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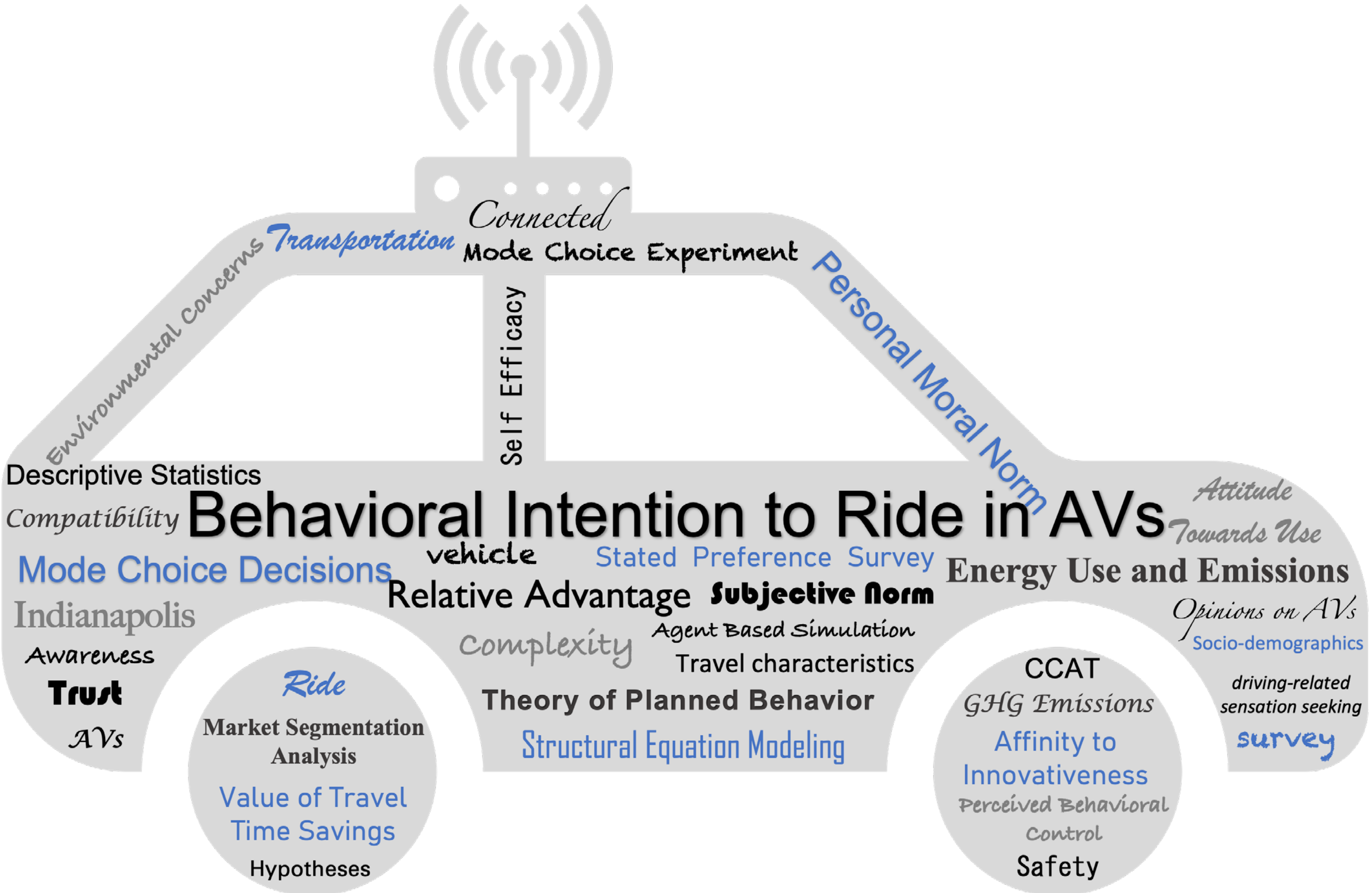


# Behavioral Intention to Ride in an AV and Implications on Mode Choice Decisions, Energy Use and Emissions

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CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

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<tr><td colspan="6">16. Abstract<br>The objective of this project is to examine the potential effects of high-level vehicle automation on energy demand and greenhouse gas (GHG) emissions from vehicles. To achieve this, improved projections of future travel demand and patterns of autonomous vehicles (AVs) were obtained using a stated preference survey distributed in Indianapolis, Indiana, and the associated energy consumption and carbon intensity levels were estimated. Also, a two-stage simulation framework based on an agent-based model was proposed. Different scenarios were designed to examine the impact of the size and composition of fleets of AVs offering single-passenger rides, on GHG emissions, air pollutants, and energy consumption.</td></tr>
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</table>

**Table of Contents**

**List of Figures**



**List of Tables**

## Abstract

The potential impacts of autonomous vehicles (AVs) are far-reaching and complex. They include direct implications for safety, vehicle operations, energy, environment, and personal mobility, as well as secondary impacts on travel behavior and land use. Although AVs' impacts in society have captured the attention of many researchers, there has been insufficient understanding of the factors that affect the behavioral intention to ride in an AV and corresponding implications on mode choice decisions, energy use, and emissions. The objectives of this project are threefold: (i) assess the behavioral intention to ride in an AV, (ii) investigate the effect of the emergence of shared AVs on mode choice decisions in the short and long run and the corresponding effect on the value of travel time savings (VTTS), and (iii) assess the energy and environmental implications due to the emergence of AVs offering single passenger rides. A stated-preference survey was designed and distributed in Indianapolis, IN, to achieve the objectives. Several factors were identified as significant determinants for both behavioral intentions to ride in an AV and potential disruption in mode shares, using a structural estimation model and mixed logit model, respectively. A market segmentation analysis was also conducted to provide insights into the characteristics of potential users/adopters (innovators, early adopters, early majority, late majority, laggards). The VTTS estimates suggest that sharing the ride for commuting trips is not preferable compared with riding alone in an AV across all market segments regardless of the time of AV implementation. Finally, a two-stage simulation framework based on an agent-based model was proposed. Different scenarios were designed to examine the impact of AVs' fleet size and fleet composition (for AVs offering single-passenger rides) on greenhouse gas emissions, air pollutants, and energy consumption. The results presented in this study can provide insights to transportation and urban planners to prepare for AVs and original equipment manufacturers to design marketing strategies to improve people's perceptions of AVs and increase market penetration. The suggested optimal demand levels and fleet size indicated for the study area can be used as a reference for future single-passenger AV service deployment.

# 1 Introduction

Transportation innovations are changing the way people move around cities. Autonomous Vehicles (AVs) are one of the expected innovations of the 21st century, estimated to be tested massively during the 2020s. Although AVs' impacts on society have captured the attention of many researchers, there has been insufficient understanding of the factors that affect the behavioral intention to ride in an AV. Therefore, there is uncertainty regarding the potential adoption of this emerging technology. At the same time, a growing trend in the sharing economy is being observed, which impacts mobility in urban areas. Shared autonomous vehicles (SAVs), for example, have started emerging as an alternative mode of transportation. These vehicles include features of car-sharing and taxi services in an autonomous setting (Fagnant & Kockelman, 2015). They can provide flexible and affordable mobility-on-demand services (Burns, Jordan, & Scarborough, 2013) in the form of driverless taxis. It is anticipated that the emergence of SAVs will satisfy the demand for new services, provide more mobility choices, and address first and last-mile problems. It will also reduce traffic congestion, emissions and fossil fuel consumption; reduce stress on finding parking space, and provide alternatives to those who cannot afford to buy a personal vehicle or choose to not own one by sharing one (Fagnant & Kockelman, 2015, 2014; Wadud, MacKenzie, & Leiby, 2016; Zmud, Sener, & Wagner, 2016).

The widespread diffusion of AVs could impact energy use and greenhouse gas emissions. Benefitting from the advanced automation equipment and system-level assignment strategy, AVs offer unprecedented opportunities for smart driving (Kocleman et al., 2016). Transportation networks can operate more efficiently with AVs than traditional non-AVs due to the precise driving of the advanced features installed in AVs and enhanced fuel economy. Smaller headways with following vehicles among AVs could reduce congestion times (Coldewey, 2012). AVs also can reduce the 16 million tons of $CO_2$ that are emitted to the atmosphere on road networks annually (Max, 2012). On the other hand, some studies indicate that the emergence of AVs may increase travel demand, thereby increasing the vehicle-miles traveled (VMT) (Fagnant & Kockelman, 2015) and resulting emissions. Additionally, VMT and fuel consumption could increase if the automation reduces drivers' value of time and the benefits of energy intensity are not realized (Wadud et al., 2016). Clearly, there is no good understanding of and consensus on the potential implications on energy use and the environment as there is uncertainty on the potential implication on travel demand or, in other words, on the potential adoption and market penetration. It is evident that additional behavioral and simulation experiments need to be conducted to assess people's attitudes on AVs and hence, provide valuable insights to researchers and transportation professionals to be prepared for large-scale operations. Furthermore, it is projected that AVs will be tested whether they can support specific services such as car-sharing and on-demand ride-sharing in the following decades. In stated-preference surveys, several 'what-if' scenarios can be introduced by testing new ideas or attribute levels that do not currently exist to inform policy-making.

In view of the above, the objectives of this project are threefold: (i) assess the behavioral intention to ride in an AV, (ii) investigate the effect of the emergence of SAVs on mode choice decisions in the short and long run and the corresponding effect on the value of travel time savings, and (iii) assess the energy and environmental implications due to the emergence of AV (Figure 1-1). of market penetration.

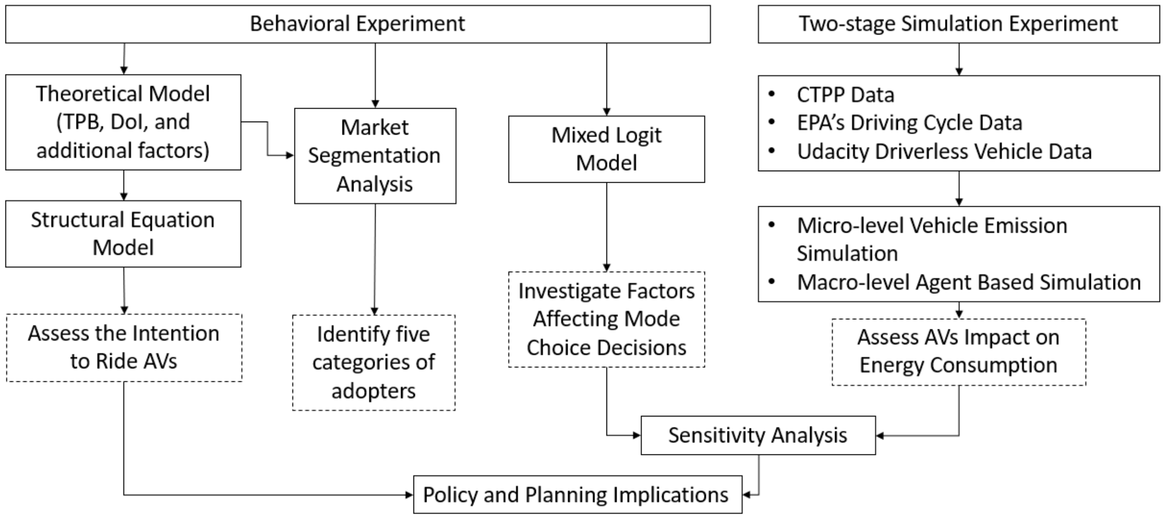


Figure 1-1 Project Framework - Behavioral Intention to Ride in an AV and Implications on Mode Choice Decisions, Energy Use and GHG Emissions

A stated-preference survey was designed and distributed in Indianapolis, IN, to achieve the study objectives. The questionnaire included five sections; the survey was based on the supporting literature summarized in Gkartzonikas & Gkritza (2019). The survey's target population were adults residing in the Indianapolis metropolitan area, soliciting a total of 400 completed responses that were representative in terms of age and gender. The behavioral intention to ride in an AV was assessed using a theoretical model based on the theories of planned behavior and diffusion of innovation and included a variety of attitudinal components. A structural equation model (SEM) was estimated based on a proposed theoretical model to examine respondents' attitudes that are associated with their behavioral intention to ride in an AV. A market segmentation analysis was estimated to classify respondents into five categories of adoption (innovators, early adopters, early majority, late majority, and laggards) and identify distinct market segments. Moreover, a choice experiment of stated preference was conducted to assess the attributes that impact people's opinions about their preferred mode of transportation due to the emergence of autonomous ride-sharing services operated through AVs at different time periods. Mixed logit models were chosen as the modeling technique to account for the heterogeneity across the respondents.

Finally, a two-stage simulation framework was designed to estimate the energy and environmental implications of single passenger AV rides. At the first stage, the task conducted a micro-level simulation on MOVES to estimate traditional vehicle and AV's emission and energy consumption index based on driving schedule data. The driving schedule data for the human driving vehicle (HDV) and AV were collected from the Environmental Protection Agency (EPA) and Udacity driverless vehicle project. Then, the simulation results from MOVES were used as input in the macro-level agent-based model (ABM). The macro-level simulation generates personal trips in each traffic analysis zone (TAZ) throughout the existing road network across the Indianapolis metropolitan area during the morning commuting period. The network and traffic TAZ data for Indianapolis metropolitan area were collected from the United States Census Bureau website. Commuting origin-destination (OD) matrix data was collected from the Census Transportation Planning Products Program (CTPP) website. The model framework was built on two essential agents (passengers and AVs), and the simulation steps were grouped into three steps: 1) generating demand, 2) dispatching AVs, and 3) monitoring fleet performance. Different scenarios have been designed to test the impact of fleet size and fleet composition on greenhouse gas emissions, air pollutants, and energy consumption.

This project is in line with CCAT's mission to conduct groundbreaking research on connected and automated vehicles and to understand future transportation needs and challenges. Specifically, this project enhances our current understanding of the factors affecting public acceptance of AVs and SAVs and their potential implications on energy use and greenhouse gas emissions. The report is organized as follows. Section 2 describes the methodology, data, SEM results. Section 3 describes the methodology and results of the market segmentation analysis. Section 4 presents the methodology, data, and mixed logit results. Section 5 present the methodology, data, assumptions, and agent-based model results. Finally, Section 5 offers overall recommendations for AVs' market acceptance and implications.

# 2 Behavioral Intention to Ride in an AV

## 2.1 Methodology

The Theory of Planned Behavior (TPB) has been extensively used to assess the behavioral intention to practice e-learning, travel to a destination for tourism, and use public transportation (Ajzen, 1991; C. F. Chen & Chen, 2010; Lai & Chen, 2011; Lam & Hsu, 2006; Park, 2018). Behavioral intention, defined as "the individual's expected or planned future behavior," represents the expectation to act in a given form (Ajzen, 1991). The application of this theory has extensively served to discover the factors that influence a person to act in a specific manner, especially when facing new options in their pool of choices.

The components of TPB are *attitude towards use, subjective norms,* and *perceived behavioral control* (Ajzen, 1991). *Attitude* is defined as the psychological emotion and valuation that arises when an individual involves in a specific behavior (C. F. Chen & Chen, 2010). In terms of AVs' adoption, when individuals have a positive attitude towards AVs (Taylor & Todd, 1995), their behavioral intentions will be positive and vice versa. *Subjective norm* is defined as the degree of social pressure a person feels regarding their behavior (Ajzen, 1991). In other words, opinions from close social connections concerning AVs can influence an individual's decision to ride in an AV. TPB also considers *perceived behavioral control*, apart from an individual's *attitude and subjective norms*. This component refers to a person's perception of the possible complications when performing a specific behavior (Ajzen, 1991). In the AVs scenario, *perceived behavioral control* will allow researchers to assess whether or not an individual can perform a specific behavior such as ride AV. P*ersonal moral norms* imply that an individual considers themself morally responsible for adopting a behavior, which reflects external social pressures (Beck & Ajzen, 1991). This can potentially increase the explanatory power of the TPB model to predict the target behavior (Fagnant & Kockelman, 2018; Petschnig, Heidenreich, & Spieth, 2014). S*elf-efficacy* implies whether someone is capable when performing a specific behavior (in this context, ride in an AV when they become available) (Taylor & Todd, 1995).

Past studies have considered enhancing the explanatory power of TBP by including additional constructs in the model. For instance, the decomposition of the model to include components from the Diffusion of Innovation (DoI) theory would also serve to understand better people's attitudes on a specific technology or emerging idea such as AVs (Rogers, 1995). The reconstruction of the relationships of psychological factors and the synergistic effects between the TPB and the DoI theory can better understand the behavioral intention to ride in an AV. The components that are part of the DoI are differentiated in Figure 2-1. *Attitudes towards use* is decomposed by including the components of *complexity*, *compatibility*, and *relative advantage* to using AVs (Moons & Pelsmacker, 2015). Including these additional components can help gain a better understanding of the characteristics of a population that help or hinder the adoption of the innovation in addition to people's perceptions and attitudes on a specific technology or emerging idea (Mustonen-Ollila & Lyytinen, 2003). *Complexity* is suspected of having a negative impact on the attitude towards use, possibly due to people's perception that riding on AVs might be a complex task. At the same time, *compatibility* and *relative advantage* are expected to have a positive influence.

Previous work has identified other factors that potentially influence the behavioral intention to ride in an AV, and hence, these factors were included and tested in this theoretical model. For instance, Gkartzonikas & Gkritza (2019) identified that *environmental concerns*, *safety concerns*, *affinity to innovativeness,* and *driving-related sensation seeking* could potentially influence the decision of an individual to ride in an AV. From the TPB theory, *perceived behavioral control* is now decomposed by the *self-efficacy* and *trust of strangers*, which are additional factors that influence behavioral intention to ride in an AV. Likely, *trust of strangers* relates to the degree of comfort~~ability~~ that an individual will feel to share a ride if AVs were available as a shared mode, similarly to existing ride-sharing services available nowadays (Bansal, Kockelman, & Singh, 2016). Another factor that is considered to affect behavioral intention directly is *environmental concerns*, which are common among younger people and can have the potential to influence consumer preferences related to the adoption of AVs (B. Brown, Drew, Erenguc, & Hasegawa, 2014). *Safety* is also a factor that has been linked with consumers' intention towards AVs, and it is evaluated as an additional component in this theoretical framework (Hulse, Xie, & Galea, 2018; Kyriakidis, Happee, & de Winter, 2015; Musselwhite, 2007). The last two components considered are the *affinity to innovativeness* and *driving related sensation seeking* (DRSS). *Affinity to innovativeness* captures respondents' tendency to adopt new ideas before others (Edison & Geissler, 2003; Egbue & Long, 2012). Finally, the model was extended by considering DRSS, which has been argued to affect the adoption of AVs (Delhomme et al., 2009; Payre et al., 2014). This component is linked to physiological factors and individual personalities, which can indicate attitudes involved in risky behaviors such as the adoption of entirely new technology (Ulleberg & Rundmo, 2003).

