2. What is your age?
   a. *sliding bar*

3. How far away do you live from campus?
   a. On campus
   b. Less than 5 miles but off campus
   c. 5-10 miles
   d. 10-20 miles
   e. 20-30 miles
   f. More than 30 miles

4. Is this your first year at George Mason University?
   g. Yes
   h. No

5. What is your student level status?
   i. Undergraduate
   j. Graduate
   k. Non-degree seeking

6. Are you supported financially in some way by a parent(s), guardian(s), or significant other?
   l. Yes
   m. No, I am financially independent

7. Please select your annual household income range
   n. Less than $15,000
   o. $15,000-$29,999
   p. $30,000-$49,999
   q. $50,000-$74,999
   r. $75,000-$89,999
   s. $90,000-$119,999
   t. $120,000-$199,999
   u. More than $200,000

8. Do you have a valid driver’s license?
v. Yes
w. No

Raffle
If you are interested in participating in a raffle to win a $20 Starbucks Gift Card, please enter your George Mason email in the space below. Five (5) winners will be randomly selected and notified at the end of the study.
[____________________________________________]
END OF SURVEY
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