


Autonomous Vehicle Adoption: Assessing Environmental and Operational Impacts

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FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

AUTONOMOUS VEHICLE ADOPTION: ASSESSING OPERATIONAL AND ENVIRONMENTAL IMPACTS
FINAL PROJECT REPORT

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Sponsorship:
CTEDD

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In cooperation with US Department of Transportation-Research and Innovative Technology Administration (RITA)

Acknowledgments

This work was supported by a grant from the Center for Transportation Equity, Decisions, and Dollars (CTEDD) funded by U.S. Department of Transportation Research and Innovative Technology Administration (OST-R) and housed at The University of Texas at Arlington.

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Technical Report Documentation Page

1. Report No.

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle

Autonomous Vehicle Adoption: Assessing Operational and Environmental Impacts

5. Report Date

12/31/2019

6. Performing Organization Code

7. Author(s)

Andrea Hicks, Soyoung Ahn, and Wissam Kontar

8. Performing Organization Report No.

9. Performing Organization Name and Address

Center for Transportation, Equity, Decisions and Dollars (CTEDD)
USDOT University Transportation Center
The University of Texas at Arlington
601 W.Nedderman Dr. Suite 103
Arlington TX 76019-0108 United States

10. Work Unit No. (TRAIS)

11. Contract or Grant No.

12. Sponsoring Organization Name and Address

United States of America
Department of Transportation
Research and Innovative Technology Administration

13. Type of Report and Period Covered

14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

Autonomous vehicles represent an evolution in transportation technology and the system of transportation itself. The vehicles will change how current transportation infrastructure is utilized, along with how people use transportation, and the environmental impacts of the transportation system. App based autonomous taxis are considered, using a stated-preference survey approach to understand how commuters value different aspects of this mode of transportation. This includes characteristics of modes such as travel time, cost, access time and other commuter specific characteristics. A case study is made of Madison, Wisconsin, a midsized city in the Midwest, which has an extensive bus system and prevalent bicycle culture. A mixed logit model is utilized to analyze the survey data, and scenarios are utilized to posit different conditions that impact the appeal of the modes of transportation. A mode choice model was developed to identify potential users of autonomous vehicles and shifts in demand between different transportation modes. The results indicate a value of time of $17 per hour for personal vehicles, $14 per hour for autonomous vehicles and $20 per hour for busses and an additional $22 per hour for access time to bus. The environmental impact due to the introduction of autonomous taxis is determined through assessing the shifts in demand for the different transportation modes, and utilizing the GREET model to categorize the environmental impacts into greenhouse gas emission, particular matter, and energy consumption. It was found that the introduction of autonomous taxis would increase the environmental impact of the transportation system, due to users switching from less environmentally intensive travel options, such as busses, to the autonomous taxis. The findings estimate an expected 5.6% increase in energy consumption (kj/mile), 5.7% increase in greenhouse gas emissions (kg/mile) and 8% increase in particulate matter (mg/mile).

17. Key Words

Autonomous vehicles, stated-preference survey, mode choice model, environmental impacts

18. Distribution Statement

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified.	Unclassified.	29	

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Abstract

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Chapter I: Background and Relevance

Fully autonomous vehicles have the potential to change how current infrastructure is utilized in order to meet future needs. This work seeks to model the potential shifts (both increases and decreases) in transit ridership due to the adoption and use of autonomous vehicles (both personal and in a shared capacity) and their environmental impacts. The introduction of autonomous vehicles is expected to change the demand for transit, along with safety, congestion, and other travel behaviors [1-3]. Multiple studies have found that increased transit use reduces the environmental impact of transportation [4-6] and that the use of shared autonomous vehicles is expected to reduce the environmental impact of driving (compared to conventional vehicle ownership) [7-9]. However, the environmental tradeoffs due to a potential decrease in transit usage induced by the introduction of autonomous vehicles has yet to be studied. Recent studies have shown that the introduction of autonomous vehicles is expected to enhance the operational capabilities of the transportation system, through congestion reduction, vehicle efficiency, traffic distribution and safety [10-13]. However, the environmental impacts of AVs is controlled by the travel behavior pattern of commuters that shifts the demand of different transportation modes, and yet remains to be analytically studied [12-14].

This research relates to multiple facets of the C-TEDD objectives regarding transportation policy research. First, this work investigates potential shifts in current infrastructure usage (transit ridership) as a function of autonomous vehicle usage. Second, the environmental impacts of shifting modes of transportation are modeled, utilizing greenhouse gas emissions and energy consumption. Third, policy scenarios are employed in the model to evaluate their impact on transit ridership and autonomous vehicle usage. This research seeks to assist in preparing infrastructure for the future, and in particular the potential widespread adoption and usage of automatous vehicles. And at the same time, it seeks to provide a better understanding of what policies may be effective in mitigating the potential increase in overall demand (number of trips) with autonomous vehicles due to their convenience and flexibility and the resulting environmental impact.

This research fits with Focus Area 1, "Creative use of existing infrastructure for future needs, and in particular – 'smart land use, and transportation designs and policies that enhance transit ridership." In particular it seeks to understand and forecast the potential shifts in transit ridership due to the adoption and use of autonomous vehicles (modeled as autonomous ridesharing). Autonomous vehicles will change the infrastructure needs of the future, in particular through potential shifts in current ridership of traditional transit systems. Autonomous vehicles, through ride sharing, may effectively function as flexible "transit" systems themselves. This work models different scenarios and market penetration of autonomous vehicles, to better understand what policy interventions may be effective at maintaining or increasing the use of transit systems in a world of autonomous vehicles. The use of autonomous vehicles (through a ride sharing system), is likely to shift transit ridership (as both a complementary and competing technology), and potentially shift the environmental impact of transportation in a regional area. With respect to complementary uses of autonomous vehicles, they could fill in the first-mile and last-mile trips and improve access to transit. This work seeks to understand what those potential shifts may look like, and their corresponding environmental impacts.