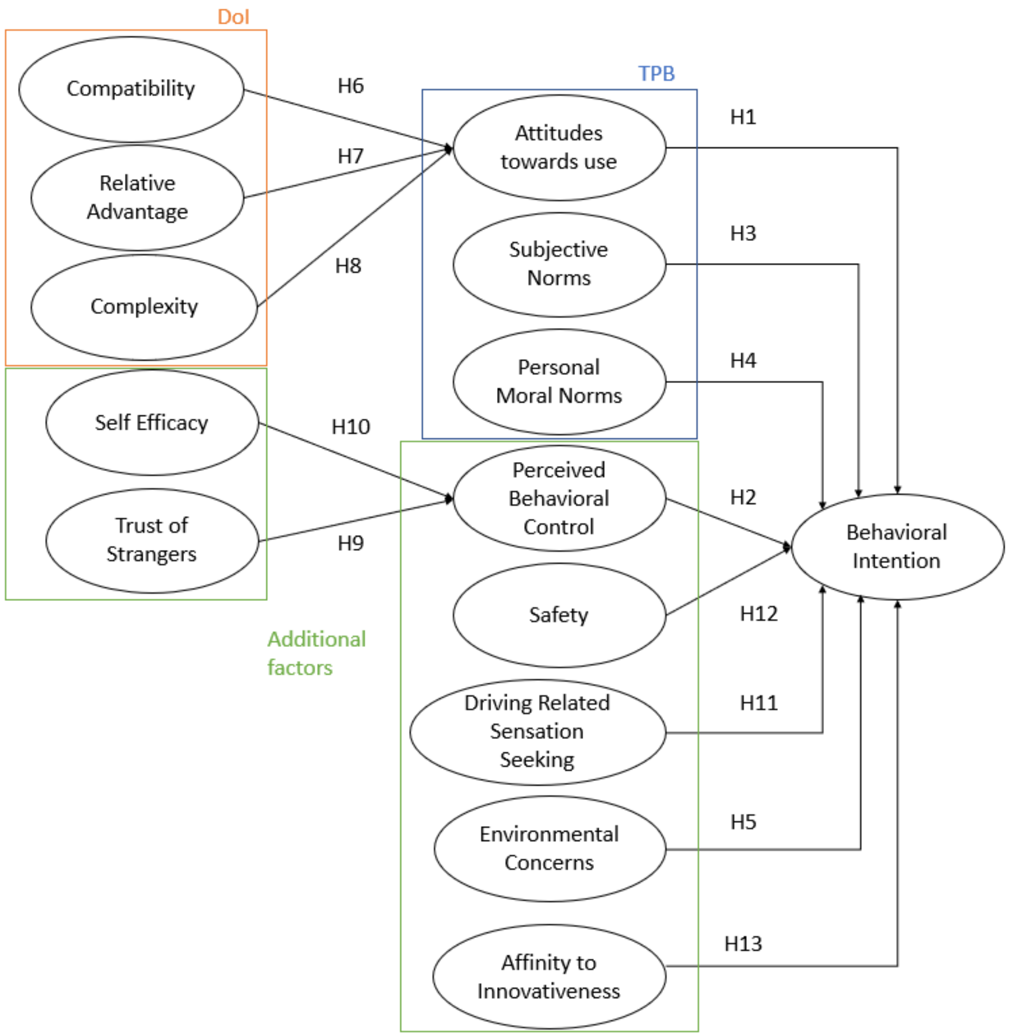


Figure 2-1 Theoretical Model – Hypotheses

### 2.1.1 Hypotheses

A theoretical model based on the TPB is proposed. The model is decomposed to include components from the DoI theory and further extended by including attitudinal variables identified in the literature. In agreement with the beforehand aforementioned stated objective and consistent with the relevant literature, this study aims to test the following hypotheses:

H1: Attitudes towards Use have a positive influence on Behavioral Intention (Ajzen, 1991; Jansson, 2011; Mooi & Sarstedt, 2011; Moons & Pelsmacker, 2015; Payre, Cestac, & Delhomme, 2014; Petschnig et al., 2014)

H2: Perceived Behavioral Control has a positive influence on Behavioral Intention (Beck & Ajzen, 1991; Fagnant & Kockelman, 2015; Nysveen, Pedersen, & Thorbjørnsen, 2005)

H3: Subjective Norms have a positive influence on Behavioral Intention (Ajzen, 1991; Moons & Pelsmacker, 2015; Petschnig et al., 2014; Venkatesh & Brown, 2001)

H4: Personal Moral Norms have a positive influence on Behavioral Intention (Ajzen, 1991; Fagnant & Kockelman, 2015; Heath & Gifford, 2002; Kaiser & Scheuthle, 2003; Petschnig et al., 2014)

H5: Environmental Concerns have a negative influence on Behavioral Intention (Bamberg, 2003; Bamberg & Möser, 2007; Roy, Potter, & Yarrow, 2004; Thøgersen & Ölander, 2006)

H6: Compatibility has a positive influence on Attitudes towards Use (Moons & Pelsmacker, 2015; Rogers, 1995, 2003)

H7: Relative Advantage has a positive influence on Attitudes towards Use (Hawes, Mast, & Swan, 1989; Pavlou & Fygenson, 2006)(Moons & Pelsmacker, 2015; Rogers, 1995, 2003)

H8: Complexity has a negative influence on Attitudes towards Use (Moons & Pelsmacker, 2015; Rogers, 1995, 2003)

H9: Trust of Strangers has a positive influence on Perceived Behavioral Control (Azam & Qiang, 2012; Hawes, Mast, & Swan, 1989; Pavlou & Fygenson, 2006)

H10: Self-efficacy has a positive influence on Perceived Behavioral Control (Ajzen, 1991; Moons & Pelsmacker, 2015; Taylor & Todd, 1995)

H11: DRSS has a positive influence on Behavioral Intention (Cestac, Paran, & Delhomme, 2011; Delhomme, Verlhiac, & Martha, 2009; Payre et al., 2014)~~(~~

H12: Safety Concerns have a negative influence on Behavioral Intention (Edison & Geissler, 2003; Egbue & Long, 2012; Moons & Pelsmacker, 2015)

H13: Affinity to Innovativeness has a positive influence on Behavioral Intention (Edison & Geissler, 2003; Egbue & Long, 2012; Moons & Pelsmacker, 2015; Rogers, 1995)~~.~~

### 2.1.2 Survey Design

A survey instrument was designed to test the hypotheses above. The questionnaire included five sections, and it was based on the supporting literature summarized in Gkartzonikas & Gkritza, (2019).

*1. Level of awareness:*

Specifically, a section of questions was included regarding people's awareness of AVs. Awareness may be used as a proxy to characterize an individual who follows AVs' news. It is hypothesized that it indicates someone who uses multiple modes of transportation for their trips. Additionally, a high level of awareness can mean innovators - the first group of people to adopt the innovation; even though a high degree of uncertainty exists, their interest in new ideas leads them out of local circles and into more cosmopolite social relationships - or early adopters - second group to adopt the new idea who are considered as 'localities' instead of 'cosmopolites,' since their peers respect them in the form of a role model in their social system - of Rogers' DoI (Rogers, 1995).

*2. Travel characteristics:*

A section on travel characteristics was included in the final questionnaire. Respondents were asked to fill out a mini travel diary regarding their mode of transportation-related to each trip purpose. Additionally, some questions were included in determining if they are 'heavy,' 'light,' or 'not-at-all' users of private vehicles, car-sharing services, and on-demand ride-sharing services. Furthermore, a table that included different attributes that affect mode choice decisions was included in the final questionnaire. Respondents were asked to indicate the level of importance (rank) that each attribute has when choosing a transportation mode for a short distance work trip (a short distance work trip is defined as a trip commuting to work that is less than 50 miles). The attributes consist of cost, travel time, waiting time, reliability (not being late), convenience and comfort, safety, distractions (such as travel companions, scenery), the flexibility of travel (being able to go wherever and whenever they want to go), and ease of traveling (minimized the required effort for travel). The attributes above were identified from supporting literature as factors valued highly regarding choice decisions, specifically from surveys about traditional modes of transportation (mostly, private vehicles, walk, and public transportation).

*3. Opinions on AVs*

The section aimed to include attitudinal questions of opinions on AVs relevant to the components of the theoretical model. As discussed in subsection 2.1., the theoretical model of the behavioral intention to ride in an AV includes three components based on the DoI (relative advantage/disadvantage, compatibility, and complexity), the components of TPB (attitude towards use, subjective norms, and perceived behavioral control), two components that may affect the perceived behavioral control (self-efficacy, trust with strangers), and other components identified in the literature used to extend the theoretical model (driving related seeking scale, affinity to innovativeness, environmental concerns, and safety). Several questions were asked per construct, which were then associated with the latent by means of estimated measurement models. All questions included a 5-point Likert-type scale, where 1 means strongly disagree, and 5 means strongly agree.

*4. Choice experiment*

A stated-preference choice experiment was conducted to investigate the effect of the emergence of autonomous ride-sharing services operated through AVs on mode choice decisions in the short and long run and the corresponding effect on the value of travel time savings (VTTS) in the short and long run. Respondents were asked to create their personal mobility portfolio based on hypothetical scenarios at different time periods. The design of the choice experiments is discussed in detail in subsection 0.

*5. Socio-demographics*

Lastly, typical socio-demographic questions were added in the final questionnaire to relate the respondents' characteristics of the previous sections to a specific socio-demographic profile. Particularly, questions were added about the gender, age group, employment situation, annual household income, the highest level of education, race, ethnicity, people living in a household, children living in a household, holders of driver's license, and brief crash history.

### 2.1.3 Sampling Methods

In general, revealed preferences are preferred over stated-preference surveys since the former represents a real setting, and the latter relies on hypothetical scenarios. However, in the case of AVs, it is difficult to conduct a revealed preference survey because the AVs are not widely available. Additionally, in stated-preference surveys, several 'what-if' scenarios can be performed, which may provide useful insights for the decision-making process by testing new ideas or attribute levels that do not currently exist. On a similar note, stated-preference surveys are preferred to revealed ones under the domain of analysis on the VTTS or choice experiments since the revealed ones do not strictly correspond to real market data. As discussed in Hensher, Rose, & Greene (2005), there are concerns about the absence of variance and measurement error.

One of the main criticisms of stated-preference surveys is that the choices are made in a hypothetical setting and do not equate to choices made in real-life settings (hypothetical bias). Potential remedies for the hypothetical bias are split into ex-ante and ex-post techniques. It was found that by including an opt-out or null alternative in the choice experiment, respondents are not forced to select a choice that improves the results (Alfnes & Steine, 2005; Lusk, Feldkamp, & Schroeder, 2004). Cheap talks (ex-ante technique) are one of the most successful attempts to reduce the influence of hypothetical bias (Cummings, Harrison, & Osborne, 1995; Cummings, Harrison, & Rutström, 1995). Cheap talks describe and discuss the tendency of the respondents to exaggerate and encourage respondents to avoid hypothetical bias (T. C. Brown, Ajzen, & Hrubes, 2003; Cummings, Harrison, & Rutström, 1995). List, Sinha, & Taylor (2006) found that including cheap talks in choice experiments can yield credible estimates of the purchase or use decision. Norwood (2005) indicated that the hypothetical bias disappeared when a scale of 1 to 10 (where 10 means very certain) was used. The completed responses of a value lower than 8 were coded as ‘no’ responses. This honesty approach can also be explored by asking the respondents to swear to tell the truth (Jacquemet, Joule, Luchini, & Shogren, 2013) by signing an oath. It can eliminate the hypothetical bias when it is combined with cheap talks. Moreover, it was found that pivoting the attribute levels of a choice experiment around a reference alternative, which has already been experienced or there is significant awareness about it (such as the mode choices of driving a private vehicle or using public transportation), can provide more accurate results (Hensher et al., 2005). For this reason, the attribute levels of the choice experiment were pivoted (percentage decrease or increase of each attribute level corresponding to its reference value) to existing reference alternatives identified in the literature.

Web-based surveys are preferred since they cost less than face-to-face interviews and telephone surveys, and the data can be obtained faster. Additionally, the web-based surveys are more interactive, visual and they have more flexibility and they can be taken any time, since the respondent does not need to be present at a specific time. It was found that people who often ignore participating in telephone surveys are more willing to participate in web-based surveys (Kellner, 2004; Loosveldt & Sonck, 2008). However, often the sample is not representative and a current practice to make the sample representative is to weight variables in regards with socio-demographic characteristics and various attitudes (Lee & Shields, 2011; Loosveldt & Sonck, 2008). Furthermore, some studies came to the conclusion that online panels attract a more knowledgeable sample than face-to-face surveys (Duffy, Smith, Terhanian, & Bremer, 2005).

In this study, the survey instruments were distributed online and hence the target populations were not a random probability sample which is almost identical with the sampled population. Instead, they were convenience samples, which is under-coverage since some people cannot be reached (either they do not have access to the internet, or they are not included in the online panel) and some of them will refuse. However, in order to minimize the limitation of the convenience sample and to have a representative sample, hard quotas were implemented related to the gender and the age groups in order to represent the ratios of each group according to the US Census Bureau, (2010).

### 2.1.4 Data Collection

As discussed previously, given that AVs are not widely available, a stated-preference survey was designed and distributed in Indianapolis, IN. This area was selected due to the high private vehicle modal share. According to the 2017 National Household Travel survey, 82% of people traveled to work using private vehicles in Indianapolis (NHTS, 2017). Additionally, cars are the most reliable mode to get around the city, since only 4% of population resides within a quarter-mile of a bus stop with service at least every 15 minutes (Owen & Murphy, 2018).

Specifically, for Indianapolis the sample consisted of almost equally with male and female and it included 17.6% of respondents to be 18-24 years old, 16.6% to be 25-34 years old, 16.6% to be 35-44 years old, 18.1% to be 45-54 years old, 14.9% to be 55-64 years old and 16.2% to be over 65 years old. The sample size of the survey was decided based on the parameters of margin of error, confidence level and the population of Indianapolis. A confidence level of 95% and a 5% of margin were adopted.

$$MoE = z\sqrt{\frac{p\,(1-p)}{n}} \quad (Eq. 2.1)$$

Where,

MoE is the margin of error (5%), z is the z-score for 95% confidence level (1.96), p is our initial estimate of p which is not known and hence a value of 0.5 is used as a conservative assumption and n is the desired sample size. Therefore, it was found that at least a sample of 385 respondents is needed to meet the requirements of the parameters. Finally, it was decided that the sample size will consist of 400 current residents of Indianapolis older than 18 years old.

The survey was distributed online using Qualtrics in Indianapolis in May 2018. The target population of the survey were adults residing in the metropolitan area~~s~~ soliciting a total of 400 completed responses to ensure a confidence level of 95% and a 5% of MoE. Additionally, the sample is considered representative in terms of age and gender because hard quotas were implemented for these groups in order to represent the ratios of US Census data (2010). It is worth acknowledging that the sample includes participants with higher level of education and income compared to the general population. Table 2-1 presents summary statistics of socioeconomic and demographic variables.

Table 2-1: Summary Statistics of Selected Socioeconomic and Demographic Variables

| Variable | Description | Freq. (sample) | *Freq. (Census) |
|---|---|---|---|
| Gender | Male | 46% | 46% |
| | Female | 54% | 54% |
| Age | 18-24 years old | 18% | 18% |
| | 25-34 years old | 17% | 17% |
| | 35-44 years old | 17% | 17% |
| | 45-54 years old | 18% | 18% |
| | 55-64 years old | 15% | 15% |
| | 65 plus years old | 16% | 16% |
| Education | High school graduate | 19% | 38% |
| | Technical training beyond high school | 5% | 5% |
| | Some college | 27% | 25% |
| | College graduate | 34% | 20% |
| | Graduate school | 14% | 12% |
| Income | Less than $25K | 18% | 26% |
| | $25K-$50K | 25% | 26% |
| | $50K-$75K | 23% | 18% |
| | $75K-$100K | 17% | 11% |
| | $100K-$150K | 12% | 11% |
| | Over $150K | 5% | 8% |

*U.S. Census 2010 data Indianapolis-MSA, IN. The same data were used to accomplish representative age and gender brackets.

### 2.1.5 Structural Equation Model

In Figure 2-1, the hypotheses are expressed in the form of a structural model for assessing the behavioral intention to ride in an AV. The assumed causal relations are presented as direct paths. The coefficients to be estimated express the magnitude and direction of the causal paths. First, the identified components (latent variables), mentioned in the hypotheses in subsection 2.1.1, were tested in terms of reliability and validity. In particular, the structure of these components was examined using confirmatory factor analysis (CFA) to form the measurement model. Second, an SEM was estimated to test the proposed theoretical framework that relies on the theories of TBP and DoI, as discussed in section 2.1. SEMs have been widely applied in travel-behavior research (Golob, 2003; Washington, Karlaftis, & Mannering, 2011). SEM was estimated in STATA/SE 15 software, and full information maximum likelihood estimates were obtained based on the covariance among the observed variables. In the estimation, the hypothesized latent variables that correspond to the theoretical constructs are related to the observed variables through the measurement models. The latent variables explored herein were complexity, compatibility, relative advantage, attitudes towards use, subjective norms, personal moral norms, self-efficacy, trust of strangers, perceived behavioral control, environmental concerns, safety, affinity to innovativeness, DRSS scale, and behavioral intention to ride in an AV. Model fit was assessed using goodness of fit statistics such as chi-square, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Root Mean Square Residual (RMSEA).

## 2.2 Findings

### 2.2.1 Confirmatory Factor Analysis (CFA)

A preliminary analysis to select the variables included in the measurement model was tested for each latent construct; however, the validity of the measurement models is evaluated concurrently with the structural model. CFA was initially conducted to test the structure of the latent variables in terms of reliability and validity. The reliability of each factor identified in the CFA was examined calculating Cronbach's alpha values. As a rule of thumb, a factor is not reliable if Cronbach's alpha value is found to be less than 0.7, at which point the factor is dismissed from further analysis. In particular, based on this analysis, the components were satisfactory in terms of reliability. The results pertaining to the validity testing from the CFA include the composite reliability (CR) and average variance extracted (AVE). CR and AVE values are higher than 0.5 and 0.7, respectively, and suggest that the revised model is reliable with no indications of convergent validity testing (Hair, 2010). The Cronbach's alpha, CR, and AVE composite reliability values are shown in Table 2-2.

