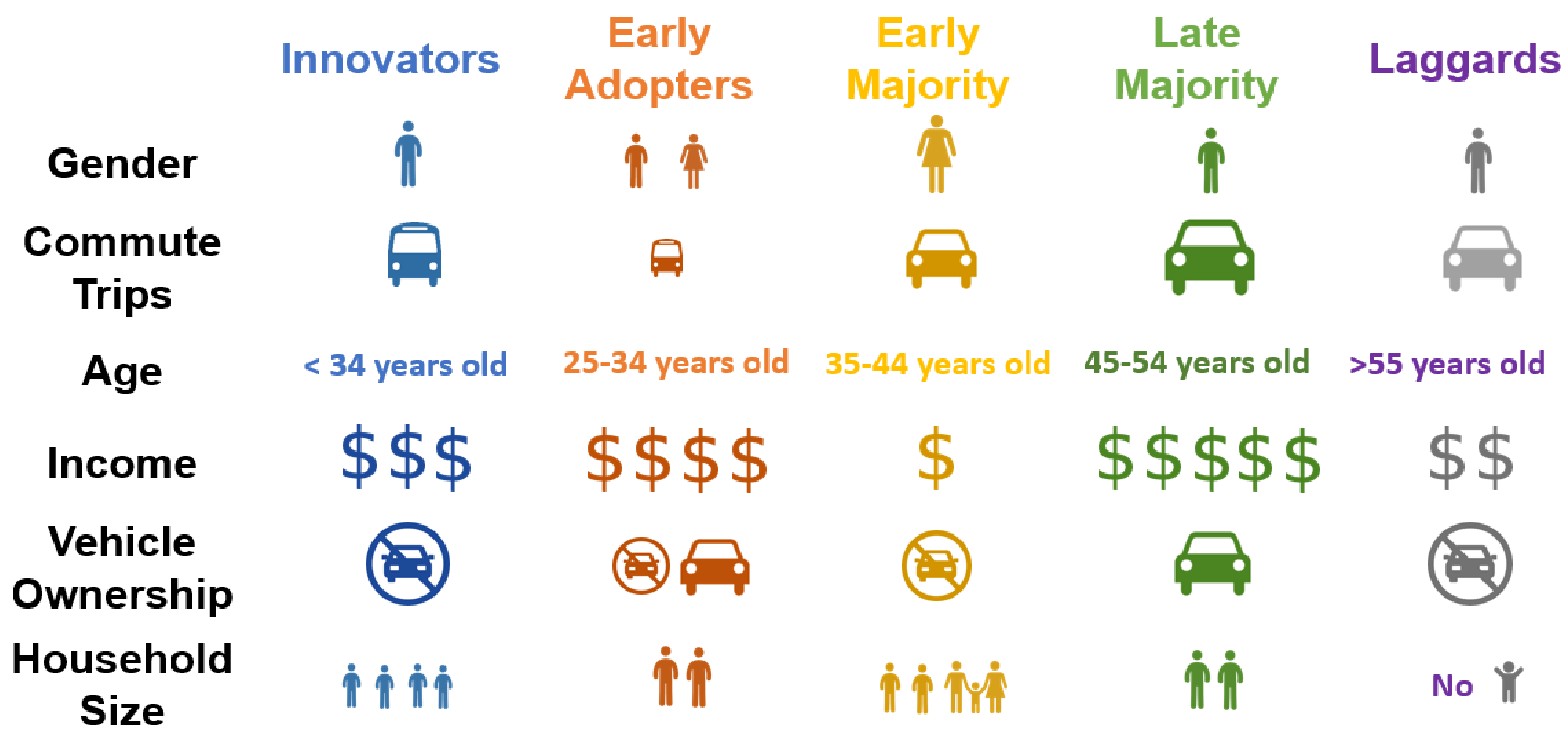
CCAT

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Final Report #32
June 2022



Public Acceptance and Socio-Economic Analysis of Shared Autonomous Vehicles: Implications for Policy and Planning

Konstantina Gkritza
Christos Gkartzonikas
Lisa L. Losada-Rojas
Raul Elizondo Candanedo

PURDUE UNIVERSITY

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Report No. 32
Project Start Date: 1/1/2018
Project End Date: 12/1/2019

June 2022

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by
Konstantina Gkritza
Professor

Christos Gkartzonikas
Graduate Student

Lisa L. Losada-Rojas
Graduate Student

Raul Elizondo Candanedo
Graduate Student

Purdue University

ACKNOWLEDGEMENTS AND DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3551747105 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation:

Gkritza, K., Gkartzonikas, C., Losada-Rojas, L., Candanedo, R.E. (2022). Public Acceptance and Socio-Economic Analysis of Shared Autonomous Vehicles: Implications for Policy and Planning, CCAT Report #32, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.