1.1. Madison WI Background

Madison is a midsized midwestern city located in the state of Wisconsin. It has a population of 258,054 people in the city itself, and 634,000 people in the metropolitan statistical area [15-16]. Madison is the capital of Wisconsin and home to the University of Wisconsin-Madison (UW-Madison), the flagship campus of the University of Wisconsin system. UW-Madison employs over 22,000 faculty and staff, has a total student body of 45,000 students, making it a significant portion of the population of the city of Madison [17]. Major private employers in the area include Epic systems, UW Hospital and Clinics, American Family Insurance, Dean Health System, and WPS Health Insurance [18].

1.2. Environmental impacts of transportation

The environmental impact of transportation varies as a function of mode. The greatest impact during the lifecycle of an automobile occurs during its usage phase, when the automobile is in service [19]. The same is true for buses across multiple fuel types, including diesel, hybrid, and compressed natural gas [20]. However, the environmental impact in greenhouse gas emissions per person-mile is greater when traveled as a single passenger in an automobile than on a bus that is operating carrying a large number of passengers. This work analyzes the environmental impact of the usage phase of the different transportation options, neglecting the raw materials, manufacturing, and end of life.

Chapter II: Methods

Multiple methods are employed in this work to analyze the challenge posed. These include survey, multiple mode choice formulations, and environmental impact tools. Each of these methods is presented in a subsection of Chapter 2.

2.1. Stated Preference Survey

The proposed framework of analyzing demand shifts due to autonomous vehicles adoption is informed from a stated-preference survey, designed to gather insights on choice behavior of commuters in Madison city, Wisconsin. The below section details the survey design, procedures and data gathered.

2.1.1. Survey Design

The survey is designed specifically to inform the mode choice model, thus gathering insights on the commuter's choice of transportation modes in different scenarios. Traditionally, stated-preference surveys present the respondent with varying attributes (i.e., travel time, wait time, walk time, cost, etc.…) across different transportation modes, of which one mode is to be chosen in every scenario. This is specifically challenging in the case where there is more than 2 attributes or modes of transportation. For instance, considering A attributes across M modes of transportation with each attribute having different levels L, will result in L^{AM} different scenarios. While this removes the statistical independency between attributes, it overwhelms the respondent and decreases the response rate for the proposed survey. Thus, the survey considers an efficient design where 40 different blocks of experiments are designed each containing 10 choice experiment. Every respondent is assigned randomly 1 block (i.e., 10 choice experiments) to respond to.

Research has shown [21] that the response quality from stated-preference survey is highly impacted by the realistic choices presented. Thus, the survey experiments were carefully designed to depict realistic travel scenarios for any commuter in the city of Madison, Wisconsin. Three different attributes were chosen; travel time, access time, and travel cost. Each attribute varies across three different levels; short, medium, long. In the survey, 4 different mode choices are available; personal vehicle[1], autonomous vehicle, bus and bicycle. In here, autonomous vehicles are considered as a driverless taxi that the user orders through a mobile application and provides a door-to-door transportation from current location towards the desired destination.

Travel times are informed from three different trip lengths which are chosen based upon desired travel destinations in Madison. Upon which, travel times are calculated and scaled to incorporate uncertainty due to potential traffic jams on rush hours (travel times were averaged from google maps observations over 3 days period at 4:00 pm). Similarly, an attribute for access time is chosen to represent the time spent walking or waiting towards the desired mode of transportation. For bus, access time is split into waiting time and walking time. Waiting time was estimated based on repeated measurements of waiting time, based on the difference between real-time bus schedule (google maps) and actual arrival time. Walking time was estimated based on location of bus stops. For personal vehicle, access time is incorporated on walking distance towards potential parking

[1] Respondents were asked to consider personal vehicles as an option even if they do not own one.

areas of vehicle. For autonomous vehicle, access time was assumed based on expected waiting time for vehicle to arrive, this was informed from observed ride hailing application (Uber/Lyft/etc.…) waiting times. Table 1 provides a summary of the choice experiment design.

Table 1: Survey design levels

	Levels			**Levels**			**Levels**		
	Trip 5km	Trip 10km	Trip 30km	Direct Access	Short Waiting	Long Waiting	Low Cost	Medium Cost	High Cost
	Travel Time (minutes)			**Access Time (minutes)**			**Total Trip Cost ($)**		
Personal Vehicle	11	27	40	2(walk)	5(walk)	8(walk)	1.5	4.5	10
Autonomous Vehicle	11	27	40	1(wait)	3(wait)	5(wait)	2.1	7.3	13.6
Bus	18	40	64	2 (walk) 5 (wait)	5(walk) 10(wait)	8(walk) 15(wait)	2	NA	4
Bicycle	13	52	90	0	0	0	0	0	0

The survey was sent using an online platform called "Conjoint.ly". The survey was initially launched on September 10, 2019 through email invitations to UW-Madison students and social media posts on official UW-Madison accounts. Figure 1 below shows how the choice experiments appear for respondents.