Table 2-2 Reliability and Validity Testing of CFA

| Latent Variable | Cronbach's alpha | Reliability | CR | AVE |
|---|---|---|---|---|
| Attitudes towards Use | 0.963 | 0.967 | 0.964 | 0.793 |
| Perceived Behavioral Control | 0.855 | 0.874 | 0.834 | 0.558 |
| Subjective Norms | 0.894 | 0.93 | 0.874 | 0.700 |
| Personal Moral Norms | 0.933 | 0.927 | 0.928 | 0.764 |
| Environmental Concerns | 0.858 | 0.846 | 0.850 | 0.533 |
| Compatibility | 0.927 | 0.931 | 0.928 | 0.810 |
| Relative Advantage | 0.845 | 0.866 | 0.843 | 0.521 |
| Trust of Strangers | 0.853 | 0.84 | 0.834 | 0.559 |
| Self-efficacy | 0.885 | 0.885 | 0.884 | 0.655 |
| DRSS | 0.874 | 0.896 | 0.875 | 0.588 |
| Safety | 1 | 1 | 0.847 | 0.740 |
| Affinity to Innovativeness | 0.806 | 0.876 | 0.855 | 0.599 |
| Behavioral Intention | 0.95 | 0.953 | 0.911 | 0.719 |

## 2.1.6 SEM Results

When the confirmatory factor analysis was completed, the structural model was evaluated. The structural parameters (paths) were estimated using standardized values, and the relationships between the latent variables were found and shown in Figure 2-2. Several goodness of fit measures, as suggested by the literature (Hu & Bentler, 1999; Lei & Wu, 2007; Tabachnick & Fidell, 2013; Washington et al., 2011), were used to evaluate the SEM developed in this study. These measures are summarized in Table 2-3. First, goodness-of-fit was evaluated using the chi-square measure divided by the degrees of freedom (df), whose value was found to be less than 3 ($\chi^2$/df=2.6, $\chi^2$=3549.21, df=1355), indicating an acceptable goodness of fit (Hu & Bentler, 1999). Additionally, RMSEA was evaluated, which is based on chi-square values and measures the discrepancy between the observed and predicted values per degree of freedom (Golob, 2003). This value was found to be around 0.064, indicating that the model fits the data well (McDonald & Ho, 2002). Additional goodness-of-fit measures were used to assess the model's fit, such as the TLI, and the CFI that were found close to 0.87 and 0.88, respectively. all of the measures used for evaluation indicate an adequate fit for the model.

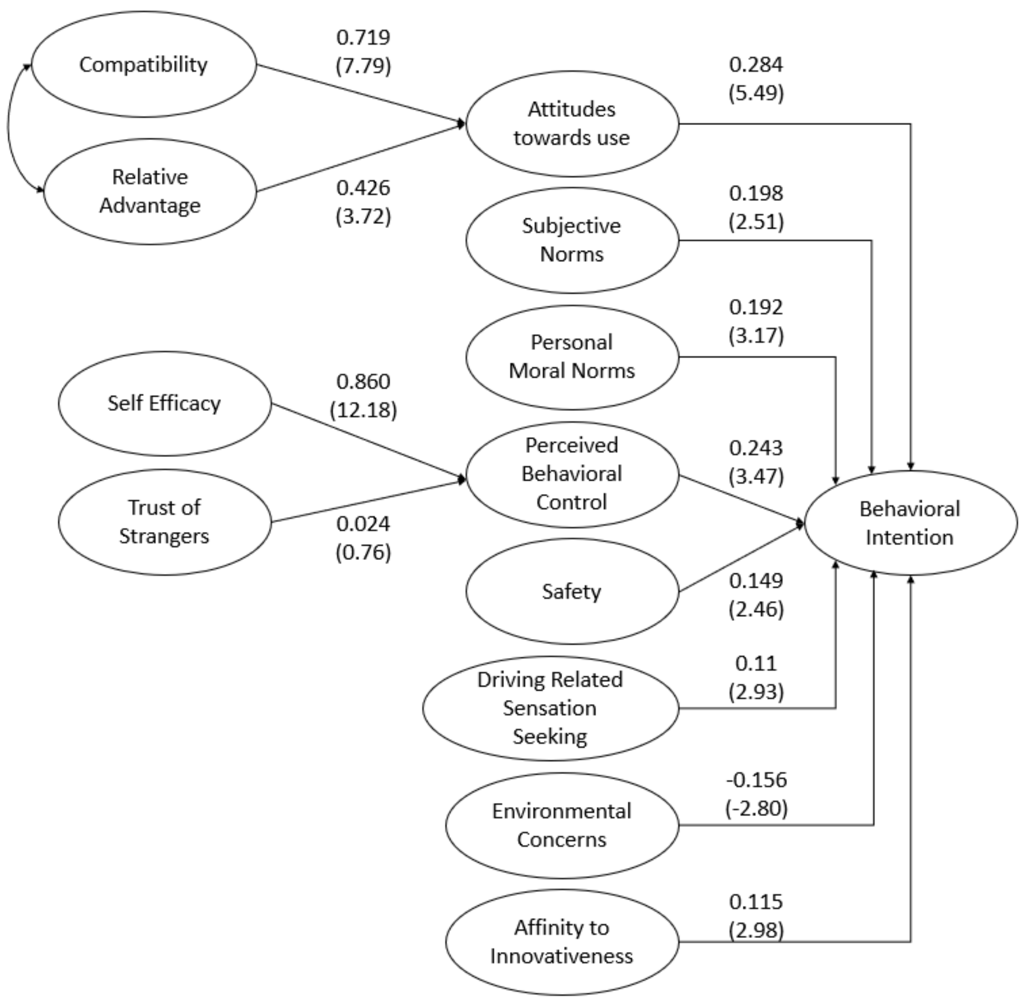


Figure 2-2 Estimated Model of Behavioral Intention to Ride in an AV

Table 2-3 Model Fit Index Summary

| Type | Index | Score | Recommended value |
|---|---|---|---|
| $\chi^2$ test | $\chi^2$ | 3549.21 | 1431 |
| | df | 1355 | |
| | $\chi^2$/df | 2.62 | <5.00 |
| Comparative fit index | CFI | 0.88 | >0.9 |
| | TLI | 0.87 | >0.9 |
| | RMSEA | 0.06 | <0.08 is acceptable |

The variance explained by each path and the significance of each hypothesized path were examined, as shown in Table 2-4. All causal paths that described behavioral intention to ride in an AV are significant and the hypotheses are supported. The most influential path, in terms of significance~~s~~, was the positive relationship of the components of attitudes towards use (β=0.284, t=5.49) and perceived behavioral control (β=0.243, t=3.47) towards the behavioral intention to ride in an AV, validating H1 and H2. Those latent variables had also a high reliability ($R^2$ ranging from 0.82 to 0.84). Similarly, the components of subjective norms (β=0.198, t=2.51) and personal moral norms (β=0.192, t=3.17) were found to have a positive influence on behavioral intention, confirming H3 and H4. Moreover, the component of environmental concerns (β=0.156, t=2.8) was found to have a negative association with the behavioral intention, confirming H5. Compatibility (β=0.719, t=7.79) and relative advantage (β=0.426, t=3.72) were also found to have a positive association with the attitudes towards use, confirming H6 and H7 supported. Hypothesis H8 was not tested within this structural model, since its inclusion in the model lowered the explanatory power of the model. Additionally, self-efficacy has a positive association with the perceived behavioral control (β=0.860, t=12.18) confirming H10, while the hypothesized positive association between trust of strangers and perceived behavioral control (β=0.024, t=0.760) was not found as statistically significant, rejecting H9. Lastly, H12 and H13 were confirmed, since it was found that the component of safety (β=0.149, t=2.46) has a negative association with the behavioral intention, while the component of affinity to innovativeness (β=0.115, t=2.8) has a positive effect. Further results on the hypotheses tested are summarized in Table 2-4. The measurement model results are presented in Appendix A. All variables considered in the measurement model resulted significant and relatively high reliabilities were found from $R^2$ ranging from 0.40 to 0.83.

Our findings suggest that a conceptual framework for predicting behavioral intention for users to ride in an AV based on TPB, DoI, and additional factors is appropriate. The various goodness of fit indices (CFI, TLI, and RMSEA) indicated that model fit is adequate. Findings showed that the component of *attitudes towards use* appears to have the largest effect on behavioral intention to ride in an AV. To boost positive attitude among Indianapolis residents, involving the residents in the new technology testing and better knowledge on the expectations might help (Kokkinaki & Lunt, 1997). In this theoretical framework, attitudes towards AVs use is decomposed by two components of the DoI: *compatibility* and relative advantage. Although, the initial model shown in Figure 2-1 of subsection 2.1-also included *complexity* to describe attitudes towards use, the corresponding latent construct was not included in the final model. Since *complexity* relates to the difficulty to ride in an AV, and AVs are not widely available yet, respondents may have faced difficulties assessing whether riding in AVs is a complex task or not. When this latent variable was added to the model, it did not increase the model's significance. Both *compatibility* and *relative advantage* resulted positively in influencing attitudes towards AVs use and accounted for 84% of its variance. *Compatibility* showed to have higher influence on the component of attitudes towards use. *Compatibility* relates to the suitability of AVs in respondents' lifestyle and can be enhanced by marketing AVs as a useful tool for everyday activities. Marketing would come mainly from policy makers and governmental institutions, and it would be easier when AVs would become widely available. Additionally, *relative advantage* and its positive influence on attitude might be strengthened by highlighting the benefits that AVs could potentially give to individuals and society. Another component from TPB that affect behavioral intention to ride in an AV was *subjective norms*. This component is related to social pressure to ride in an AV. Thus, individuals and people around them would consider autonomous vehicles as preferred, accessible, safer, environmentally friendly, and adequate for different purposes.

Table 2-4 SEM Results

| Hypotheses | Causal path | Estimates | Standard error | t-value | Test results |
|---|---|---|---|---|---|
| H1 | Attitudes towards Use→ Behavioral Intention | 0.284 | 0.052 | 5.49*** | Accepted |
| H2 | Perceived Behavioral Control→ Behavioral Intention | 0.243 | 0.070 | 3.47*** | Accepted |
| H3 | Subjective Norms→ Behavioral Intention | 0.198 | 0.079 | 2.51* | Accepted |
| H4 | Personal Moral Norms→ Behavioral Intention | 0.192 | 0.061 | 3.17** | Accepted |
| H5 | Environmental Concerns →Behavioral Intention | -0.156 | 0.056 | -2.8** | Accepted |
| H6 | Compatibility→ Attitudes towards Use | 0.719 | 0.092 | 7.79*** | Accepted |
| H7 | Relative Advantage→ Attitudes towards Use | 0.426 | 0.115 | 3.72*** | Accepted |
| H8 | Complexity →Attitudes towards Use | - | - | - | Not Tested |
| H9 | Trust of Strangers→ Perceived Behavioral Control | 0.024 | 0.032 | 0.760 | Rejected |
| H10 | Self-efficacy→ Perceived Behavioral Control | 0.860 | 0.071 | 12.18*** | Accepted |
| H11 | DRSS→ Behavioral Intention | 0.111 | 0.038 | 2.93** | Accepted |
| H12 | Safety → Behavioral Intention | 0.149 | 0.061 | 2.46** | Accepted |
| H13 | Affinity to Innovativeness→ Behavioral Intention | 0.115 | 0.041 | 2.8** | Accepted |

Note: * p<.1, ** p<.05, *** P < .01.

From TBP, perceived behavioral control was additionally considered in this study. That latent construct was further decomposed in two additional components found in the literature: *self-efficacy* and *trust of strangers*. Both components positively influenced perceived behavioral control and explained 82% of its variance. Perceived behavioral control usually has the strongest effect on behavioral intention (Chen, Fan, & Farn, 2007; Mathieson, 1991). Our results confirmed that, as perceived behavioral control had the second strongest effect on behavioral intention after *attitudes towards use*. Therefore, it is expected that a person's perceived constraints to ride in an AV affect whether that behavior will be performed. From the two latent constructs that described perceived behavioral control, *self-efficacy* has indirect and positive impact on behavioral intention to ride in an AV. Although *trust of strangers* was not found significant, it was kept in the model as it helped increase its explanatory power. It is expected that trust would be an important determinant of the intention to share rides in AVs, rather than ride alone in AVs.

From the additional factors that were incorporated to the framework in order to fully assess the behavioral intention to ride in an AV, *safety, affinity to innovativeness,* and *DRSS* were found to have a positive and direct effect on it. *Safety* had the strongest direct effects among those additional factors. *Safety* is widely marketed as a major advantage of AVs, since most of the accidents nowadays are caused by human errors, the adoption of this technology could decrease the number of annual crashes (Hulse et al., 2018; Kyriakidis et al., 2015). Although it was expected that safety concerns would have negative impact on the behavioral intention, the questions considered in this framework were framed to highlight the positive safety characteristics of the technology thus the sign of the path is now expected to be positive as it resulted. Promoting how the AVs' features would create a safer environment to transport individuals and can influence consumers' preferences towards AVs. *Affinity to innovativeness* and *DRSS* were also found to influence directly and positively the behavioral intention to ride in an AV. The sign and the magnitude of these latent constructs resulted as expected. The last additional factor included in framework was *environmental concerns*. As expected, this factor negatively affected behavioral intention to ride AVs. By promoting the relative advantages of AVs compared to non-AVs, such as benefits in mobility, society and environment, the perceptions of individuals towards the AVs would improve and therefore, the behavioral intention from users to ride in an AV could increase.

# 3 Market Segmentation Analysis

A market segmentation analysis followed to classify respondents into five categories of adoption adopters based on the DoI theory (Rogers, 2003): a) innovators – people that adopt the innovation first, even though a high degree of uncertainty exists, b) early adopters – people who are respected by their peers in a form of a role model in their social system, c) early majority - people that adopt the new idea before the average member of a system, d) late majority, and e) laggards, as discussed next.

## 3.1 Methodology

As discussed in the Section 2, the theoretical model to assess the behavioral intention to ride in an AV included the following components: attitudes towards use, perceived behavioral control, subjective norms, personal moral norms, environmental concerns, compatibility, relative advantage, complexity, trust of strangers, driving related sensation seeking, safety, affinity to innovativeness. These components were included to conduct a cluster analysis so as to classify similar observations into clusters (Mooi & Sarstedt, 2011). The k-means procedure was selected as the partitioning method of the cluster analysis. This procedure was selected since it is least affected by outliers and it is commonly used when modeling ordered data (Mooi & Sarstedt, 2011). The respondents were classified using the five adopter categories established in Rogers, (2003), which include innovators, early adopters, early majority, late majority, and laggards. This analysis will provide the market penetration share of AVs and identify the socio-demographic groups that share similar attitudes towards AVs and their travel patterns.

## 3.2 Findings

Figure 3-1 shows the distribution of adopter categories as resulted from the cluster analysis. It seems that a higher percentage of people (38.25%) belong in the first two extreme categories (innovators and early adopters) rather than the last two (35.50% including late majority and laggards), indicating a higher willingness to adopt AVs. Furthermore, the distribution of the adopter category (early majority) shows that people are still skeptical about the technology (26.25%). Lastly, to profile each market segment, different socio-demographic variables and trip characteristics were used. The summary of the cluster characteristics for each category of adopters is shown in Appendix B. it was found that people who classified as 'innovators' or 'early adopters' were more likely to use other modes for commuting than their private vehicles (walk, bike, or public transportation) and they own or have access to fewer vehicles compared to their counterparts. Furthermore, people of the first two groups (innovators and early adopters) were more likely to be members of ride hailing and car sharing services, younger individuals, people who work full time, and people with higher income and education attainment.

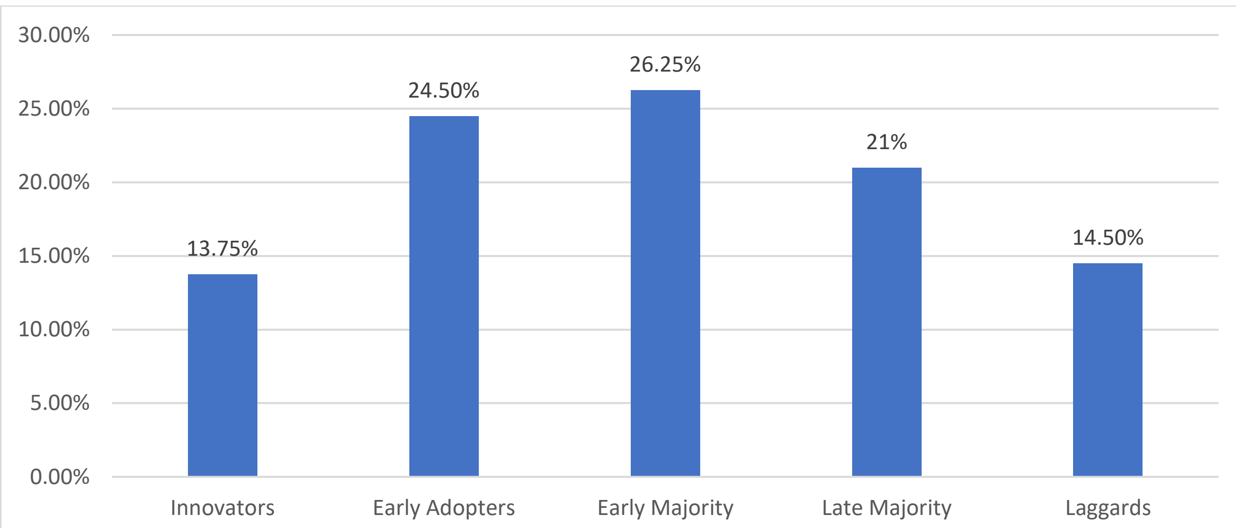


Figure 3-1 Distribution of Adopter Categories

# 4 Implications on Mode Choice Decisions

## 4.1 Methodology

### 4.1.1 Design of Choice Experiment

In total, 9 scenarios were designed for the short term (AVs are implemented in the study area two weeks prior to the experiment). The first scenario (base case) included the transportation modes that are already available in the area (bike, private vehicle, public transportation, and ride-hailing service with non-AVs). The rest of the scenarios included the chosen transportation mode based on the base case scenario plus two hypothetical transportation modes; ride-hailing service operated through AVs where the passenger is traveling alone, and ride-hailing service operated through AVs where the passenger shares the ride. The same rationale was used for the design of scenarios for the long run (AVs are implemented in the study area one year prior to the experiment). The choice experiment was designed for commuting trips, since AVs have the potential to alter commuting patterns that can also affect land use and could result in urban sprawl (Haboucha et al., 2017; Howard & Dai, 2014). Additionally, for different trip purposes such as social/recreational trips, it is difficult to capture the mode choice decisions for all existing modes; since for example, some public transportation modes may not be available during the trip time. Similarly, social/recreational trips usually include shorter trips made usually on foot; which is not the case for commuting trips. The two attributes that were included in the choice experiments were the cost (in dollars) and traveling time (in minutes) as these attributes are very important when evaluating commuting trips.

The choice experiment was designed accordingly to the recommendations included in Hensher et al., (2005). Specifically, the choice experiment includes six alternatives, allowing for examination of behavioral conditions rather than simplistic binary choice. Additionally, the choice experiment introduced some elements of revealed preferences. In other words, the first four alternatives (bus, private vehicle, public transportation, and ride-hailing services with non-AVs) correspond to the actual travel behaviors of users. Furthermore, two hypothetical alternatives were introduced that correspond to stated-preference. As suggested by Hensher et al., (2005) the inclusion of stated-preference choices with existing alternatives is important for choice experiments.