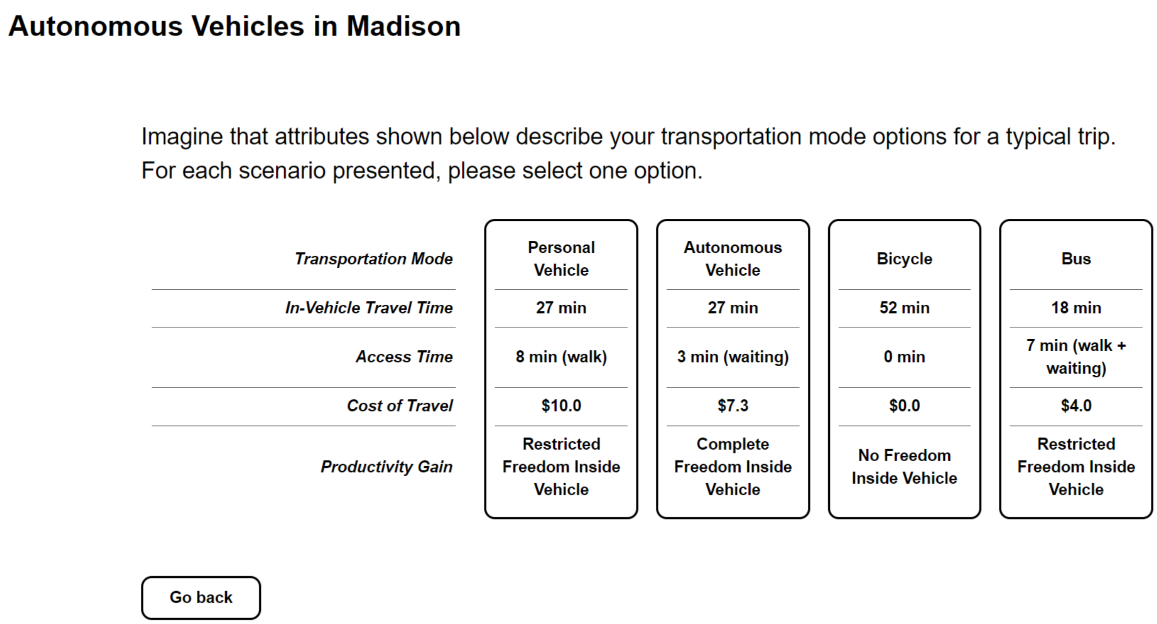

Figure 1: Survey platform

2.1.2. Response Filtering

To assure a desired quality of responses, a filtering mechanism was adopted. Figure 2 details survey responses received. In total, 859 surveys were submitted of which 614 where used in the analysis process. The filtering mechanism focused on quality assurance, where incomplete responses and missing choice experiments where automatically eliminated. Manual filtering was performed to check the time spent by each respondent on the survey. Responses with less than 2 minutes spent on answering the choice experiments were also disqualified as they imply a hasty decision making, which could impact the quality of mode choice model. Respondents who successfully completed the survey were incentivized with a $5 Amazon Gift Card.

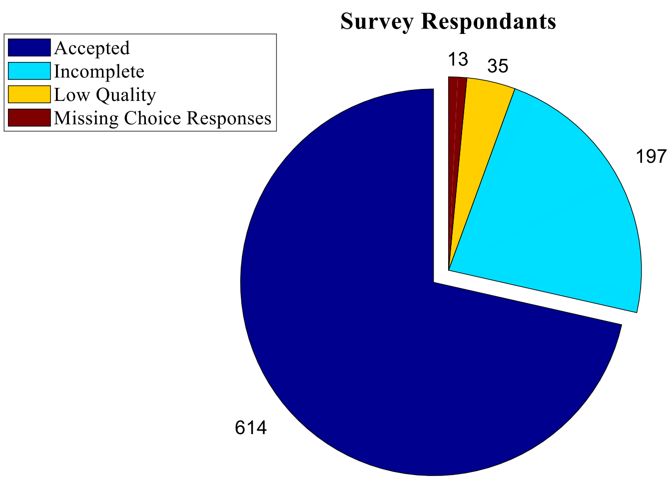

Figure 2: Survey respondents

2.2. Model Formulation

A random utility maximization method was adopted to formulate the mode choice model, informed from the gathered survey data [22].This is a highly applied formulation to translate stated-preference surveys into mode choice model to gather insights on travel behavior and mode splits.

2.2.1. Mode Choice Model Formulation

Two models are adopted to formulate the mode choice mode: multinomial logit and mixed logit. The core mathematical formulation of the mode-choice model can be summarized as follows:

$$U\left(X_i, C_p\right) = V_{i,p} + \epsilon_{i,p}$$

$$V_{i,p} = V\left(C_p\right) + V(X_i) + V(C_p, X_i)$$

Where; U Represents the utility function; i Represents a mode-choice from a set of choices ; X_i is a vector containing various attributes for each mode of transportation (travel time, access time, travel cost, etc.); C_p Is a vector containing commuter specific attributes that influence the decision (income, ownership of a bicycle, housing location, age, etc.) ; $V_{i,p}$ is a portion of utility that can be measured from survey data, including transportation mode attributes (X_i) and commuter specific attributes C_p

Thus, it follows that the probability of choosing an alternative is then

$$P(\epsilon_1 < V_0 - V_1 + \epsilon_0, \dots, \epsilon_i < V_i - V_0 + \epsilon_0)$$

Assuming the error term ϵ follows the Gumbel distribution [23] whose density function is expressed as

$$f(z) = \frac{1}{\theta} e^{-\frac{z-\mu}{\theta}} e^{-e^{-\frac{z-\mu}{\theta}}}, F(z) = \int_{-\infty}^{z} f(t)dt = e^{-e^{-\frac{z-\mu}{\theta}}}$$

Then, the conditional and unconditional probabilities are:

$$(P_i \mid \epsilon_i) = \prod_{j \neq 1} e^{-e^{-(V_i - V_j + \epsilon_i)}}$$

$$P_i = \int_{-\infty}^{+\infty} \prod_{j \neq 1} e^{-e^{-(V_i - V_j + \epsilon_i)}} e^{-t} e^{-e^{-t}} dt.$$

The closed formulation is simplified into

$$P_i = \frac{e^{v_i}}{\sum_{j=1}^{J} e^{V_j}}$$

In this work, a mixed logit model is adopted with panel data, as to represent the different choice experiment from single respondent, while considering the random parameters (i.e., parameters vary from one respondent to another). Then following the random parameter and panel data estimation, if $V_{i1} = \beta_i^T x_{i1}$,the closed formulation becomes

$$P_i = \prod_t \prod_j \frac{\sum_j y_{itj} e^{\beta_i x_{itj}}}{\sum_j e^{\beta_i x_{itj}}}$$

2.3. Environmental Impact Assessment

To assess the environmental impacts of the adoption of autonomous vehicles, the mode choice model developed is used to predict the share of the transportation modes under different scenarios. This allows to quantify the percentage distribution of commuters using each mode of transportation, and accordingly quantify the environmental impacts. In here, the impacts are categorized into; energy consumption, greenhouse gas emissions, and air quality. The findings are explained in chapter 3

2.3.1. The GREET Model

The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model is used to estimate the environmental impact of different transportation modes. GREET uses a life cycle assessment approach, considering well-to-wheel impact of each transportation mode. In here autonomous vehicles, personal vehicles and busses are assumed to be compression ignition direct injection (CIDI) vehicles powered by an internal combustion engines (ICE) running on a mixture of 20% biodiesel and 80% conventional diesel by volume (BD20). Accordingly, the environmental impacts are computed per mile bases for autonomous and personal vehicles, and per passenger mile for buses [24].

Chapter III: Results and Discussion

3.1. Survey results

Data gathered from survey branched into three different categories: demographic, travel behavior, and choice experiments. This section details the data gathered and analyzes the responses received. The data presented here is based only on the 614 accepted responses after the filtering procedure.

3.1.1. Survey Demographics

Table 2 presents the demographics of the survey alongside that of Madison city (adopted from census data[2]). Gender representation is similar to that in Madison city. It is noticeable that age distribution in the survey overrepresents young population 15-24. The level of educational attainment of the respondent is in general higher than that of the city of Madison resident overall. This shows the principal representation of students, specifically University of Wisconsin-Madison students, in the survey.

Table 2: Survey vs. Madison city demographics

	Survey Demographics	Madison Demographics
Age		
15-19	41.0%	7.40%
20-24	37.0%	16.3%
25-29	14.5%	10.2%
30-34	4.10%	8.80%
35-39	2.30%	6.70%
40-44	0.30%	5.30%
45-49	0.50%	5.20%
60-64	0.20%	4.90%

[2] U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates. Retrieved from: https://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml

85-over	0.20%	0.50%
Male	53.8%	52.6%
Education		
Less than high school	0.81%	17.1%
Highschool graduate	48.5%	40.1%
College or associate degree	14.3%	11.7%
Bachelor's degree	22.0%	21.4%
Graduate or professional	14.3%	9.70%
Income		
$0-$10,000	19.4%	5.70%
$10,000-$14,900	7.50%	10.6%
$15,000-$24,900	10.1%	9.90%
$25,000-$34,900	8.00%	21.6%
$35,000-$49,900	6.40%	21.5%
$50,000-$74,900	12.1%	14.6%
$75,000-99,900	9.40%	9.50%
$100,000-$149,900	11.6%	4.60%
$150,000-199,900	7.20%	0.70%
$200,000+	8.50%	1.30%

3.1.2. Travel Behavior

In the survey, majority of respondents owned a bus pass and a bicycle, while 60% of them did not own a personal vehicle. Bus commuting represented the highest frequency of usage within survey respondents with an average usage of 2.9 days per week in comparison with 1.65 days per week (personal vehicle), 1.92 days per week (bicycle) and 1 day per week (ride hail applications). Figure 3 presents the availability of transportation modes for survey respondents and the respective frequency of usage.

Respondents were asked to enter their typical commuting activities while traveling, which were grouped into 4 main themes; gaming, reading, social media browsing and sleeping. This provided an insight into the intensity of desired commuting activities which relates to the level of freedom to do activities other than commuting or driving. Figure 4 shows the distribution of commuting activities. Interestingly, nearly half of the respondents either sleep or read during commuting which requires a high level of freedom inside the vehicle (i.e., commuter is not involved in the driving act).