The number of the hypothetical scenarios was based on the fractional factorial design in order to avoid confounded main effects and achieve orthogonality. Therefore, 9 scenarios were included in total for each choice experiment (base case and 8 scenarios based on the fractional factorial design). The design table is shown below in Appendix C, where high values (+1) indicate a 10% increase of the value adopted in the base case scenario and low values (-1) indicate a 10% decrease of the value adopted in the base case scenario.

Cheap talks and text were added to the choice experiments to account for the hypothetical bias of this specific section of the stated-preference survey, as discussed in subsection 2.1.3. Figures D1 (base case scenario), D2 (short), D3 (long) in Appendix D indicate an example of the cheap talk and choice sets in the short and long run. The values of the parameters used in the scenarios were based on relevant literature based on scientific journal papers, technical reports (AAA, 2018; Barclays, 2016; Deloitte, 2017; IndyGo, 2017; Litman, 2019; Morgan Stanley, 2016).

## 4.1.2 Modeling Technique of Mode Choice Decisions

The modeling technique that was used in order to investigate the attributes that affect mode choice decisions due to the emergence of ride-sharing services operated through AVs (SAVs) in the short and long run was the mixed logit model. The data are presumed to be well-modeled by using a random parameter logit model (mixed logit model) due to the heterogeneity across observers and estimate a personal mobility portfolio for each respondent. Two mixed logit models were estimated in order to identify the attributes that affect mode choice decisions due to the short- and long-term emergence of ŧ the automated ride-sharing services.

The standard form of multinomial logit model as it is described in Washington et al. (2011) is shown below.

$$P_n(i) = \frac{EXP\ [\beta_i X_{in}]}{\sum \exp(\beta_i X_{in}]} \quad (Eq. 4.1)$$

, where $P_n(i)$ estimates the probability of having i discrete outcomes. As mentioned above, the mixed logit model is used in this analysis to account for the parameters' variability across respondents (Washington et al., 2011). McFadden & Train, (2000) and Train,(2009) developed the mixed logit models by taking into account a function that estimates discrete outcome probabilities. The mixed logit model that the outcome probabilities are set as $P_n^m(i)$ and $f\left(\beta\,\middle|\varphi\right)$ is defined as the density function of $\beta$ with $\varphi$ is set as the vector of parameters of the set density function is shown below

$$P_n^m(i) = \int P(i)\, f\left(\beta\,\middle|\varphi\right) d\beta \ldots (Eq.4.2)$$

Substituting equation 4.1 into equation 4.2 gives the mixed logit model shown in equation 4.3.

$$P_n^m(i) = \int \frac{EXP\ [\beta_i X_{in}]}{\sum \exp(\beta_i X_{in}]}\, f\left(\beta\,\middle|\varphi\right) d\beta \ldots (Eq.4.3)$$

This expression shows that the mixed logit probabilities $P_n^m(i)$ are the weighted average of the standard MNL probabilities $P_n(i)$ with the weights determined by the density function $f\left(\beta\,\middle|\varphi\right)$. The estimation of mixed logit models is developed by applying maximum likelihood using simulation approaches due to the difficulty in computing these probabilities. The Halton draws are shown to be provide more efficient estimates rather than random draws (Halton, 1960), giving accurate probability estimations with fewer draws (Bhat, 2003; Train, 2000). For this analysis, 200 Halton draws were used, a sufficient number in order to calculate accurate estimates as it is suggested by Bhat, (2003) and Gkritza & Mannering, (2008).

The independent variables regarding people's opinion on AVs (willingness to be an early adopter, adherence to subjective norms, distrust of strangers, compatibility with the respondent's lifestyle, and safety concerns) may have endogeneity issues with the dependent variables. As a remedy to account for the potential inherent endogeneity, binary ordered probit models were calculated with the endogenous independent variables as dependent variables, modeled with exogenous variables (demographic, socio-economic and transportation-related variables). Therefore, the calculated probabilities of the ordered probit models were used as the independent variables in the final models to evaluate the factors affecting mode choice decisions. Lastly, alternative specific constants in the analysis for each choice were included so as to capture the heterogeneity between the different alternatives and unobserved effects that could not be captured in the case of unlabeled alternatives and generic constants for all the choices.

#### *4.1.2.1 Estimating the Value of Travel Time Savings (VTTS)*

Building on previous work calculating values of willingness-to-pay and travel time savings (Brownstone & Train, 1998; Daziano, Sarrias, & Leard, 2017; Kolarova, Steck, & Bahamonde-Birke, 2019) the VTTS values were estimated using the marginal rate of substitution for travel time and cost as the ratio of the coefficients of travel time and cost for different alternatives in the short and long run. The marginal rate of substitution is defined as "the amount of a product that a consumer is willing to give away for another product, assuming that both products are equally satisfying". As suggested in Hensher et al., (2005) using the marginal rate of substitution to capture the trade-off between the cost and travel time; the VTTS can be calculated that describes how much the travel cost changes for a 1 unit change of the travel time. In other words, the importance of the VTTS in choice studies in the transportation context is that it can estimate the amount of money someone is willing to spend in order to save a unit of travel time. The VTTS value can be easily compared with the average value of travel time for personal travel; evaluating the hypothetical modes separately. The VTTS-was calculated for the general sample, but also for the different adopter categories derived from the market segmentation analysis as shown in Figure 3-1. The group of early adopters consists of people who were classified as 'innovators' and 'early adopters' (38.25%), the group of mid adopters includes people who were classified as 'early majority' (26.25%), and the group of late adopters, people who were classified as 'late majority' and 'laggards' (35.50%).

## 4.2 Findings

### 4.2.1. Descriptive Statistics/Trends

The survey consisted of 400 responses residing in Indianapolis and seven transportation modes were considered during the initial analysis to identify the commuting trends: a) walking; b) biking; c) private vehicle; d) public transportation; e) ride hailing service; f) ride sharing service; and g) car sharing service. Figure 4-1 includes the primary transportation mode that the participants responded for work/school trip purposes. Then, moving to the choice experiments respondents indicated their willingness to commute shifting from their current commuting mode (as reported in the base case scenario) to the hypothetical modes of single passenger or shared AV rides. The responses of the participants are showed in Figure 4-1 till Figure 4-6.

Figure 4-1 shows that at least four out of five respondents were commuting using their private vehicles. Only one out of ten respondents opted for active transportation modes (walking and biking). Lastly, approximately 10% of respondents were using shared transportation modes for their commuting trips (public transportation, ride hailing, ride sharing and car sharing services).

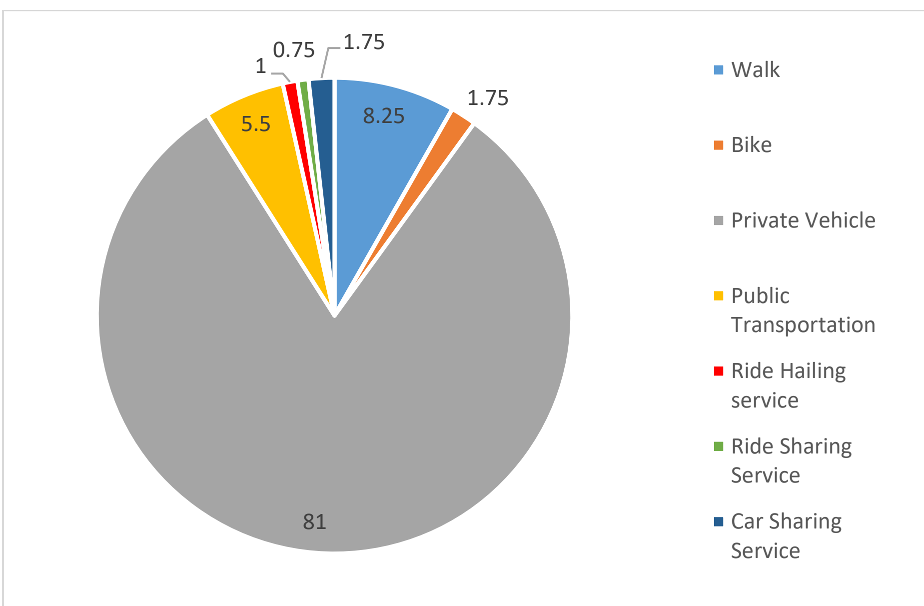


Figure 4-1 Primary Mode for Work/School Trip Purpose

Figure 4-2 shows the willingness of participants (in %) who commute to their work by cycling to shift to single passenger and shared AV rides in the short and long run. Four out five respondents are willing to keep using their bikes for their commute in the short term, whereas seven out of ten showed the same willingness in the long run. In the short run, the respondents who are willing to change their mode prefer almost equally the single passenger and shared AV rides. However, in the long run more people prefer the single passenger AV rides.

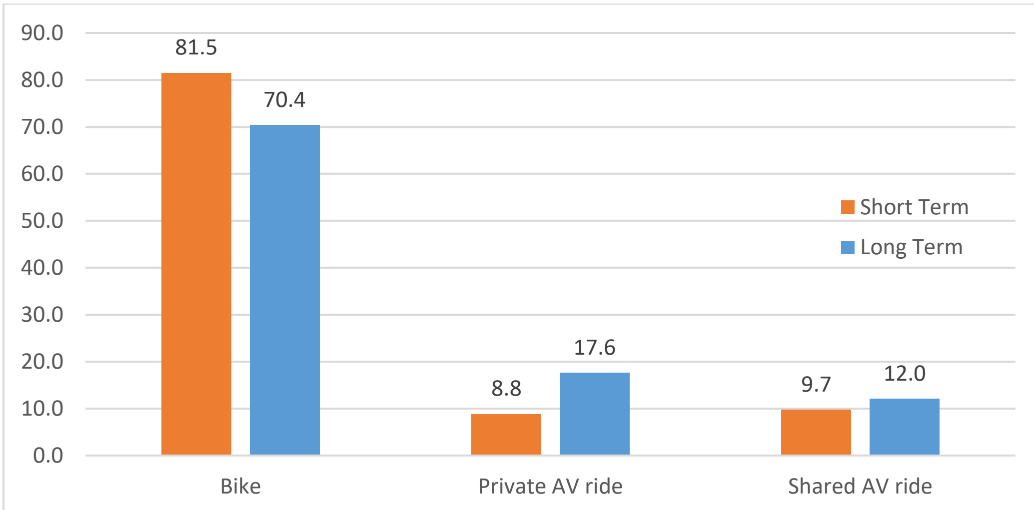


Figure 4-2 Choice Experiment – Bike

Figure 4-3 shows the percentage of respondents who are commuting using their private vehicles. It seems that almost an equal number of respondents is willing to change their transportation mode to single passenger and shared AV rides regardless of the time period. Additionally, it is shown that in the long run people are more willing to opt in using a shared AV fleet rather than a single passenger one.

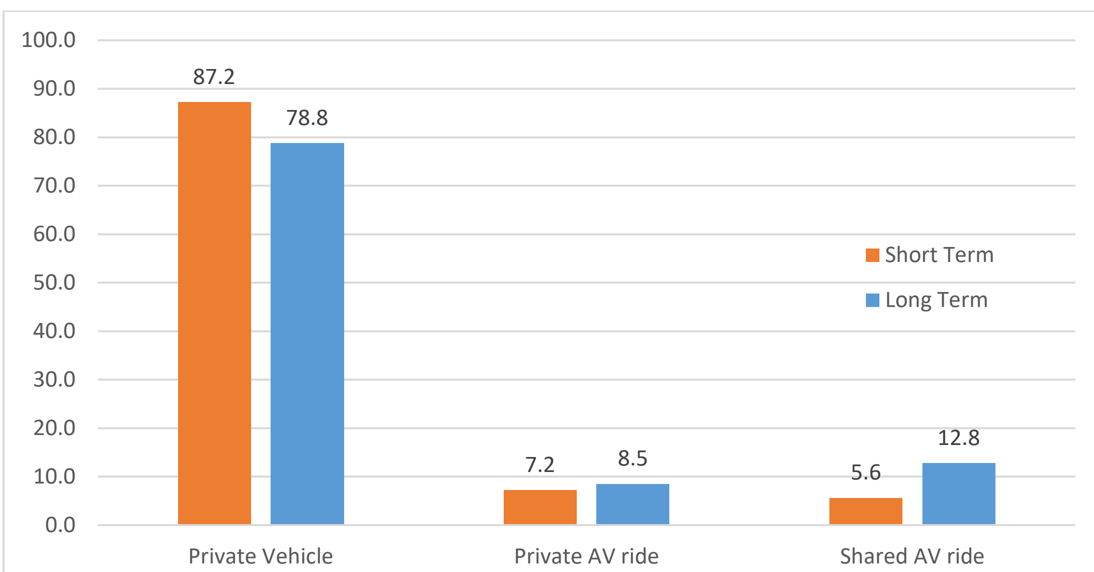


Figure 4-3 Choice Experiment – Private Vehicle

Figure 4-4 shows the willingness of people who commute using public transportation to shift to single passenger and shared AV rides. Approximately two out of three and three out of five respondents showed a willingness to not opt in for automation in the short and long run, respectively. These percentages are lower compared to biking and private vehicles, indicating a higher willingness of people using public transportation towards AVs. On a similar note, a higher percentage of people still prefers to use a shared transportation mode (shared AV rides) rather than single passenger AV rides, regardless of the time period.

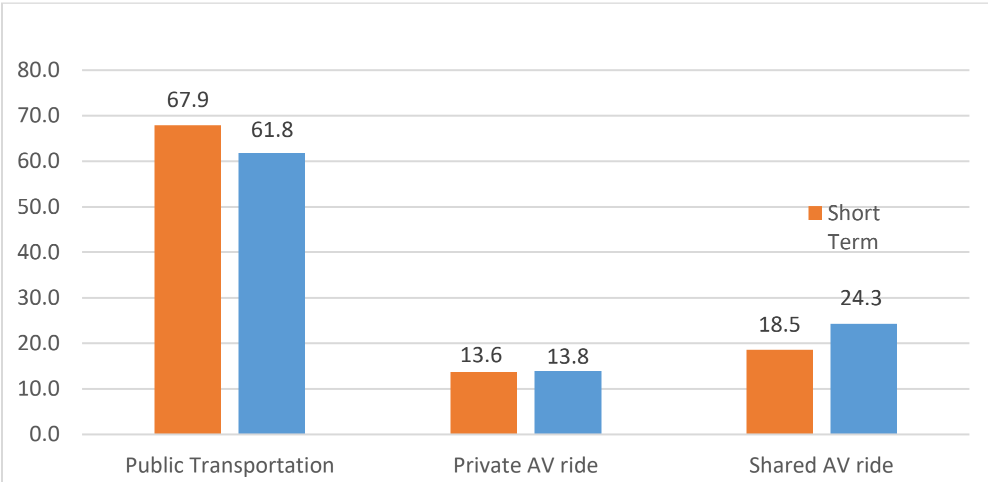


Figure 4-4 Choice Experiment – Public Transportation

Figure 4-5 shows the respondents who are commuting using ride hailing services without AVs. Approximately 15% of the respondents indicated that would be willing to continue using ride hailing services utilizing traditional vehicles once AVs are available; the lowest percentage of all the modes included in the choice experiment. Furthermore, almost the same percentages were reported for the single passenger and shared AV rides in the short and long run; where shared AV rides attracted a greater share of respondents.

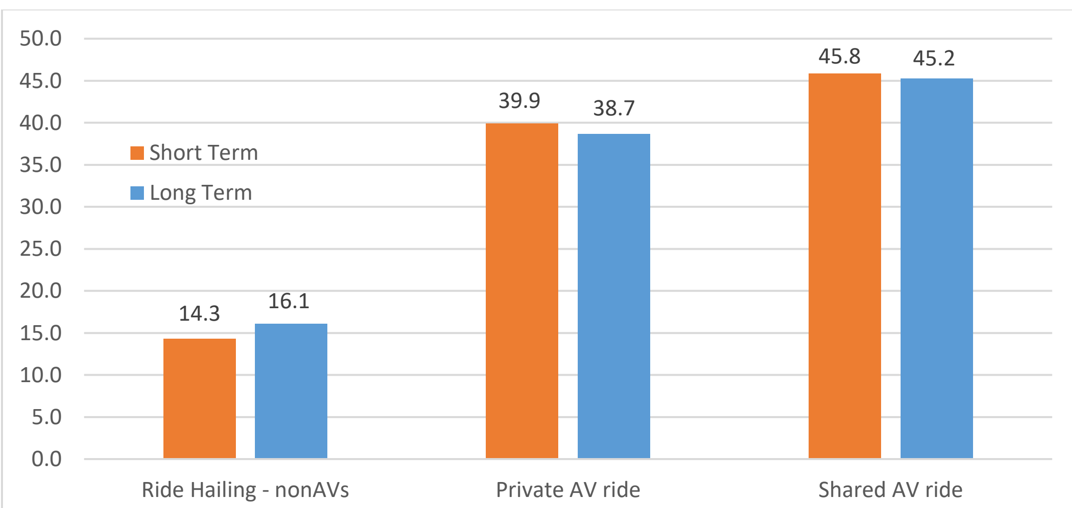


Figure 4-5 Choice Experiment – Ride Hailing w/o AVs - Short Term

Figure 4-6 summarizes the willingness of respondents to adopt AVs as reported in the choice experiments involving all the transportation modes. Unsurprisingly, commuters who already use ride-hailing services without AVs to commute are very interested in adopting AV ride-hailing, with little change between short- and long-term adoption; followed by public transportation, bikes and lastly, private vehicles.

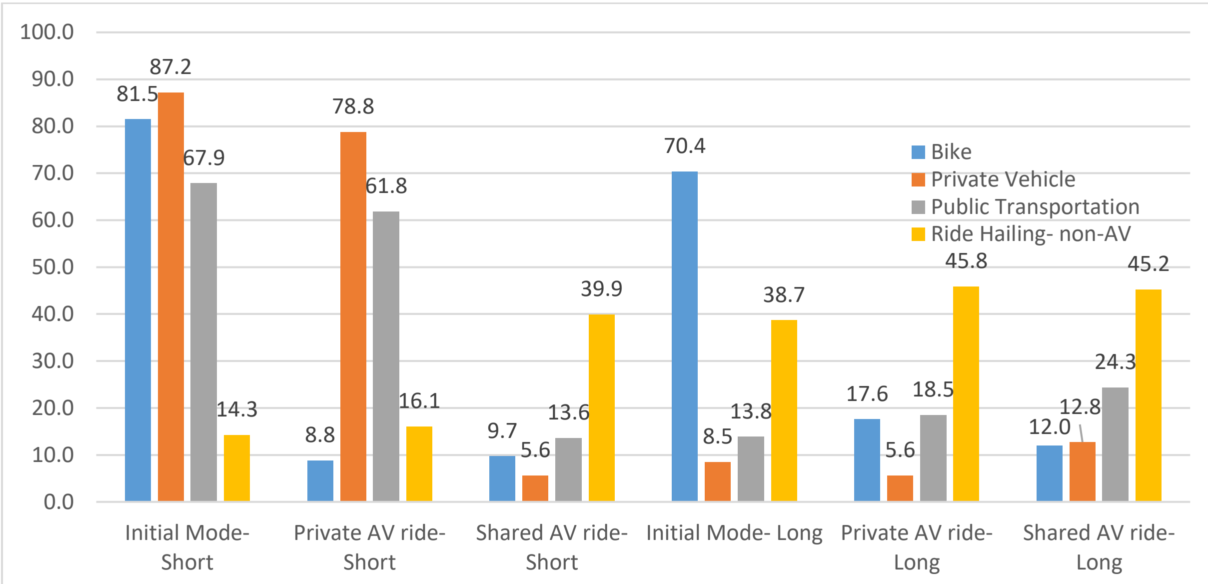


Figure 4-6 Choice Experiment – Willingness to Adopt AVs

## 4.2.2. Mixed Logit Estimation Results

The estimation results of the mixed logit models that impact mode choice decisions due to the emergence of ride-sharing services operated through AVs in the short run and long run are presented in Table 4-1, respectively.

The findings of both models show that the level of awareness regarding AVs is an attribute that influences mode choice decisions towards automation and has a greater effect on shared AV rides rather than single passenger AVs. Results from other studies show a similar trend; that is, a higher awareness is associated with a higher willingness to accept AVs (Bansal et al., 2016; Sanbonmatsu, Strayer, Yu, Biondi, & Cooper, 2018). Additionally, respondents who make fewer social/recreational trips on a weekly basis are more likely to keep using the transportation mode that they chose in the base case scenario and do not opt in for automation. This could be explained because people might believe that trips with single passenger or shared AV rides are more suitable choices for social/recreational trips than other trip purposes, such as commuting. On the other hand, people who have a car sharing account or ride hailing account seem to be willing to use automated riding sharing services, which is also supported by other studies (Haboucha et al., 2017). Furthermore, it was found that people who tend to drive less than the average U.S. driver (the average annual mileage per person in the U.S. is around 13,000 miles (FHWA, 2018)) are willing to use single passenger and shared AV rides for their trips. However, people who perceive reliability as an important factor in their mode choice decisions seem to keep using their preferred mode choice in the base case scenario and do not prefer to use ride hailing services operated through AVs.

Regarding attributes related to respondents' attitudes, the analysis shows that people with a higher affinity for innovativeness, a higher tendency to be influenced by their social circles, and fewer safety concerns about AVs are more willing to use single passenger and shared AV rides in the short and long run scenarios. In particular, people who can be considered as early adopters and tend to adopt new ideas faster than others are associated with a higher tendency to use AVs for their trips. This is in line with other studies as well (Haboucha et al., 2017). Similarly, people who adhere to subjective norms and their social circle can influence their decisions show an analogous tendency as the people with a higher affinity for innovativeness; a finding that is also supported by the literature (Kyriakidis et al., 2015). Lastly, people who have more safety concerns towards AVs show a different behavior and they prefer to keep using their selected mode choice that they indicated in the base case scenario.

As expected, socio-demographic variables are also associated with mode choice decisions in the short and long run. People between 18 and 34 years or students have a higher willingness to use single passenger and shared AV rides for their trips, in the short and long run. On the other hand, people who are older than 55 years old show an opposite behavior and they prefer to keep using their selected mode choice that they indicated in the base case scenario; possibly due to the higher uncertainty of people about AVs especially in the short run. Moreover, people with income higher than $100,000 seem to be indifferent to using ride hailing services operated by AVs than their counterparts regardless of the time period. These findings are supported by other studies as well (B. Brown et al., 2014; Ipsos Mori, 2014; Shaheen, Cohen, & Jaffee, 2018). In the short-term scenarios, it was found that people who own or have access to more than one vehicle in their households are not willing to use single passenger or shared AV rides for their trips; another indication of the higher uncertainty and the willingness of people to switch to AVs, specifically in the short run.

Table 4-1 Mixed Logit Model Estimation Results

| | Short run | | | Long run | | |
|---|---|---|---|---|---|---|
| **Variable** | **Mode choice (base case)** | **Single passenger AV ride** | **Shared AV ride** | **Mode choice (base case)** | **Single passenger AV ride** | **Shared AV ride** |
| | **Estimated Parameter (p-value)** | | | | | |
| Constant | - | -1.014 (<0.001) | -1.549 (<0.001) | - | -1.260 (<0.001) | -1.871 (<0.001) |
| Time | -0.217 (<0.001) | -0.194 (0.031) | -0.104 (0.018) | -0.283 (<0.001) | -0.207 (0.019) | -0.148 (0.005) |
| Cost [St. dev.] | -0.669 (<0.001)* [1.042 (0.003)] | -0.733 (<0.001)* [0.925 (0.014)] | -0.603 (<0.001)* [0.846 (0.021)] | -0.804 (<0.001)* [1.151 (0.003)] | -0.873 (<0.001)* [1.009 (0.011)] | -0.979 (<0.001)* [1.238 (0.008)] |
| **Awareness** | | | | | | |
| Respondents with highest level of awareness of Uber's self-driving vehicles (1: yes, 0: no) | - | 0.271 (0.024) | 0.271 (0.024) | - | 0.318 (0.048) | 0.318 (0.048) |
| Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no) | - | - | - | - | 0.196 (<0.001) | 0.196 (<0.001) |
| **Mode choice-related factors** | | | | | | |
| Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no) | 0.196 (0.039) | - | - | 0.172 (0.026) | - | - |
| **Travel characteristics variables** | | | | | | |
| Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no) | - | - | - | 0.472 (0.023) | - | - |
| Respondents who indicated that they make 1 or less social/recreational trips per week (1: yes, 0: no) | 0.403 (0.037) | - | - | - | - | - |
| Respondents who indicated that they have a car-sharing account (1: yes, 0: no) | - | 0.761 (0.008) | 0.761 (0.008) | - | 0.834 (<0.001) | 0.834 (<0.001) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Respondents who indicated that they drive less than 5,000 miles per year (1: yes, 0: no) | - | - | - | - | 0.412 (0.031) | 0.412 (0.031) |
| Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no) | - | 0.384 (0.046) | 0.384 (0.046) | - | - | - |
| **Perceptions / Opinions / Attitudes** | | | | | | |
| Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters** | - | 0.802 (<0.001) | 0.802 (<0.001) | - | 0.694 (<0.001) | 0.694 (<0.001) |
| Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms** | - | 1.017 (<0.001) | 1.017 (<0.001) | - | 0.851 (<0.001) | 0.851 (<0.001) |
| Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns** | 0.942 (0.021) | - | - | 0.717 (0.015) | - | - |
| **Socio-demographics** | | | | | | |
| Respondents who are between 18 and 34 years old (1: yes, 0: no) [St. dev.] | - | 0.371 (0.018)* [0.542 (0.039)] | 0.371 (0.018)* [0.542 (0.039)] | - | 0.469 (<0.001)* [0.583 (0.019)] | 0.371 (0.018)* [0.542 (0.039)] |
| Respondents who are 55 years old or older (1: yes, 0: no) | 0.392 (0.044) | - | - | - | - | - |
| Respondents who indicated that they are students (1: yes, 0: no) | - | 0.493 (0.029) | 0.493 (0.029) | - | - | - |
| Respondents who have an annual income over $100,000 (1: yes, 0: no) | 0.247 (0.046)* [0.309 (0.028)] | - | - | 0.261 (0.039)* [0.372 (0.016)] | - | - |
| Respondents who indicated that they own or have access to more than 1 vehicle in their household (1: yes, 0: no) | 0.163 (0.031) | - | - | - | - | - |
| Pseudo R-squared | 0.293 | | 0.261 | | | |
| Log-likelihood function | -1987.421 | | -2013.396 | | | |
| Restricted log-likelihood | -2812.973 | | -2725.621 | | | |

*Random parameter (not fixed)

**Predicted probabilities calculated using an estimated binary probit model

### 4.2.3. Value of Travel Time Savings (VTTS) Estimates

Table 4-2 below shows the results of this analysis. It was found that VTTS is lower for the option of sharing the ride in an AV with other passengers rather than riding alone regardless the time period, indicating that the first alternative is more attractive. In other words, the results suggest that the VTTS is higher associated with the single passenger AV ride rather than the shared AV ride, possibly due to the higher level of comfort and lower travel time. It can also be observed that the VTTS for the option of the single passenger AV ride is higher than the hourly VTTS of $14.20/hour reported in USDOT, (2018), whereas the VTTS related to the option of people sharing the AV ride was found to be lower than the reported value by USDOT. The estimated trend between single passenger and shared AV rides in the short-term scenarios (two weeks after the introduction of AVs in Indianapolis) holds for the long-term scenarios as well (one year after the introduction of AVs in Indianapolis). Interestingly, Kolarova et al., (2019) found no significant changes in the VTTS between riding alone and sharing the ride with others for commuting trips based on a stated-preference study in Germany. No statistically significant differences in VTTS were reported for leisure or shopping trips. Lastly, as expected, VTTS is higher for people who were classified as early adopters, followed by the group of mid adopters and finally the group of late adopters. Early adopters seem to perceive riding in AVs as a more valuable activity, possibly due to decreased levels of stress or increased productivity during the trip, compared to the other groups. Note that the VTTS for the group of early adopters is found to be higher than the reported USDOT average value, whereas the value for the group of mid adopters is similar with the average and the value for late adopters is lower.

Table 4-2 Value of Travel Time Savings – Short and Long Run

| | General Population | | Across Clusters | | |
|---|---|---|---|---|---|
| | Single passenger AV ride | Shared AV ride | Early adopters | Mid Adopters | Late Adopters |
| Short term - WTP ($/hour) | 15.88 | 10.34 | 21.18 | 14.72 | 11.05 |
| Long term - WTP ($/hour) | 14.22 | 9.07 | 20.63 | 13.49 | 8.26 |

# 5 Implications on Energy Use and Emissions

## 5.1 Methodology

### 5.1.1. Overview of Agent-based Models

An Agent-based model (ABM) approach is proposed to address the third research objective of this project. ABM is set up starting with agents (individuals in the system) and their interaction rules. As described in Bonabeau, (2002), ABM "consists of describing a system from the perspective of its constituent units". Complex systems such as urban AV systems have many decision makers/agents with dispersed control. When these systems are simulated using ABM, their behaviors emerge due to the interactions of agents to agents and/or agents to environment. An urban network with AVs, as a complex system, involves numerous decision makers (AV, passengers) behaving separately on the basis of different strategies (route searching, vehicle assignment, etc.). The ABM approach enables setting specific behavior rules for each agent and it is appropriate to model complex systems. For example, it is practical to define AV system's dispatching strategy by setting rules of how one AV reacts to passengers.

The ABM approach has found applications in several fields and disciplines, such as sociology (Macy & Willer, 2002), ecology (Matthews et al., 2011), and economics (Garcia, 2005; Hauser, Tellis, & Griffin, 2006; Negahban & Yilmaz, 2014). In the field of AVs, a number of studies have applied ABM to simulate AVs to evaluate their response time, traveling distance, vehicle occupancy, fleet size among other characteristics. However, few studies focused on the environmental impact that AV fleets might have. A brief summary of previous studies on AVs using ABM is provided below.

Fagnant & Kockelman, (2014) designed a framework of ABM for AVs, comparing different vehicle relocation strategies to minimize passengers' waiting time; the results indicated that 1 AV could replace 11 conventional vehicles, while total traveling distance increased by 10 times. Liu, Kockelman, Boesch, & Ciari, (2017) studied passengers' mode choice behavior based on a AV ABM simulation in Austin, Texas. By conducting a VMT-based estimation, they found that comparing to traditional vehicle, AV could reduce emissions by 16.8% to 42.7% across five emission types. In a follow-up work, (Fagnant & Kockelman, 2018) included dynamic ride-sharing behavior in the simulation and optimization problem of fleet size and profitability of AV fleet. The results suggest that the emergence of DRS could reduce both passengers' response time and traveling cost.

In term of the AVs' impact on mobility, Levin, Kockelman, Boyles, & Li, (2017) imbedded cell transmission model into agent-based simulation to describe the flow status and traffic congestion more accurately. Similarly, they conducted simulations based on different fleet compositions and found that ride-sharing could substantially mitigate traffic congestion at commuting time . Bischoff & Maciejewski, (2016) designed a real-time dispatching algorithm for simulating autonomous taxis in Berlin, by providing different relocation strategies according to oversupply and undersupply conditions. The results suggest that 100,000 AVs will be enough to serve Berlin's passengers' travel demand. Turning to parking demand, Zhang, Guhathakurta, Fang, & Zhang, (2015) developed a simulation model and examined different system operation scenarios to assess the effect of AVs on urban parking demand by implementing different system operation scenarios. Results indicated that even when the market penetration rate is as low as 2%, the parking demand for users of AVs can be reduced up to 90%.

In general, current studies related with ABM mainly focused on AVs' direct implications on travel demand and mobility. These studies show that ABM is an appropriate modeling technique to test various simulation scenarios of AVs and the mechanism of AV's assignment strategy as well. However, studies evaluating the environmental impact of single passenger and shared AVs, which is considered to be an important benefit that AV might bring, based on macro-simulation have been scarce. This study is trying to fill the gap by designing a framework to estimate the environmental impact of AVs at a city-level simulation area using ABM. The proposed model could compare the environmental performance of AVs with that of traditional vehicle by designing different scenarios. Secondly, this study showcases the proposed framework using the case study of the Indianapolis metropolitan area. A scenario was run to estimate whether AVs could reduce greenhouse gas and air pollutant emissions. Note that the type of AVs included in the simulation are owned by transportation network companies (not privately owned) and provide service to one passenger at a time (single passenger AV rides).

## 5.1.2. Design of Simulation Model

This section presents the general simulation framework adopted for estimating the environmental and energy implications of AVs in Indianapolis metropolitan area. As discussed in Section 2.2.1, the choice experiment included nine scenarios soliciting the preferred mode of transportation for commuting trips in the short and long run. As such, the ABM was designed to simulate trips by AVs that happened during the morning peak period, which is from 6:00 am to 9:00 am, as defined by Indiana Department of Transportation (INDOT).

*5.1.2.1 Data/Inputs*

The basic unit that generates and attracts traffic demand in this ABM simulation is the traffic analysis zone (TAZ). The network and TAZ data of Indianapolis Metropolitan Area (Indianapolis MSA) were collected from the United States Census Bureau website and shown in Figure 5-1. The related road attributes information data such as road classification and speed limit were collected from OpenStreetMap.

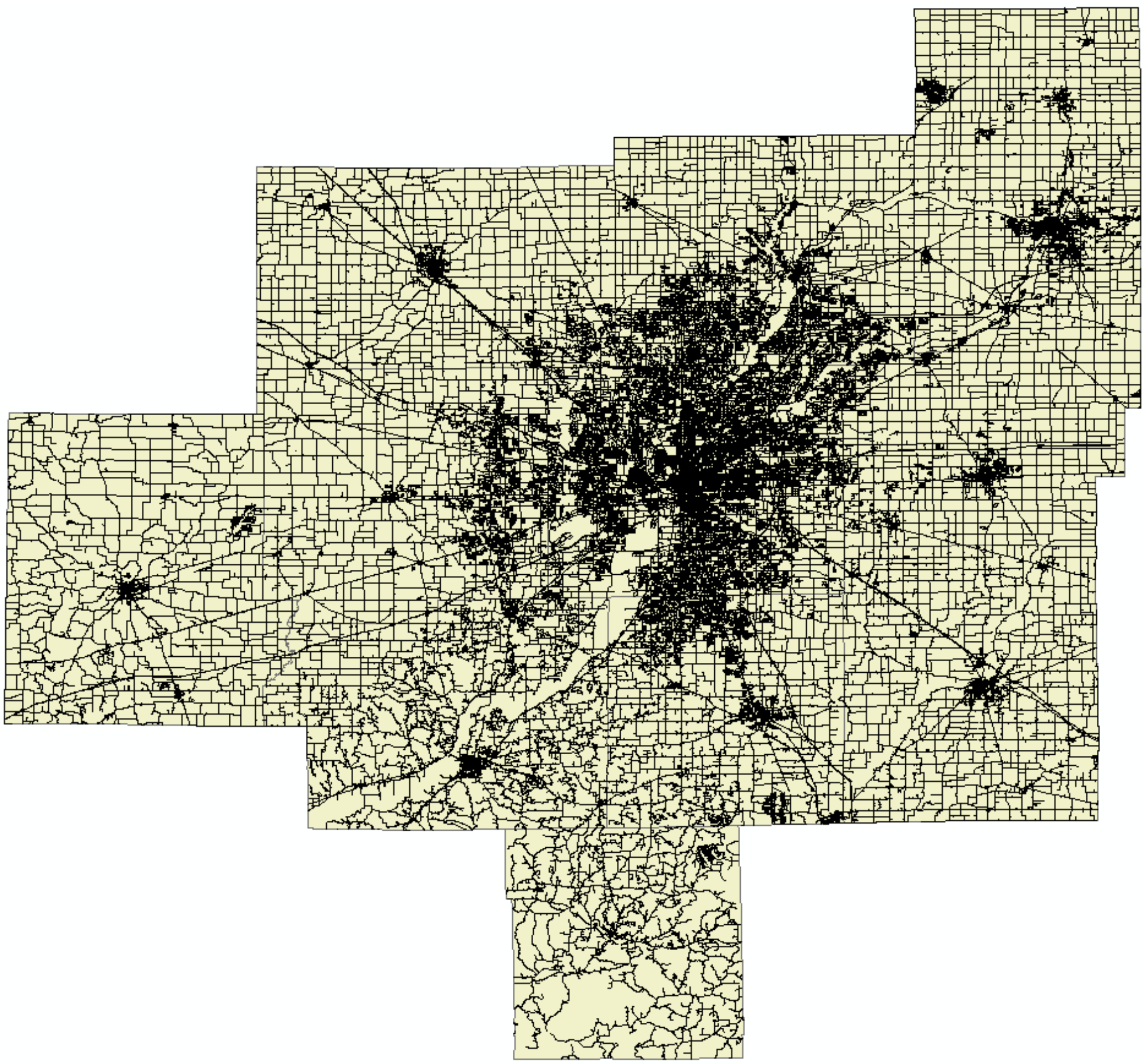

Figure 5-1 Indianapolis MSA Road Network and TAZ

The travel demand origin-destination (OD) matrix data was collected from the Census Transportation Planning Products Program (CTPP) website. CTPP contains the flow data from home to work during 2012-2016 at different geographic levels of analysis. In total, 897,783 private vehicle commuting trips occurred in the study area during the morning peak hour (6:00 AM-9:00 AM). The commuting OD matrix was created by aggregating the flow data from home to work, which only covers the morning commuting flow. An aggregated OD matrix at the county level is shown in Table 5-1.