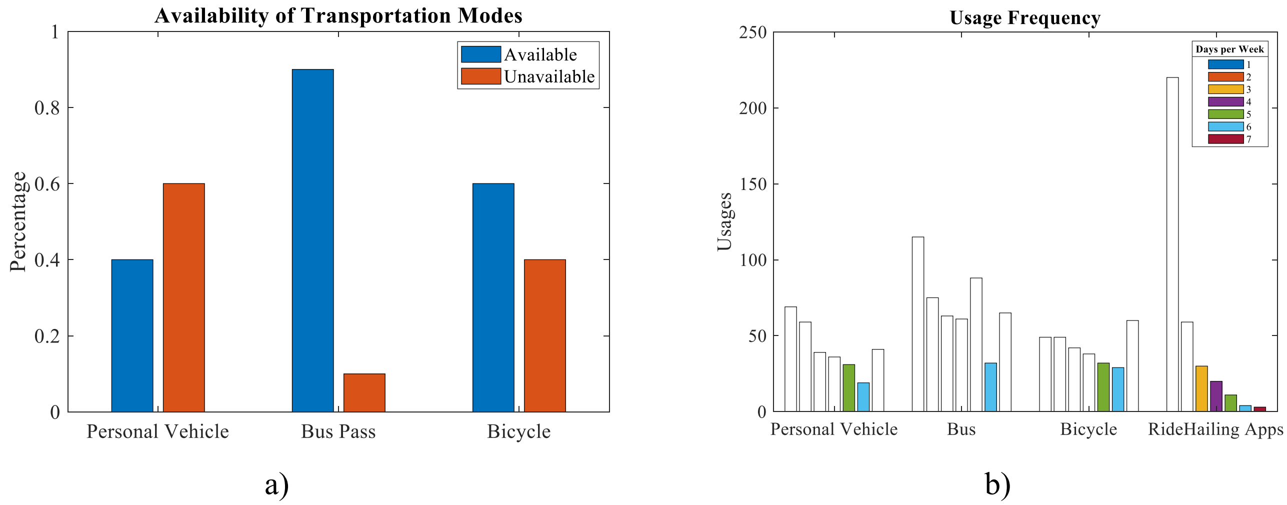

Figure 3: a) Transportation modes availability. b) Frequency of usage

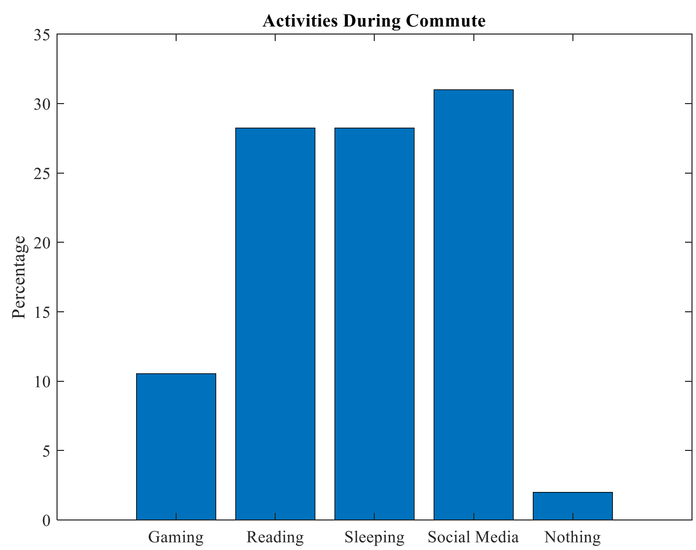

Figure 4: Activities during commuting

3.2. Mode Choice Modeling Results

The survey data was utilized to develop two mode choice models; multinomial logit model and mixed-logit model with panel data. Both models were estimated using the R package *mlogit*. The mixed logit model performed much better than the multinomial model with a McFadden R2 of 0.372 and a log likelihood of -4982, thus all the analysis presented hereafter is based on this model. Under the developed model, the respondents were found to choose 22% personal vehicle, 31% autonomous vehicle, 27% bicycle and 20% bus. Under both models, all significant parameters retained the same sign which validates the efficacy of the model. These estimates are used to explain the travel behavior of commuters under the adoption of autonomous vehicles and predict the demand for each.

3.2.1. Value of Time

According to the model estimates in Table 3, the value of time denoted as VOT can be computed as to determine the desire of commuters for each mode of transportation with respect to monetary value of time, both in-vehicle travel time and access time. Since, the mixed logit models assume random coefficients of cost, travel time, and access time parameters then the VOT is estimated using the second order approximation as in [25].

$$VOT = E[\frac{\beta_{time}}{\beta_{cost}}] \approx \frac{E[\beta_{time}]}{E[\beta_{cost}]} - \frac{Cov(\beta_{time}, \beta_{cost})}{E^2[\beta_{cost}]} + \frac{Var[\beta_{cost}] \times E[\beta_{time}]}{E^3[\beta_{cost}]}$$

We can see that commuter's choice of bus is highly influenced by the access time and the in-vehicle travel time the most. This is due to the long waiting times and trip durations as compared to other modes of transportation, which eventually decreases the utility of bus mode. For personal vehicle and autonomous vehicle, the access time was not significant that is due to the relatively short waiting times where the respondent disregarded it directly. These results emphasize the importance of access time in travel behavior for commuters. For instance, the long waiting times for bus are shown here to influence a high disutility for commuters choosing the bus, while it does not represent a significant disutility for autonomous vehicles or personal vehicles. The app based autonomous taxi presented in the survey, showed a potential of applicability due to low access times as compared to transit systems. In the survey, the respondents were asked to state their typical activities done during commuting, it was seen that nearly half of respondent enjoy sleeping or reading while traveling which requires no driving related tasks while commuting. Autonomous vehicles present commuters with high freedom inside the vehicle, thus having a higher utility for those valuing time savings in terms of activities performed while commuting.

Table 3: Value of time

Value of time	Personal Vehicle	Autonomous Vehicle	Bus
In-vehicle travel time (minutes)	$18.0	$14.5	$20.0
Access time (minutes)	Not significant	Not significant	$22.0

3.2.2. Model Parameters

The coefficients estimate for the two mode choice models developed are presented in Table 4.