Table 5-1 OD Matrix of Indianapolis Metropolitan Area at the County Level

| | Boone | Brown | Hamilton | Hancock | Hendricks | Johnson | Madison | Marion | Morgan | Putnam | Shelby |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Boone | 12,565 | 25 | 3,265 | 50 | 1,250 | 85 | 80 | 11,460 | 40 | 10 | 0 |
| Brown | 0 | 2,510 | 25 | 0 | 10 | 830 | 4 | 1,055 | 170 | 0 | 30 |
| Hamilton | 1,690 | 10 | 79,655 | 895 | 1,065 | 545 | 2,150 | 63,425 | 50 | 65 | 95 |
| Hancock | 185 | 0 | 2,505 | 13,470 | 105 | 555 | 630 | 15,270 | 4 | 0 | 1,060 |
| Hendricks | 1,320 | 0 | 2,935 | 100 | 31,680 | 690 | 70 | 36,675 | 1,005 | 725 | 95 |
| Johnson | 190 | 95 | 1,250 | 185 | 895 | 32,285 | 90 | 29,540 | 875 | 0 | 830 |
| Madison | 185 | 0 | 6,450 | 1,375 | 100 | 150 | 33,040 | 6,765 | 15 | 0 | 90 |
| Marion | 5,000 | 25 | 30,465 | 2,950 | 17,935 | 11,720 | 1,010 | 355,320 | 1,955 | 255 | 1,185 |
| Morgan | 155 | 80 | 330 | 80 | 3,565 | 1,790 | 45 | 11,065 | 12,770 | 305 | 10 |
| Putnam | 50 | 0 | 45 | 0 | 1,590 | 85 | | 2,080 | 275 | 9,930 | 20 |
| Shelby | 20 | 0 | 175 | 730 | 120 | 1,190 | 10 | 4,275 | 65 | 0 | 12,515 |

Considering the temporal variation of traffic distribution over morning peak hours, the commuting flow distribution data of Indianapolis MSA was aggregated from GEOSTAT, which includes the distribution of traffic for each county from 5:00 AM to 11:00 AM in every half hour. The average temporal traffic distribution of the 11 study counties has been used as a reference for generating traffic demand for the simulation, as shown in Figure 5-2.

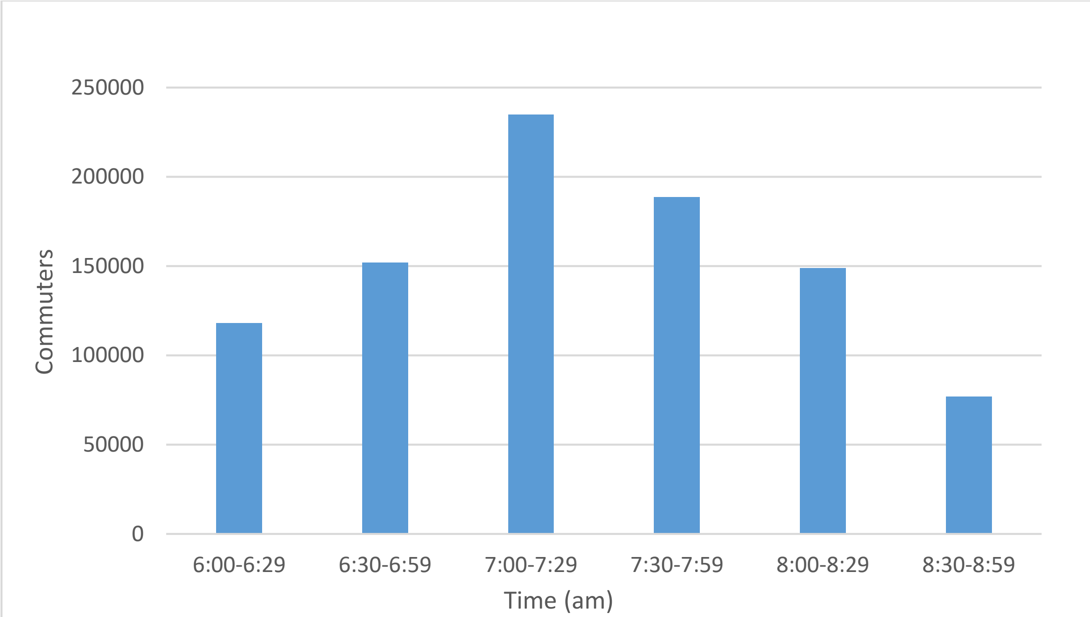


Figure 5-2 Morning Hour Traffic Distribution of Indianapolis MSA

*5.1.2.2 Model Design*

The simulation was conducted in MATSim, which is a "highly developed transportation simulator to implement agent-based simulations with a co-evolutionary process among individual agents across a network" (Axhausen & ETH Zürich, 2016). MATSim also includes a GIS-based visualization software, Via, which allows for presenting the whole simulation process (Simunto, 2019). By providing the O-D matrix, road network and other related data, as discussed in the previous section, the model operates by generating personal-trips in each TAZ throughout the actual road network across the Indianapolis Metropolitan Area during the morning commuting period. The model framework is built on two important agents (passengers and AVs) and the simulation steps are grouped into three steps: 1) generating demand; 2) dispatching AVs; and 3) estimating energy use and greenhouse gas emissions. The remainder of this section discusses the simulation methodology in greater detail.

*Step 1: Generating demand*

This step introduces estimated AV traffic demand into the simulation. An estimation of potential AV demand is generated by multiplying the total travel demand and adoption rate estimated as part of the choice experiment discussed in Section 0. The system will generate traffic in the simulation dynamically according to the distribution information provided. Previous other AV ABM simulation projects suggest simulation time step ranges from 5sec to 30sec (Fagnant & Kockelman, 2015; Loeb & Kockelman, 2019). In our case, the whole simulation period is conducted in the step of 10s, which could save computation resources; at every 10s, new traffic demand is generated, and AV's assignment strategy is updated.

*Step 2: Dispatching AVs*

The design of dispatching strategy was based on previous work (Levin et al., 2017). Note that since the OD matrix data was recorded at TAZ level, it is not possible to locate each traveler's origin and destination accurately. A key assumption was made to simplify the model – that each TAZ has a centroid point located at its geometric center, and hence, all the trips depart and arrive at the centroid points where AVs also pick-up and drop-off passengers (Fagnant, Kockelman, & Bansal, 2016). These centroid points will not deviate much from the real pick-up and drop-off points in smaller TAZs where most of the demand is located, but there might be a discrepancy in larger TAZs; since these larger areas only account for a small portion of the total demand, this assumption is acceptable.

The modeling framework comprises of agent rules and assumes that each AV in the system could get the real-time information of other AVs and passengers, which could help the agent make decisions on trip assignment and route choice. All the decisions are triggered by two events: a new demand for AV appears and an AV finishes its last trip service. To explain the framework more precisely, the network could be denoted as N(C, P, V, R, T), where C denotes the nodes of the network, which is considered as the location where passengers and AVs activates, P represents the set of passengers, V represents the set of AVs, R represents the set of routes, T represents the time.

<u>Case 1: A new demand for AV appears</u>

When a passenger p calls an AV, the dispatcher will go through the following rules to ensure that passenger get picked:

1. When a passenger p calls an AV at centroid C, the dispatcher first checks whether there are any AVs already parked at this centroid. If it is free, the dispatcher will directly assign the passenger to the AV.

2. If there are no free AVs at C, the dispatcher will search for the parked AV which is closest within 10 minutes driving distance (Boesch, Ciari, & Axhausen, 2016; Liu et al., 2017) to C. If there is one free, it gets assigned to the passenger.

3. If there are no free AVs within the serving radius of C, then a stochastic mode choice model proposed in Loeb & Kockelman, (2019) will be used to decide whether an AV outside the serving radius of C will be assigned to the passenger:

$$P(accept) = \frac{e^{\beta_0+\beta_1 t}}{e^{\beta_0} + e^{\beta_0+\beta_1 t}} \ldots (Eq. 5.1)$$

Where P(accept) is the probability that a passenger will accept a ride given response time t. $\beta_0$ is the time coefficient and $\beta_1$ is the alternative specific constant (ASC). $\beta_0$ is based on Gaudry & Tran, (2012) who calculated the time coefficient on waiting for a taxi to be −0.1351. An ASC of 1 was chosen to give a tail of approximately 12.5 minutes, within which time a user will not reject a trip.

<u>Case 2: An AV arrives at a centroid</u>

When an AV arrives at centroid C and has completed its last trip, the dispatcher will go through the following rules to ensure that an AV gets assigned to a passenger:

1. If an AV finishes its trip and arrives at centroid C and there is already a passenger waiting at this centroid, the AV will be directly dispatched to that passenger.

2. If there is no demand waiting at centroid C, the AV will search for any passenger within its 10 minutes serving radius.

3. If there is no passenger within its serving radius, using the stochastic mode choice model (Eq 5.1), it will search for any passenger out of serving radius.

4. If all of the passengers in step 3 reject the service, the vehicle will stop at its current location until the next round of assignment.

### 5.1.3. Estimating AV's Energy Use and Greenhouse Gas Emissions

The study employs a two-stage simulation of SAV's emission performance. First, a microsimulation based on MOVES was conducted, using the drive cycle/schedule (relationship between vehicle's speed and time) of human driven vehicle (HDV) and AV of both urban roadway scenario and highway scenario as input. The MOVES outputs included HDV's and AV's energy consumption and five types of greenhouse gas emissions. It is assumed that both HDV and AV are using gasoline as fuel. As a next step, the MOVES' emission outputs are used for estimating vehicle's greenhouse gas emission in the MATSim simulation. To explore the impact of different factors involved in the simulation, scenarios for different fleet size and demand were designed, as discussed next.

## 5.2 Findings

### 5.2.1. AV's Driving Cycle and Environmental Performance

The driving cycles of HDV in urban and highway environments (Figure 5-3 and Figure 5-4) are represented by the U.S. Environmental Protection Agency's driving cycles data, which is used to test for compliance with Corporate Average Fuel Economy (CAFE) standards for light-duty vehicles (US EPA, 2015).

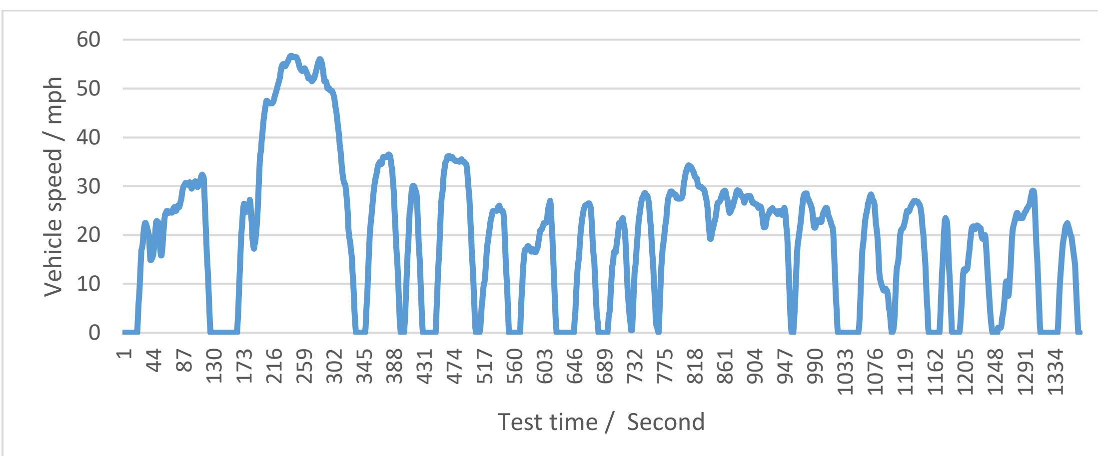


Figure 5-3 EPA Urban Dynamometer Driving Schedule

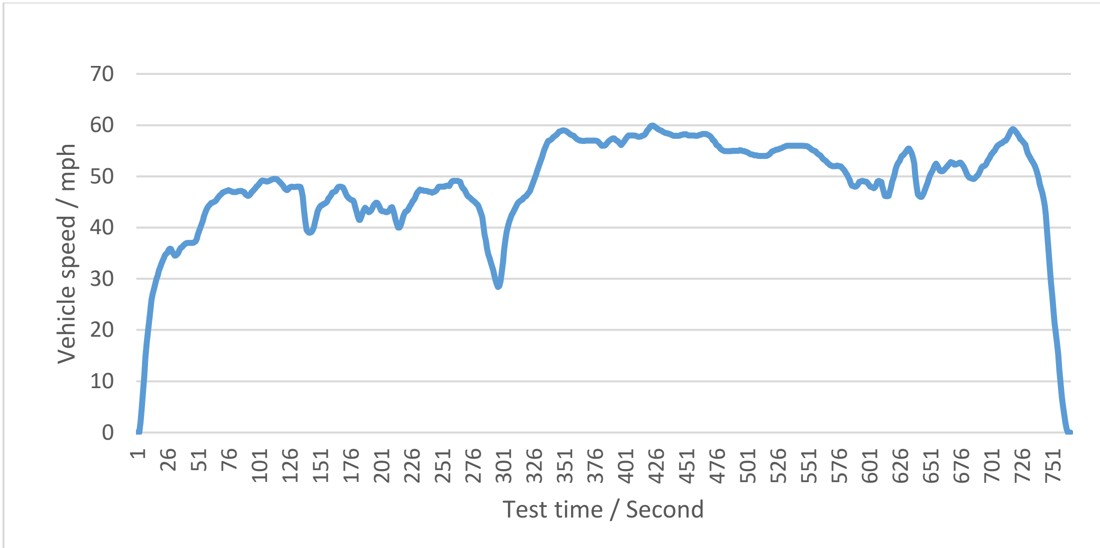


Figure 5-4 EPA Highway Fuel Economy Driving Schedule

The driving cycle data for AV was collected from the Udacity driverless car project. The original data includes 223GB of image frames and trajectory data of Google's driverless car on two separate days in 2016 in Mountain View, California (MIT, 2016). The data contains real time spatial-temporal information and traveling characteristic information (speed, gear, steering angle) of vehicle, which is needed to estimate AV's driving cycle (a snapshot of the dataset is shown in Figure 5-5). Two sub datasets for urban roadway and highway scenario were selected. The first dataset includes 221 seconds of driving records in the downtown area of Mountain View, where the average speed for AV is 17.9 mph, close to the average speed 20.1 mph in EPA urban roadway test. The second dataset includes 791 seconds of driving records on a two-lane divided freeway, where the average speed for AVs freeway test is 40.2 mph, close to average speed 38.9 mph in EPA freeway test.

```
Latitude, Longitude, Gear, Brake, Throttle, Steering Angle, Speed, FileName
37.399960, -122.131840, 4, 0.147433, 0.307836, 0.005236, 10.150000, images/1475187707065512506.png
37.399813, -122.132192, 4, 0.213535, 0.149950, 0.024435, 0.000000, images/1475187679161015902.png
37.398688, -122.134251, 4, 0.147890, 0.285496, 0.144862, 6.222222, images/1475187468081761839.png
37.401403, -122.139691, 4, 0.147280, 0.263645, 0.038397, 20.450001, images/1475187502136833882.png
37.403349, -122.142816, 4, 0.147860, 0.194278, -0.024435, 14.280556, images/1475187566745658396.png
37.399197, -122.134144, 4, 0.148913, 0.164965, 1.951278, 6.938889, images/1475187647407128007.png
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37.396867, -122.132384, 4, 0.210590, 0.149950, 0.033161, 18.194445, images/1475187389621094591.png
```

sample.log hosted with ♡ by GitHub  view raw

Figure 5-5 Example of the Udacity Driverless Car Project Dataset (MIT, 2016)

The driving cycles of HDV and AV are then fed into EPA's MOVES model to calculate the corresponding distance-based energy consumption rate and greenhouse gas emissions rate. The MOVES' simulation results are shown in Table 5-2 and Table 5-3. It can be observed that AV performs better than HV in terms of energy consumption and greenhouse gas emissions under both the urban roadway scenario and highway scenario. The enhanced performance of AVs on urban roadways is more apparent than that on freeways, considering the aforementioned speeds.

Table 5-2 Energy Use and Emission Estimates-Urban Roadway Scenario

| | Gasoline (MPG) | VOC (Grams per mile) | $PM_{2.5}$ (Grams per mile) | CO (Grams per mile) | $NO_X$ (Grams per mile) | $CO_2$ (Grams per mile) |
|---|---|---|---|---|---|---|
| Urban Dynamometer Driving Schedule | 24 | 0.092 | 0.0157 | 2.621 | 0.382 | 393.2 |
| AV Urban Test | 27 | 0.084 | 0.0153 | 2.58 | 0.353 | 381.7 |
| Absolute Value | | 0.008 | 0.0004 | 0.041 | 0.029 | 11.5 |
| Percent | | 8.70% | 2.55% | 1.56% | 7.59% | 2.92% |

Table 5-3 Energy Use and Emission Estimates-Freeway Scenario

| | Gasoline (MPG) | VOC (Grams per mile) | $PM_{2.5}$ (Grams per mile) | CO (Grams per mile) | $NO_X$ (Grams per mile) | $CO_2$ (Grams per mile) |
|---|---|---|---|---|---|---|
| Highway Fuel Economy Driving Schedule | 33 | 0.054 | 0.0023 | 1.997 | 0.273 | 281.7 |
| AV Highway Test | 35 | 0.053 | 0.002 | 1.925 | 0.266 | 279.8 |
| Absolute Value | | 0.001 | 0.0003 | 0.072 | 0.007 | 1.9 |
| Percent | | 1.85% | 13.04% | 3.61% | 2.56% | 0.67% |

As also shown in Figure 5-6, all of the greenhouse gas emissions in the two simulation scenarios are lower for AVs. The VOC and NOX show the largest reduction under the urban scenario, , which have reductions of 8.70% and 7.59% when compared to HDV, respectively. PM2.5 shows the most evident decrease under the freeway scenario. Comparing these two scenarios, the results indicate that for different driving cycles, greenhouse gas emission reduction will present different patterns. Overall, AVs seem to have a positive effect on emission reduction.

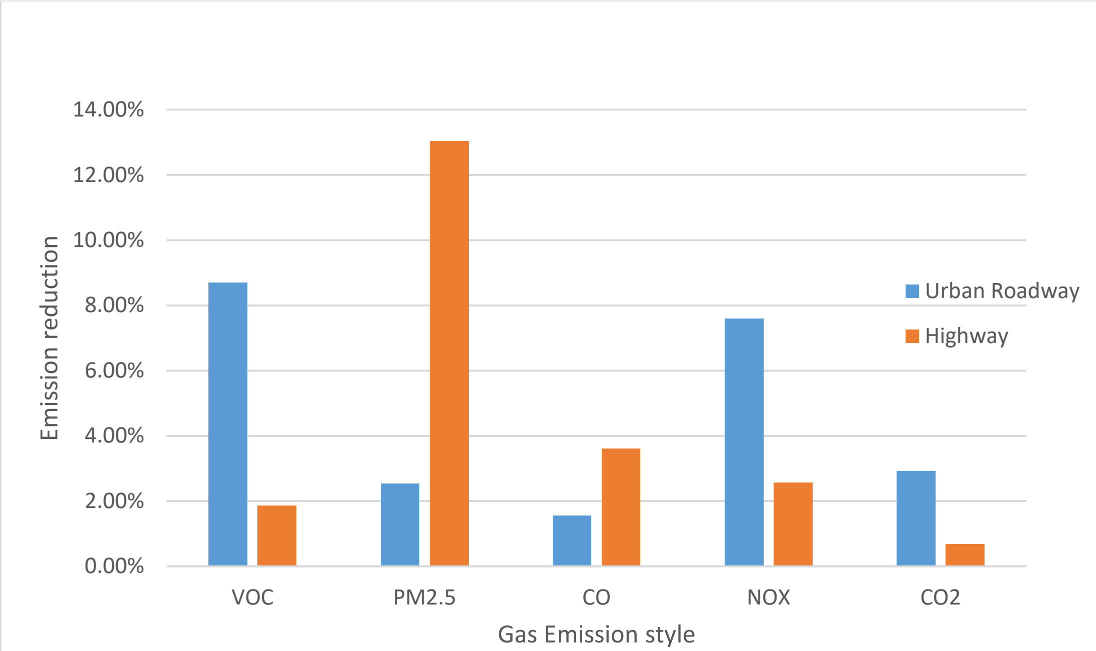


Figure 5-6 MOVES Simulation Result

### 5.2.2. Agent Based Simulation Model Results

According to Figure 4-3, the demand for AV services in the study area in the short-run could range between 5.6% to 12.8%. We used this range to conduct sensitivity analysis of the ABM results. Herein, we present representative scenario and sensitivity analysis results, as follows.

Table 5-4 shows the simulation results for the scenario with potential demand of 100,000 trips and 12,000 AVs[1]. Table 5-4 indicates that all five types of greenhouse gas emissions have experienced reductions, with $CO_2$ emission decreasing most.

[1] To estimate the initial AV fleet size, it is assumed that the fleet size will be large enough to serve the busiest period during the whole morning peak hours, which is from 7:00 AM to 7:30 AM. The traffic flow during this time accounts for 26% of total trips of morning peak hours. According to INDOT, the average commuting time for Indianapolis Metropolitan Area is 28 minutes. If each AV only serve one time during 7:00 AM-7:30 AM, the reasonable fleet size for 50,000 traffic demand will be 50000*0.26/30*27, or close to 12,000.

Table 5-4 Scenario Simulation Outputs

| Grams per mile | Total Traveling Distance (miles) | Total Gasoline Consumption reduction (gallons) | VOC reduction (gram) | $PM_{2.5}$ reduction (gram) | CO reduction (gram) | $NO_X$ reduction (gram) | $CO_2$ reduction (gram) |
|---|---|---|---|---|---|---|---|
| Scenario (100,000 demand, 12,000 fleet size) | 1,290,000 | 5,099 | 5,805 | 451.5 | 72,885 | 23,220 | 8,643,000 |

Figure 5-7 shows the reduction in terms of $CO_2$ emissions for different demand scenarios given a fixed fleet size of 12,000 AVs. The results indicate that as the potential demand for AV increases, the total $CO_2$ emission reduction reaches its maximum value when the potential travel demand is set to 100,000. As the potential demand increases again, the total $CO_2$ reduction decreases. Note that a fixed fleet size of 12,000 AVs may not be large enough when the total demand exceeds 100,000. Moreover, the AV occupancy rate slightly decreases from 0.72 in the 100,000 trips scenario to 0.7 in the 120,000 trips scenario. This might reflect the insufficient service capacity of the current fleet size.

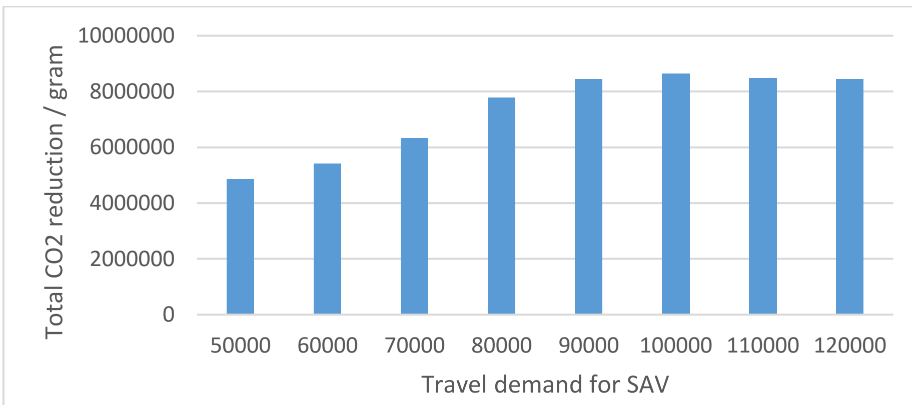


Figure 5-7 Total $CO_2$ Emissions Reduction as a Function of Travel Demand

Figure 5-8 shows the trends in $CO_2$ emissions as the fleet size changes, for a fixed demand of 50,000. It can be observed that as the fleet decreases, the total $CO_2$ emissions is the lowest for a fleet size of 8,000 SAVs.

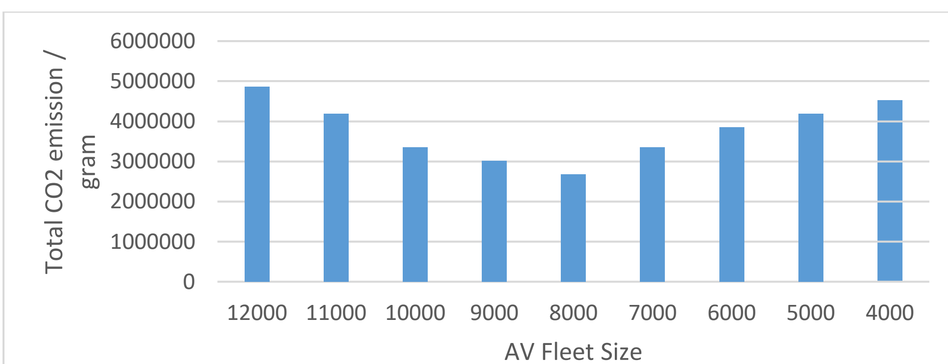


Figure 5-8 Sensitivity Analysis of AV Fleet Size

Lastly, several simulations were run to explore the relationship between the potential demand and its corresponding optimal fleet size. The trendline in Figure 5-9 suggests that as the demand increases, each AV will be able to serve more passengers and still have positive implications on energy use and greenhouse gas emission. With higher demand, AV's driving distance when it is at vacant status could be shorter, and as a result serve passengers within given time.

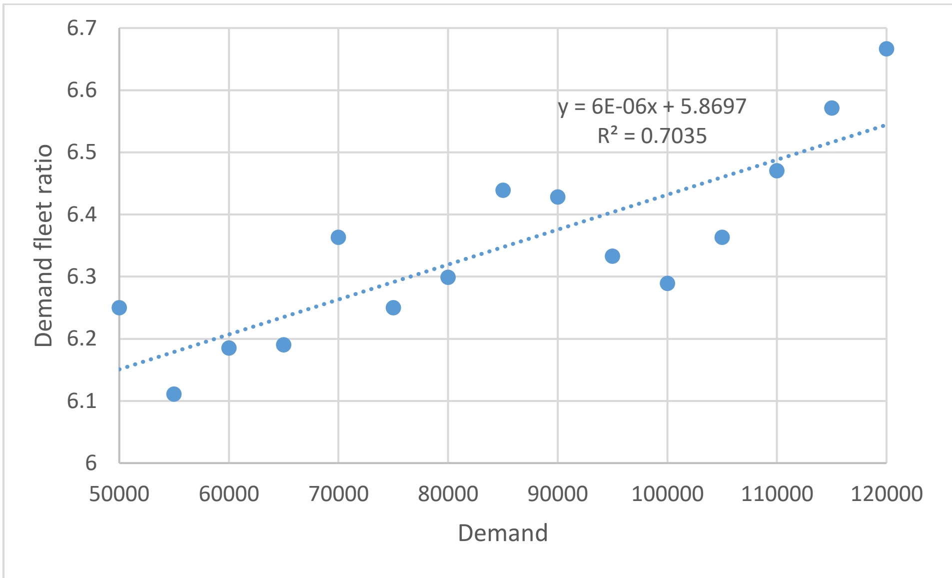


Figure 5-9 Relationship between Demand-Fleet Ratio and Demand

# 6 Recommendations

This study examined the factors affecting public acceptance of AVs and SAVs and their potential implications on energy use and greenhouse gas emissions based on different levels and timing of market penetration. In specific, the behavioral intention to ride in an AV was assessed by designing and evaluating a theoretical model based on the TPB theory (Ajzen, 1991), that was decomposed to include components of the theory of DoI (Rogers, 1995), and extended to evaluate whether other attitudinal components can also be determinants of the behavioral intention to ride in an AV. A stated-preference survey was designed to include the components of the decomposed and extended TPB model and was distributed online to adult residents of the Indianapolis metropolitan area, soliciting 400 responses. Explanatory and confirmatory factor analyses were conducted to test the validity and reliability of the components included in the theoretical model, followed by SEM estimation. It was found that the TPB components have a direct influence on behavioral intention to ride in an AV. In terms of the DoI components, only two of them were found to have an indirect positive impact on the behavioral intention to ride in an AV. From the additional components that were considered in this analysis, self-efficacy had a positive indirect impact on behavioral intention through the perceived behavioral control and safety, driving related sensation seeking, and affinity to innovativeness had a direct and positive influence; whereas the association of trust of strangers with behavioral intention was not found significant. The proposed theoretical model developed in this report can be implemented and distributed in other urban areas in order to compare results on the diffusion of the emerging technology of AVs and provide a pathway to the adoption and deployment of AVs.

As there is not much data available on market acceptance of AVs, the market segmentation analysis further provided some insights on the characteristics of potential users/adopters (innovators, early adopters, early majority, late majority, laggards). It was found that people who were classified as 'innovators' or 'early adopters' were more likely to use other modes for commuting than their private vehicles (walk, bike, public transportation) and they own or have access to less vehicles compared to their counterparts. Additionally, members of ride hailing and car sharing services, younger individuals, people who work full time, people with higher income and education attainment were more likely to be classified in the first two groups (innovators and early adopters) compared to people in the last two groups (late majority and laggards).

Furthermore, this study shed light into how the emergence of autonomous ride-sharing services operated through AVs (i.e., SAVs) can affect the mode choice decisions (bike, private vehicle, public transportation, ride hailing services operated in non-AVs) in the short and long run. A number of factors were identified as significant determinants of the potential disruption in mode shares that include (but not limited to): level of awareness, number of social/recreational trips on a weekly basis, ride hailing/car sharing service membership, annual mileage, mode-choice related factors (e.g. reliability), attitudinal variables (such as tendency to be influenced by their social circles, affinity to innovativeness, and safety concerns towards AVs), and socio-economic variables (such as age, annual income and private vehicle ownership). The value of travel time savings was also calculated for the general sample and for the different adopter categories that were identified the market segmentation analysis (early adopters, medium adopters, late adopters) to capture preference heterogeneity. Our results seem to suggest that the option of sharing the ride is not as preferred as the single passenger one across all market segments which may challenge the benefits that this emerging technology can bring to shared transportation modes. In specific, it was found that the value of travel time savings is lower for the option of sharing the ride in an AV with other passengers rather than riding alone in an AV regardless of the time period of AV implementation and the market segment. Therefore, a stronger effort needs to be made in order to make this option more popular to people (e.g. incentives, trip cost reduction).

Lastly, a two-stage simulation framework based on ABM was designed that can compare the environmental performance of AVs with that of traditional vehicle under different scenarios. The proposed framework was demonstrated using the case study of the Indianapolis metropolitan area. Different scenarios were designed to examine the impact of fleet size of AVs offering single passenger rides and fleet composition on greenhouse gas emissions, air pollutants, and energy consumption. By comparing driver cycles, it was found that an AV has a better environmental performance than a tradition vehicle for the same fuel type and at similar speeds. The results also suggested optimal demand levels and fleet size for the study area, which can be used as a reference for future AV service deployment.

The conclusions presented in this report can provide insights to transportation and urban planners to prepare for AVs as well as original equipment manufacturers so as to design marketing strategies to improve people's perceptions of AVs and increase market penetration. Based on findings of this study, policy makers, developers, and governmental agencies are thought to play a key role on smoothing the transition to new technology. To enhance most of the factors that influence the intention to ride in an AV, it is necessary that those stakeholders market the benefits of the technology, allow individuals to be an active part of the transition, either by listening to their expectation and concerns or by involving them in the technology testing. For that, exhibits or events where AVs are showcased for the public might increase public acceptance. By promoting the relative advantages of AVs compared to non-AVs, such as benefits in mobility, society and environment, the perceptions of individuals towards the AVs would improve and therefore, the behavioral intention to ride in an AV could increase. The evaluation of the values of travel time savings of SAVs (single passenger and shared AV rides) related to commuting can further provide quantitate information to policymakers and AV operators related to pricing.

Note that the inferences made in this study are subject to the limitations of stated-preference surveys, which ask questions that are hypothetical in nature. The methods applied herein attempted to address these limitations through appropriate data preparation and analysis, such as the removal of incomplete responses, cases of over-coverage, and passive responses; the inclusion of "cheap talk" to address hypothetical bias; and rigorous econometric modeling. Moreover, this study is cross-sectional and evaluates a snapshot of a given point in time. It would be interesting to conduct a longitudinal study covering several points in time to evaluate whether the factors affecting behavioral intention to use AVs and the adoption of AVs change throughout different time periods.

Turning to the simulation framework results, the inferences made should be viewed in light of the following assumptions. The type of AVs included in the simulation are owned by transportation network companies (not privately owned) and provide service to one passenger at a time (single passenger AV rides). The potential AV demand is based on the stated-preference survey with the limitations as stated above. The TAZ centroid was used as the starting and end point for trips (pick-up and drop off locations), which may not reflect the real situation for all single passenger AV rides commuting trips. Moreover, AV speeds in the simulation were limited by the roadway speed limit; the impact of congestion on speeds during the morning peak hours was not accounted for in the simulation. Future work can address these shortcomings and further, include the ride sharing behavior and relocating strategy in the simulation framework design. Ride sharing behavior can reduce total traveling distance and corresponding energy use and greenhouse gas emissions and relocating the free AVs could help enhance the efficiency of AV fleets and decrease the waiting time of passengers. Lastly, it was assumed that both HDV and AV are gasoline-fueled; future work can consider alternative energy sources (such as electricity) and explore the combined benefits of automation and clean energy on the environment.

# 7 Synopsis of Performance Indicators

## 7.1 Part I

The research from this advanced research project was disseminated to over 180 people from industry, government, and academia. The research was presented at several conferences, including the 2017 Transportation Research Forum Annual Conference in Chicago, the 2018 CCAT Annual Symposium in Ann Arbor, the 2018 (5th) International Conference in Travel Behavior Research in Santa Barbara, the 2019 Purdue Road School in West Lafayette, the 2019 (3rd) International Symposium on Multimodal Transportation, Singapore, and the 2019 ITE (Purdue Chapter) Annual Dinner. This project supported 3 students, 1 master's level and 2 doctoral level.

During the study period: (a) 1 undergraduate and 1 graduate transportation-related course were offered that were taught by the PI and/or teaching assistants who are associated with this project; (b) 1 undergraduate student and 3 graduate students participated in this research project and were funded by this grant during the study period; (c) three transportation-related advanced degree programs that utilized grant funds during the reporting period – 1 masters level program and 2 doctoral level programs, (d) 3 students supported by this grant received degrees – 1 undergraduate degree, 1 masters degree, and 2 doctoral degrees. Some of these students were also partially supported by another CCAT project. This study involved 1 applied research project with a dollar value of $65,000.

## 7.2 Part II

Research Performance Indicators: 6 conference articles and 2 peer-reviewed journal articles were produced from this project. One (1) other research projects was funded by sources other than UTC and matching fund sources. At the time of writing, there are no new technologies, procedures/policies, and standards/design practices yet that were produced by this research project.

Leadership Development Performance Indicators: This research project generated 1 media engagement, 6 academic engagements, and 2 industry engagements. The PI held positions in 2 national organizations that address issues related to this research project. Two (2) of the CCAT-affiliated students who worked on this project hold leadership positions.

Education and Workforce Development Performance Indicators: The methods, data and/or results from this study are being incorporated in the syllabus for the next version (Fall 2022) of Transportation Systems Evaluation, a mandatory graduate level course at Purdue University's transportation engineering program.

The outputs, outcomes, and impacts are described in Section 8 below.

# 8 Outputs, Outcomes, and Impacts

## 8.1 Outputs

8.1.2 Publications and Conference Proceedings

The results of this work have been published or presented in various journals and conferences, as reported below:

- Christos Gkartzonikas, Lisa Lorena Losada-Rojas, Sharon Christ, V. Dimitra Pyrialakou, Konstantina Gkritza, "A multi-group analysis of the behavioral intention to ride in autonomous vehicles: evidence from three U.S. metropolitan areas", Transportation (2022). https://doi.org/10.1007/s11116-021-10256-7
- Gkartzonikas, C., and Gkritza K., "What Have We Learned? A Review of Stated Preference and Choice Studies on Autonomous Vehicles", Transportation Research Part C: Emerging Technologies (2019). https://doi.org/10.1016/j.trc.2018.12.003
- Zimo, Z., Hua, C. Gkritza, K. 'Assessing the Energy and Environmental Implications due to the Emergence of Autonomous Vehicles'. 3rd International Symposium On Multimodal Transportation, Singapore, December 2019
- Clawson R. & Gkritza K., "CATV Policy and Innovation: Discussion of Real-World Implications", Presented at 105th Purdue Road School Transportation Conference & Expo, March 4–7, 2019.
- Gkartzonikas, C., and Gkritza, K. Podium Presentation "Assessing the Behavioral Intention to Ride in Autonomous and Shared Autonomous Vehicles and Market Segmentation Analysis" at 15th International Conference on Travel Behavior Research, July 15-20, 2018, Santa Barbara, CA.
- Gkartzonikas, C., and Gkritza, K. Poster Presentation "Factors Influencing the Behavioral Intention to Ride in Autonomous Vehicles" at 2018 Global Symposium for Connected and Automated Vehicles and Infrastructure on March 7-8, 2018, Ann Arbor, MI.
- Gkartzonikas, C., and Gkritza K., Podium Presentation "A Literature Review on Surveys for Autonomous Vehicles" at 58th Annual Transportation Research Forum on April 20-21, 2017, Chicago, IL.
- Gkartzonikas, C., and Gkritza K., Poster Presentation "Modeling the Behavioral Intention to Ride in Autonomous Vehicles: The Case of Chicago" at ITE Great Lakes District Annual Meeting, April 19-20, 2017, Ann Arbor, MI.