Table 4: Mode choice parameters estimates (p-value: 0(***), 0.001(**), 0.01(*), 0.05(^))

Model attributes	Mixed logit		Multinomial logit	
	Value	Std. error	Value	Std. error
Alternative specific constants (base: PV)				

Autonomous Vehicle	0.983	0.145***	1.778	0.269***
Bus	1.024	0.261***	1.397	0.318***
Bicycle	0.846	0.164***	1.227	0.337***
General mode attributes				
Cost	-0.254	0.009***	-0.172	0.006***
Alternative specific attributes				
In-vehicle travel time (min)				
Personal Vehicle	-0.0752	0.0028***	-0.035	0.0014***
Autonomous vehicle	-0.061	0.0019***	-0.044	0.002***
Bus	-0.0834	0.0031***	-0.042	0.0023***
Bicycle	-1.01	0.0053***	-0.07	0.002***
Access time (min)				
Personal Vehicle	-0.038	0.089	-0.055	0.031
Autonomous Vehicle	-0.21	0.378	-0.189	0.213
Bus	-0.094	0.017***	-0.039	0.006***
Bicycles	-0.16	0.353	0.231	0.292
Individual specific attributes				
Vehicles usage frequency				
Autonomous Vehicle	-0.122	0.024***	-0.061	0.02**
Bus	-0.149	0.032***	-0.092	0.025***
Bicycles	-0.125	0.029***	-0.123	0.026***
Ride hail usage frequency				
Autonomous Vehicle	0.179	0.032***	0.171	0.029***
Bus	0.04	0.042	0.043	0.0347
Bicycles	-0.138	0.047**	-0.142	0.04***
Bus usage frequency				
Autonomous Vehicle	-0.031	0.021	-0.0201	0.0181
Bus	0.131	0.027***	0.146	0.0208***
Bicycles	-0.042	0.027	-0.0164	0.0222
Commute activities (base: Light)				
Heavy commute activities				
Autonomous Vehicle	0.275	0.132*	-0.274	0.113*
Bus	-0.15	0.163	-0.218	0.131^
Bicycles	-0.248	0.172	-0.213	0.144
Medium commute activities				
Autonomous Vehicle	-0.201	0.107^	-0.137	0.089
Bus	-0.088	0.125	-0.163	0.103

Bicycles	-0.442	0.134**	-0.381	0.111***
Socio-economic attributes				
Age (base: Adults 25-39)				
Young (15-24)				
Autonomous Vehicle	-0.276	0.126*	-0.133	0.103
Bus	-0.538	0.144***	-0.444	0.117***
Bicycles	-0.053	0.166	0.033	0.131
Boomers (40+)				
Autonomous Vehicle	1.068	0.428*	0.882	0.376*
Bus	0.971	0.581^	0.423	0.434
Bicycles	1.84	0.801*	1.171	0.465*
Annual household income (base: less than $10,000)				
Annual household income $10,000-$35,000				
Autonomous Vehicle	-0.129	0.143	-0.109	0.117
Bus	-0.028	0.167	-0.1	0.135
Bicycles	-0.053	0.181	-0.053	0.1459
Annual household income $35,000-$100,000				
Autonomous Vehicle	-0.291	0.136*	-0.204	0.113^
Bus	-0.05	0.162	-0.063	0.129
Bicycles	-0.307	0.167^	-0.247	0.141^
Annual household income $100,000+				
Autonomous Vehicle	-0.225	0.137	-0.186	0.1132
Bus	-0.372	0.169*	-0.323	0.134*
Bicycles	-0.455	0.173**	-0.448	0.142**
Housing location (base: Central business district)				
Housing location urban				
Autonomous Vehicle	-0.018	0.209	0.0561	0.174
Bus	-0.594	0.235*	-0.279	0.191
Bicycles	0.582	0.281*	0.441	0.233^
Housing location suburban				
Autonomous Vehicle	0.0534	0.228	0.183	0.19
Bus	-0.532	0.263*	0.268	0.211
Bicycles	0.688	0.306*	0.474	0.254^
Housing location rural				
Autonomous Vehicle	0.089	0.323	0.211	0.265
Bus	-0.632	0.387	-0.143	0.306
Bicycles	0.171	0.431	0.294	0.357
Male gender (base: female)				
Autonomous Vehicle	0.5025	0.091***	0.378	0.076***

Bus	0.099	0.111	0.088	0.09
Bicycles	0.724	0.120***	0.555	0.095***
Dummy variables (base: no)				
Personal Vehicle Available				
Autonomous Vehicle	-0.391	0.109***	-0.321	0.088***
Bus	-0.731	0.134***	-0.482	0.107***
Bicycles	-0.855	0.137***	-0.625	0.111***
Bus Pass				
Autonomous Vehicle	-0.145	0.149	-0.161	0.13
Bus	0.394	0.210^	0.163	0.181
Bicycles	-0.191	0.208	-0.259	0.169
Bicycle Available				
Autonomous Vehicle	0.188	0.093^	0.128	0.077^
Bus	0.263	0.112*	0.259	0.0914**
Bicycles	1.233	0.122***	1.01	0.099***
Random parameters (normal distribution) - Std.dev				
Cost	0.162	0.009***	NA	NA
In-vehicle travel time	0.056	0.002***	NA	NA
Access time	0.075	0.006***	NA	NA
Quality of fit test				
McFadden R2	0.372		0.276	
Likelihood ratio test: Chi2	5895.1		4379.2	
Log-likelihood	-4982		-5740.8	

The model results displayed in Table 4 show that it is male gender is statistically more likely to choose autonomous vehicles as their mode of transportation. Additionally, it was seen that younger aged respondents 15-24 were least likely to adopt choose autonomous vehicles, which was a surprising finding. Respondents aged above 40 are the most likely to choose autonomous vehicles over other modes of transportations. This would be due to the fact that as a working force, they value a more reliable and accessible mode of transportation that can cut in commuting time and cost, while youngsters generally are more flexible in commuting time.