**8.1.2 Other outputs**

- As part of the Sustainable Transportation Systems Research Group Website, we have a tab dedicated to disseminating the CCAT projects led by Dr. Konstantina Gkritza. The website can be access using the following link: https://engineering.purdue.edu/STSRG/research/CCAT/P_CCAT
- Two databases were created as part of the data collection efforts. Given Purdue's Institutional Review Board restrictions, those can be access upon request to the author of this report.
- Fall 2018 & Fall 2019 & Fall 2020: CE 299 Smart Mobility, Lecture on Estimating Transportation Demand for Conventional and Emerging Modes.

## 8.2 Outcomes

- This project reviews stated preference/choice studies related to autonomous vehicles.
- The benefits, barriers, and opportunities associated with AV deployment are summarized in this project.
- Lessons learned and research gaps associated with AV adoption/deployment are provided.
- This project examined the factors affecting public acceptance of AVs and SAVs and their potential implications on energy use and greenhouse gas emissions based on different levels and timing of market penetration

## 8.3 Impacts

- The findings of this project reinforce the need for broader testing of AV technology in urban areas coupled with public education campaigns to harvest public awareness and acceptance.
- To enhance most of the factors that influence the intention to ride in an AV, as presented in this report, it is necessary that those stakeholders market the benefits of the technology, allow individuals to be an active part of the transition, either by listening to their expectation and concerns or by involving them in the technology testing.
- Evaluating the values of travel time savings of SAVs (single passenger and shared AV rides) related to commuting can further provide quantitative information to policymakers and AV operators related to pricing.

## 8.4 Technology Transfer

Not Applicable.

## 8.5 Challenges and lessons learned

- It would be interesting to conduct a longitudinal study covering several points in time to evaluate whether the factors affecting behavioral intention to use AVs and the adoption of AVs change throughout different periods.
- The types of AVs included in the simulation are owned by transportation network companies (not privately owned) and provide service to one passenger at a time (single passenger AV rides). The potential AV demand is based on the stated-preference survey with the limitations as stated in the report.
- AV speeds in the simulation were limited by the roadway speed limit; the impact of congestion on speed during the morning peak hours was not accounted for in the simulation. Future work can address these shortcomings, and further include the ride-sharing behavior and relocating strategy in the simulation framework design.

## List of Acronyms

| | |
|---|---|
| AV | Autonomous Vehicles |
| ABM | Agent-Based Model |
| AVE | Average Variance Extracted |
| CFA | Confirmatory Factor Analysis |
| CFI | Comparative Fit Index |
| CR | Composite Reliability |
| CTPP | Census Transportation Planning Products Program |
| DoI | Diffusion of Innovation |
| DRSS | Driving Related Sensation Seeking |
| EPA | Environmental Protection Agency |
| HDV | Human Driving Vehicle |
| INDOT | Indiana Department of Transportation |
| MoE | Margin of Error |
| MSA | Metropolitan Statistical Area |
| OD | Origin Destination |
| RMSEA | Root Mean Square Residual |
| SAVs | Shared Autonomous Vehicles |
| SEM | Structural Equation Model |
| TAZ | Traffic Analysis Zone |
| TLI | Tucker Lewis Index |
| TPB | Theory of Planned Behavior |
| USDOT | U.S. Department of Transportation |
| VMT | Vehicle-Miles Traveled |
| VTTS | Value of Travel Time Savings |

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# 9 Appendix

## Appendix A Measurement model results

| Latent Construct | Survey Questions | Mean | Std. Dev. |
|---|---|---|---|
| Affinity to innovativeness | I am adventurous and eager to be the first to try new innovations. | 3.30 | 1.11 |
| | I adopt innovations and influence others to do so. | 3.16 | 1.06 |
| | I am willing to follow the lead of others in adopting innovations. | 3.46 | 0.94 |
| | I need to be convinced of the advantage of innovations by peers. | 3.26 | 0.99 |
| | I am suspicious of innovations. | 2.84 | 1.01 |
| | I am always looking for innovations. | 3.32 | 0.96 |
| | My opinion about innovations is respected by peers. | 3.39 | 0.83 |
| | I will adopt innovations but do not attempt to influence others to do so. | 3.24 | 0.90 |
| | I go along with innovations out of necessity. | 3.19 | 1.00 |
| | I am resistant to change. | 2.58 | 1.10 |
| Environmental Concerns | I think that people should live in harmony with nature in order to achieve sustainable development. | 3.86 | 0.87 |
| | I think individuals have responsibility to protect the environment. | 4.20 | 0.76 |
| | I think environmental problems are becoming more and more serious in recent years. | 4.00 | 0.99 |
| | I think we are not doing enough to save scarce natural resources from being used up. | 3.87 | 1.05 |
| | I think that people should sort and recycle their waste | 4.14 | 0.84 |
| | I think it is not necessary to use your personal vehicle for every trip | 3.32 | 1.02 |
| Driving Related Sensation Seeking | I would like to drive without a preplanned route and without a schedule. | 3.21 | 1.12 |
| | I often feel like being a race car driver. | 2.28 | 1.19 |
| | I would like to drive on roads with many sharp turns. | 2.35 | 1.12 |
| | I would like to learn to drive cars that can exceed the speed of 180 mph. | 2.29 | 1.32 |
| | I do not have patience for people who drive cars in a predictable and boring manner. | 2.51 | 1.05 |
| | I think I would enjoy the experience of driving very fast on a steep road. | 2.38 | 1.31 |
| Trust to strangers | Most people will try to take advantage of someone else, if they get the chance to do it. | 3.27 | 1.04 |
| | Most people only look after themselves. | 3.33 | 1.00 |
| | You cannot trust most people. | 2.98 | 1.08 |
| | You cannot trust strangers. | 3.17 | 1.03 |
| | I do not look the entrance door of my house/apartment | 1.72 | 1.08 |
| | I believe that I am a trustworthy person | 4.31 | 0.77 |
| | I lend money to friends | 3.30 | 1.08 |
| | I lend personal belongings to friends | 3.58 | 0.99 |
| | AVs offer more benefits to our society than non-AVs. | 3.12 | 1.00 |

| | | | |
|---|---|---|---|
| Relative Advantage | Riding in AVs would reduce the number of accidents compared to riding in non-AVs. | 3.10 | 1.09 |
| | Riding in AVs would be more environmental-friendly than riding in non-AVs. | 3.22 | 1.00 |
| | Riding in AVs would reduce the time that I spend sitting in traffic congestion than riding in non-AVs. | 2.92 | 1.10 |
| | I would be free to make the most of my time spent in a vehicle, if I am riding in an AV rather than riding in non-AVs. | 3.48 | 1.05 |
| | Riding in AVs would relieve parking problem/stress than non-AVs | 3.24 | 1.05 |
| Complexity | It would be easy for me to ride in an AV. | 3.03 | 1.17 |
| | I will find it easy to make the AV do what I want. | 2.97 | 0.97 |
| | I think I cannot manage to ride in an AV | 2.84 | 1.15 |
| Compatibility | The thought of riding in AVs suits my lifestyle. | 2.96 | 1.13 |
| | Riding in an AV suits my daily needs. | 2.95 | 1.13 |
| | Riding in an AV fits well with my habits. | 2.88 | 1.13 |
| Attitudes towards use | I dislike/like the thought of riding in AVs. | 3.11 | 1.31 |
| | Riding in AVs would be a bad/good idea for me. | 3.09 | 1.29 |
| | I would find riding in AVs useless/useful for my purposes. | 3.17 | 1.32 |
| | Riding in AVs sounds stupid/smart to me. | 3.26 | 1.22 |
| | Riding in AVs sounds scary/fun to me | 2.96 | 1.37 |
| | Riding in AVs would be not suitable/suitable for my needs. | 3.11 | 1.36 |
| | For me, riding in AVs is undesirable/desirable. | 2.99 | 1.40 |
| Subjective Norms | People who are important to me will support my decision on riding in an AV. | 3.50 | 0.96 |
| | The media make it more appealing for me to ride in an AV. | 2.88 | 1.03 |
| | People who are important to me would try to convince me to ride in an AV. | 2.86 | 1.05 |
| | People who are important to me would want me to ride in an AV. | 3.02 | 1.07 |
| | People who are important to me would prefer I rode in an autonomous vehicle. | 2.76 | 1.06 |
| | Articles in the media influence my intention to ride an AV | 2.95 | 1.05 |
| Personal Moral Norms | Because of my own principles, I would feel an obligation to ride an AV, if one is accessible, due to its lower fuel consumption. | 2.84 | 1.15 |
| | Regardless of what other people do, I would feel morally obliged to ride in an AV, if one is accessible, due to its lower emissions. | 2.75 | 1.17 |
| | I would feel a moral obligation to ride in an AV, if one is accessible, as it is expected to be friendlier to the environment. | 2.81 | 1.18 |
| | I would feel obligated to focus on the advantages of AVs, when making travel model choice | 3.06 | 1.13 |
| Self-Efficacy | I will have the knowledge to ride in an AV. | 3.37 | 1.02 |
| | I would be capable to ride in an AV. | 3.59 | 1.00 |
| | It would be easy for me to control all things relevant to riding in an AV. | 3.20 | 1.07 |

| | | | |
|---|---|---|---|
| Perceived Behavioral Control | When AVs become widely available, I would know enough to ride in one. | 3.47 | 1.05 |
| | When AVs become widely available, I believe I would afford to purchase one. | 2.75 | 1.17 |
| | When AVs become widely available, I believe I would afford to ride in one. | 3.16 | 1.10 |
| | When AVs become widely available, I believe I will have the necessary means and skills to ride in an AV. | 3.48 | 1.05 |
| | When available, I will have the ability and opportunity to ride in an AV if I want to. | 3.46 | 1.05 |
| Safety | The automated driving technology installed in AVs is likely to be a better driver than I am. | 3.00 | 1.13 |
| | Riding in an AV will enable me to reach my destination safer than riding in a non-AV. | 3.09 | 1.06 |
| | I have safety concerns about riding in AVs | 3.69 | 1.10 |
| | I believe that riding in an AV requires increase attention than non-AVs | 3.31 | 1.03 |
| | While riding in an AV, I will not need to pay attention to the traffic. | 2.46 | 1.16 |
| Behavioral Intention | I intend to ride in an AV when AVs become available. | 3.08 | 1.21 |
| | I intend to ride in an AV in the near future. | 2.72 | 1.18 |
| | I intend to frequently ride in an AV in the near future. | 2.56 | 1.18 |
| | I would recommend the use of AVs to other people. | 2.98 | 1.09 |
| | I intend to ride in an AV in the foreseeable future. | 2.97 | 1.24 |
| | I intend to frequently ride in an AV in the foreseeable future. | 2.67 | 1.20 |

**Appendix B Summary of cluster characteristics**

| Innovators | Early adopters | Early majority | Late majority | Laggards |
|---|---|---|---|---|
| Highest level of awareness on AVs | Higher than average level of awareness on AVs | Lower than average level of awareness on AVs | Higher than average level of awareness on AVs | Lowest level of awareness on AVs |
| 25% use public transportation or walk to their commute trips as primary modes, 4% bike commute | 15% use public transportation or walk to their commute trips as primary modes | 80% use their personal vehicles for their commute trips | 90% use their personal vehicles for trips regardless the trip purpose | 90% use their personal vehicles for trips regardless the trip purpose, only 3% walk |
| 10% do not own a vehicle. They drive about 12,000 mi/year (highest of any group) | 10% do not own a vehicle. They drive about 10,000 mi/year on average | 10% do not own a personal vehicle | 2% do not own a personal vehicle | 5% do not own a personal vehicle, though this group drives the least on (avg 9000 mi/year) |
| 65% use ride-hailing services, 20% have a car-sharing service account | 40% use ride-hailing services, 5% have a car-sharing service account | 40% use ride-hailing services | 20% use ride-hailing services and none of them use car-sharing services | 10% use ride-hailing services, 0 respondents had a car sharing account. |
| 64% are male | 54% are female | 58% are female | 64% are female | 52% are female |
| 55% are Millennials (<34 y.o.) | Avg. age 29 y.o. | 32% are Millennials (<34 y.o.) | 35% are Millennials (<34 y.o.) | 55% are people over 55 years old and 23% over 65 years old |
| 60% work full time, 13% are students | 38% work full time, 8% unemployed | 44% work full time, 15% part time | 24% have retired | 22% have retired, 10% unemployed |
| Higher than average income – 52,000 on average | Higher than average income – around 50,000 | Lowest average income – around 45,000 | Average income around 48,000 | Average income around 48,000 |
| 40% finished college degree, 10% did not graduate high school | 32% finished undergraduate degree | 21% are not high school graduates | 17% are not high school graduates, 35% college graduates | 41% finished college degree |

**Appendix C Fractional factorial design table**

| Scenarios | Choice 2 – cost | Choice 3 – cost | Choice 2 – travel time | Choice 3 – travel time |
|---|---|---|---|---|
| 1 | -1 | -1 | -1 | -1 |
| 2 | +1 | -1 | -1 | +1 |
| 3 | -1 | +1 | -1 | +1 |
| 4 | +1 | +1 | -1 | -1 |
| 5 | -1 | -1 | +1 | +1 |
| 6 | +1 | -1 | +1 | -1 |
| 7 | -1 | +1 | +1 | -1 |
| 8 | +1 | +1 | +1 | +1 |
| SUM (needs to be 0 for orthogonality) | 0 | 0 | 0 | 0 |

*high values are noted as +1 and low values are noted as -1

2 levels of each attribute and vary cost and travel time of ERs (not conventional lanes)

- 2 levels for 4 attributes (cost of ERs and travel time of ERs)
- Full factorial design: 24 scenarios = 16 scenarios
- Fractional factorial design to achieve orthogonality and not having confounded main effects: 2(4-1) = 8 scenarios

## Appendix D Choice Experiment

For this section of the survey, you will be provided with a number of scenarios about your daily commute to work. Please imagine that your house and your work place are located in Indianapolis. Not all information is given, but please imagine to the best of your ability to reach a decision. There are no right or wrong responses; we are merely interested in your personal opinions.

In this scenario, the different modes of transportation that are available for your daily commute to work are: a) walk, b) bike, c) private vehicle, d) public transportation. As indicated in the table below, you can see the time (in minutes), the cost (in dollars) for each mode of transportation. Which mode of transportation will you choose for your daily commute to work?

Scenario 0 - base case scenario

| Attribute/Mode Choice | Bike | Private Vehicle | Public Transportation | Ride-sharing service with non-autonomous vehicles |
|---|---|---|---|---|
| Time (minutes) | 35 | 20 | 37 | 24 |
| Cost (dollars) | 0 | 3 | 1.75 | 12 |

Your choice

| Bike | Private vehicle | Public transportation | Ride-sharing service with non-autonomous vehicles |
|---|---|---|---|
| ○ | ○ | ○ | ○ |

Figure D1: Example of base case scenario in the choice experiment

Autonomous vehicles became available in Indianapolis two weeks ago. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. Considering these two new modes and your previous choice, which mode of transportation will you choose for your daily commute to work?

Scenario 1a

| Attribute/Mode Choice | Private Vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|---|
| Time (minutes) | 20 | 24 | 28 |
| Cost (dollars) | 3 | 4.5 | 3 |

Your choice

| Private vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|
| ○ | ○ | ○ |

Scenario 1b

| Attribute/Mode Choice | Private Vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|---|
| Time (minutes) | 20 | 24 | 32 |
| Cost (dollars) | 3 | 6 | 3 |

Your choice

| Private vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|
| ○ | ○ | ○ |

Figure D2: Example of scenarios in the choice experiment in the short run

Autonomous vehicles became available in Indianapolis a year ago. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. Considering these two new modes and your previous choice, which mode of transportation will you choose for your daily commute to work?

Scenario 2a

| Attribute/Mode Choice | Private Vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|---|
| Time (minutes) | 20 | 24 | 28 |
| Cost (dollars) | 3 | 3.6 | 2.4 |

Your choice

| Private vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|
| ○ | ○ | ○ |

Scenario 2b

| Attribute/Mode Choice | Private Vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|---|
| Time (minutes) | 20 | 24 | 28 |
| Cost (dollars) | 3 | 4.8 | 2.4 |

Your choice

| Private vehicle | Ride-sharing service with AV – only one taking the ride | Ride-sharing service with AV – sharing the ride |
|---|---|---|
| ○ | ○ | ○ |

Figure D3: Example of scenarios in the choice experiment in the long run

## APPENDIX E

## Behavioral Intention to Ride in an AV and Implications on Mode Choice Decisions, Energy Use and Emissions

### Published Related Work

**1.Gkartzonikas, C., Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles, Transportation Research Part C 98(1), 323-337. https://www.sciencedirect.com/science/article/pii/S0968090X18303589**

**Abstract**
This paper provides a review of studies published in peer-reviewed journals, conference proceedings, and technical academic and private sector reports on surveys about autonomous vehicles (AVs) from 2012 onward. The studies and respective surveys are categorized in this paper based on the study objectives and methodology applied. More than half of the reviewed studies on AVs focus on capturing individuals' behavioral characteristics and perceptions. The second most prevalent category includes studies about individuals' willingness to pay to use AVs. The reviewed studies were also categorized according to the study population. The paper identifies and classifies attitudinal questions in each survey into different components that may affect behavioral intention to ride in AVs and provides information on specific hypotheses that were set in the studies. Moreover, a discussion of the benefits, barriers/concerns, and opportunities related to the deployment of AVs is presented. The paper concludes by summarizing the lessons learned and outlining the research gaps.

**2.Gkartzonikas, C., Losada-Rojas, L.L., Christ, S., Pyrialakou, V.D., Gkritza, K. (2021). A multi-group analysis of the behavioral intention to ride in autonomous vehicles: evidence from three U.S. metropolitan areas, Transportation. https://doi.org/10.1007/s11116-021-10256-7.**

**Abstract**

This paper proposes a well-grounded theoretical model to assess the factors influencing the intention to ride in autonomous vehicles (AVs). The model is based on the Theory of Planned Behavior (TPB), which has been decomposed to account for key components of the Diffusion of Innovation (DoI) theory and extended to include other influential attitudinal components (such as driving-related sensation seeking, safety perceptions, environmental concerns, and affinity to innovativeness). The extent to which these factors are expected to affect the diffusion of AVs uniformly across different urban settings is also examined. Data were collected through stated preference surveys targeting adult residents in three metropolitan statistical areas, Chicago (Illinois), Indianapolis (Indiana), and Phoenix (Arizona). Confirmatory factor analysis was conducted to test the validity and reliability of the components included in the theoretical model, followed by the estimation of a multi-group structural equation model. The findings of the measurement model show that the survey questions are measured equally across the three areas, and hence, the theoretical model is transferrable. The results of the structural model suggest that the synergistic effects between TPB and DoI can better explain the behavioral intention to ride in AVs. It was also found that the effect of the TBP components is similar across various areas; however, this is not the case for the DoI components. In general, the findings reinforce the need for wider testing of AV technology in urban areas coupled with public education Campaigns to harvest public awareness and acceptance.