Interestingly, the model results show that those with high frequency usage of ride hailing application are significantly more likely to choose autonomous vehicles as a mode of transportation over other modes. This presents a powerful finding towards the favorability of mobility-at-demand which can potentially gain more grounds with the adoption of autonomous vehicles. Another, affirmative finding showed that it is significantly likely to choose autonomous vehicles for those with heavy commute activities. This is rather an expected result as autonomous vehicle present high level of freedom for commuters to perform all kind of activities while traveling. Additionally, those who own a personal vehicle are significantly unlikely to choose autonomous vehicles, and that shows that autonomous vehicle as an app taxi operation is not currently able to take over personal vehicle usage. Housing location had no significant impact in the usage of autonomous vehicles. As for income, the model shows that those with annual household income between $35,000-$100,000 are significantly less likely to choose autonomous vehicles.

3.2.3. Mode Shifts Prediction

The developed mixed logit model with panel data is adopted to predict the percentage distribution of the transportation modes (vehicle, AV, bus, bicycle) for the survey population under different scenarios. This is done through calculating the aggregate elasticity which is estimated by taking the derivative of choice probability around a certain parameter. In this case, the parameters of cost, in-vehicle travel time and access time are varied and percentage of each mode of transportation is estimated. To preserve the prediction power of the mode choice model, we limit the parameters within $[-20\%, +20\%]$ of the original value (i.e., as in the survey).

The formulation of the aggregate elasticity of the population sample (614 responses) is estimated as below (in here x_i refers to an alternative specific attribute, $P_n(i)$ is the probability of choosing of individual in choosing mode n)

$$E_{x_i}^{P_n(i)} = \frac{dP_n(i)}{dx_i} * \frac{x_i}{P_n(i)}$$

We assume everyone in our sample is represented by a weight computed as

$$W_i = \frac{1}{n}\sum_n w_n P_n(i)$$

Thus,

$$E_{x_i}^{W_i} = \frac{dW_i}{dx_i} * \frac{x_i}{W_i} = \frac{1}{n}\sum_n \frac{dP_n(i)}{dx_i} * \frac{x_i}{W_i}$$

$$E_{x_i}^{W_i} = \frac{1}{n}\sum_n w_n E_{x_i}^{P_n(i)} * \frac{P_n(i)}{W_i}$$

Then the aggregate elasticity of the population sample is computed as:

$$E_{x_i}^{W_i} = \sum_n E_{x_i}^{P_n(i)} \frac{w_n P_n(i)}{\sum_n w_n P_n(i)}$$

In this case, we assume $w_n = 1$ suggesting that individuals take their mode choices decisions independently. The prediction was performed on followed hypothetical scenarios designed to gather insights on potential policies than can affect transportation system in near future, and eventually shifting the demand for a specific mode. The scenarios are summarized in Table 5.

Table 5: Scenarios description

Scenario	Description
Sc1	20% increase in autonomous vehicle cost
Sc2	20% decrease in autonomous vehicle cost
Sc3	20% decrease in bus access time
Sc4	20% increase in car cost
Sc5	20% decrease in bus travel time
Sc6	20% increase in personal vehicle and autonomous vehicle travel time
Sc7	10% increase in autonomous vehicle cost with 20% decrease in travel time

Figure 5 shows the percentage distribution of each mode of transportation under different case scenarios. The mode choice distribution of the current situation is adopted from 2018 UW-Madison transportation survey [26]. This was chosen as a reference point for comparison between scenarios, as it best represents the survey demographics presented in this work, were the respondents are mostly UW-Madison students or affiliated personnel. The survey base case refers to the percentage distribution of responses from choice experiments gathered from the survey.

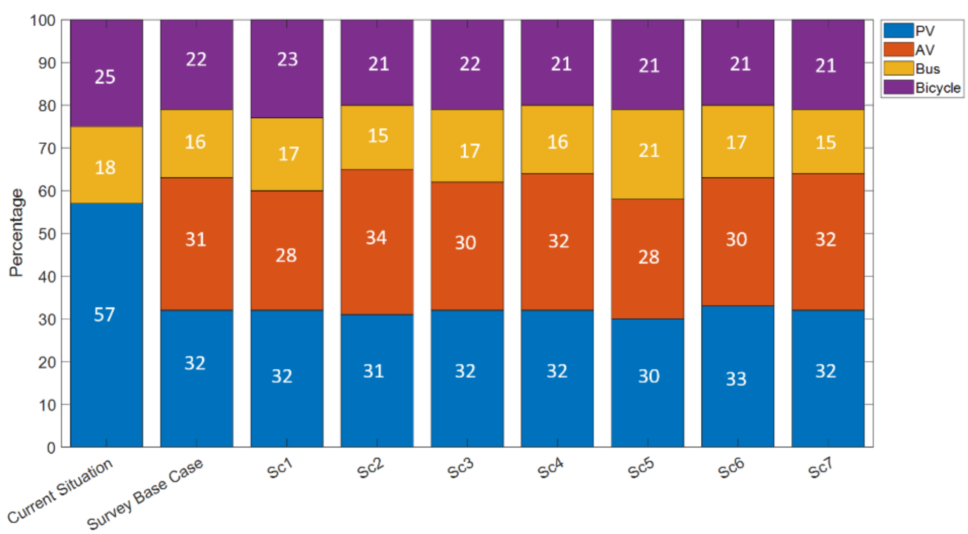

Figure 5: Predicted mode split

3.3. Environmental Impacts

To quantify the environmental impacts as a result of adoption of autonomous vehicles, the predicted mode splits are fused with GREET model environmental criteria. Figures 6-8 showcase the environmental impact under each environmental category.

It is evident that the adoption of autonomous vehicles leads to an increase in environmental impacts along all the three categories. While different policies influence the magnitude of increase in environmental impact, none will decrease the impacts. Table 6 summarizes the percentage increase under each scenario.

Table 6: Percent increase in environmental impacts as compared to current situation

	Survey	Sc1	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7
Energy (kj/mile)	5.63%	3.63%	8.34%	5.42%	8.03%	4.41%	7.41%	7.38%
GHG-100 (kg/mile)	5.71%	3.67%	8.46%	5.50%	8.13%	4.34%	7.47%	7.50%
PM 2.5 (mg/mile)	8.06%	5.19%	12.18%	7.36%	11.10%	2.55%	9.27%	11.01%

The analysis shows that a decrease in the cost of autonomous vehicles with lead to a significant mode shift from busses towards autonomous vehicles leading to the highest environmental impacts (scenario 2). However, as predicted, a decrease in travel time for bus (scenario 5) acts as an effective incentive for commuters to favor the bus over other modes of transportation leading to a positive environmental impact. Interestingly, it is noticeable from scenarios 3, that a decrease in travel time of bus is environmentally more effective than a decrease in access time. Since, in scenario 3 there was no significant reduction in environmental emissions or energy consumption. This suggests that the in-vehicle travel time of a bus is hindering its potential to compete with other modes of transportation, specifically with the adoption of autonomous vehicles.

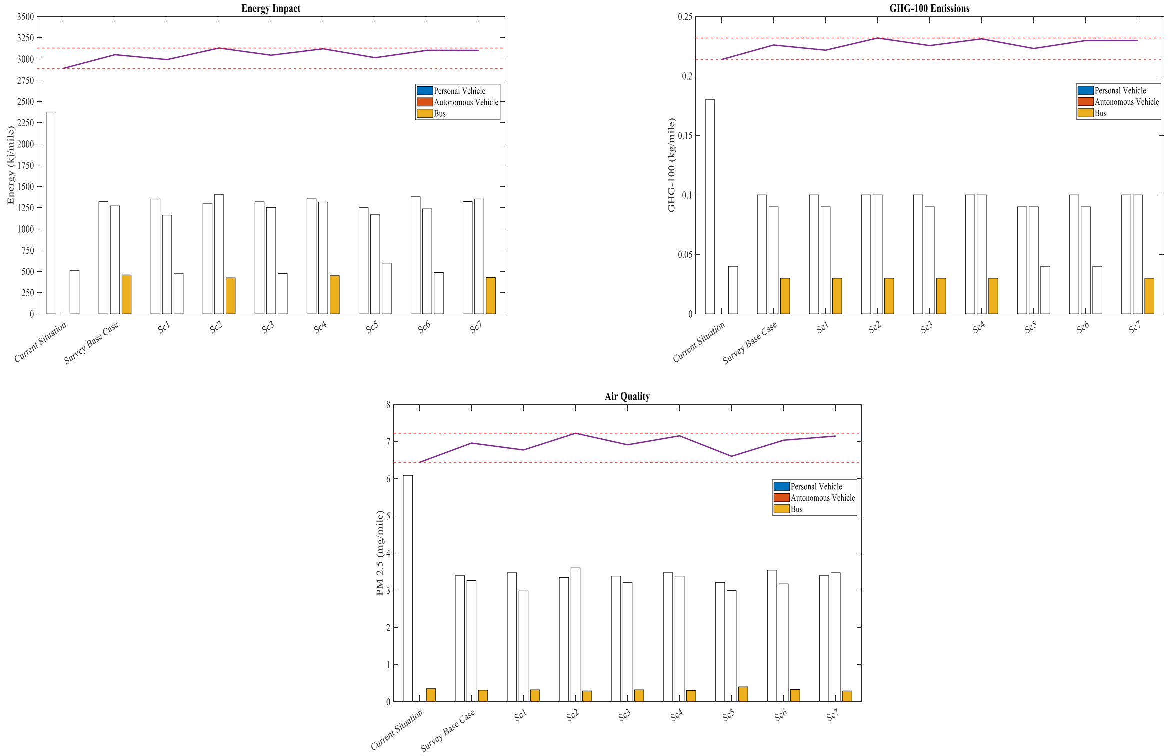

Figure 6: Environmental impacts

Understanding how commuters value different attributes of transportation in presence of autonomous vehicles is crucial in minimizing the environmental impacts of their adoption. It is clear till now, that autonomous vehicles present a favorable option that competes with transit systems and thus reduces their usage. Yet, the magnitude of transit usage reduction is contingent on adopted policies, specifically those targeting the effectiveness of transit systems; providing shorter travel time. Practitioners and policy makers are thus advised towards pushing for a shared autonomous vehicle, which can compete with personal vehicles by presenting a comfortable, efficient, economical and environmental alternative to traditional transit systems.

Chapter IV: Conclusions

Autonomous vehicles represent an evolution in transportation technology. This evolution, however, comes with changes in human behavior and environmental impacts. This work utilizes a survey-based approach to better understand how the introduction of autonomous taxis would change mode choice, and thus environmental impacts using a scenario based methodology. Based on the modeling done in this work, it is anticipated that the introduction and adoption of autonomous vehicles will increase the use phase environmental impacts of transportation. The analytical approach adopted in this research presents a novel understanding on the travel behavior of commuter in presence of autonomous vehicles, so that the future of this technology can be shaped to minimize and eliminate the environmental impacts.

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