Contacts

For more information

Samuel Labi
3000 Kent Ave., West Lafayette, IN
Phone: 7654945926
Email: labi@purdue.edu

Konstantina Gkritza
550 Stadium Mall Dr, HAMP G167B
Purdue University
Phone: 765-494-4597
Email: nadia@purdue.edu

CCAT
University of Michigan Transportation Research Institute
2901 Baxter Road
Ann Arbor, MI 48152

uumtri-ccat@umich.edu
(734) 763-2498
www.ccat.umtri.umich.edu

Technical Report Documentation Page

<table>
<tr><td>1. Report No.
CCAT Report #32</td><td>2. Government Accession No.</td><td>3. Recipient's Catalog No.
N/A</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Public Acceptance and Socio-Economic Analysis of Shared Autonomous Vehicles: Implications for Policy and Planning</td><td>5. Report Date
June 2022</td></tr>
<tr><td>6. Performing Organization Code
N/A</td></tr>
<tr><td colspan="2">7. Author(s)
Konstantina Gkritza, Christos Gkartzonikas, Lisa L. Losada-Rojas, Raul Elizondo Candanedo</td><td>8. Performing Organization Report No.
N/A</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Center for Connected and Automated Transportation
Purdue University, 550 Stadium Mall Drive, W. Lafayette, IN 47907;
and University of Michigan Ann Arbor, 2901 Baxter Road, Ann Arbor, MI 48109</td><td>10. Work Unit No.
N/A</td></tr>
<tr><td>11. Contract or Grant No.
Contract No. 69A3551747105</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
1200 New Jersey Avenue, SE, Washington, DC 20590</td><td>13. Type of Report and Period Covered
Final Report (1/1/18 to 12/31/19</td></tr>
<tr><td>14. Sponsoring Agency Code
OST-R</td></tr>
<tr><td colspan="3">15. Supplementary Notes
Conducted under the U.S. DOT Office of the Assistant Secretary for Research and Technology's (OST-R) University Transportation Centers (UTC) program.</td></tr>
<tr><td colspan="3">16. Abstract
Shared transportation has grown significantly as renewed interest in urbanism and growing social and economic concerns have strengthened the need for sustainable alternatives. Shared autonomous vehicles (SAVs) are emerging as an alternative mode of transportation that could improve mobility and accessibility. However, the implications of SAVs on social equity are still under research and uncertainty exists regarding the potential adoption and market penetration within transportation-disadvantaged populations. The objective of this study is to assess the extent to which transportation-disadvantaged groups intend to adopt SAVs at two study areas with different density and travel characteristics, and to identify the potential geographical areas where SAVs could be effectively deployed. Public acceptance towards SAVs was assessed via stated preference surveys while a multi-spatial perspective approach was adopted to identify transportation disadvantaged groups in the two study areas. The results of the spatial market segmentation analysis showed that most of the respondents located in areas in Indianapolis identified as transportation disadvantaged are classified as early adopters and innovators, while the opposite conclusion was reached for the respective areas in Chicago, except for those closer to the downtown area. The results of this study could be useful to three stakeholders: ridesharing service providers, for their marketing and pricing-scheme decisions; public transportation planning agencies, for their policy making and investment decisions; and transportation planners, for infrastructure preparations towards the emergence of SAVs.</td></tr>
<tr><td colspan="2">17. Key Words
Autonomous vehicles, Shared autonomous vehicles, Shared mobility, Transportation-disadvantaged areas, Adoption, Stated preference</td><td>18. Distribution Statement
No restrictions.</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
49
22. Price</td></tr>
</table>

Form DOT F 1700.7 (8-72)   Reproduction of completed page authorized

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1 Introduction

Autonomous vehicles (AVs) are expected to be the transportation revolution of the 21st century. Several carmakers are working towards the creation and deployment of AVs, which are anticipated to be available in major metropolitan areas by 2030 (Martínez-Díaz & Soriguera, 2018). Shared Autonomous Vehicles (SAVs) are likely to be implemented alongside personally owned AVs. SAVs can offer services of single passenger rides or current pooled ridesharing services accommodating multiple riders. Pooled SAVs are similar to existing pooled ridesharing services without a driver that can accommodate multiple riders at different point simultaneously (Krueger et al., 2016).

AVs and SAVs are expected to provide many benefits, including increased access to more mobility choices, addressing first and last mile problems, reducing traffic congestion, mitigating various forms of pollution, reducing pressure on parking space, improving efficiency and providing alternatives to those who cannot afford to buy a personal vehicle or choose to not own one by sharing one (Fagnant & Kockelman, 2014, 2018; Milakis et al., 2017; MIT Energy Initiative, 2019; Wadud et al., 2016; Zmud et al., 2016). Other benefits attributed to these technologies are related to social equity and public health (Milakis et al., 2017). Many researchers have already started examining some of those benefits. For instance, it is known that AVs can provide flexible and affordable mobility on-demand services (Burns et al., 2013) in the form of driverless taxis. In another study, Litman (2017) stated that AVs can provide independent mobility for non-drivers, including people with disabilities, adolescents, and others who for any reason cannot or should not drive (Litman, 2017). AVs could induce up to 14% additional travel demand from non-driving, elderly, and people with travel-restrictive conditions (Harper et al., 2016). AVs could offer accessibility benefits to vulnerable population (Harper et al., 2016) and also, cause a significant jump in accessibility to opportunities (Hulse et al., 2018). Meyer et al. (2017) argued that AVs can provide the door to door, individual travel experience of privately-owned cars at low prices without financial burden (Meyer et al., 2017).

The advent of SAVs can have both direct and indirect socio-economic implications (Narayanan et al., 2020). In particular, social impacts not only arise from the physical presence of a transportation facility, but also from its increased usage due to travel generated or induced (i.e., increased total vehicle miles travel (VMT) compared with what would otherwise occur) (Sinha & Labi, 2007). The diffusion of SAVs is expected to alter transportation patterns (increase in ridesharing, mode shift from walking and transit), thus affecting accessibility and mobility (i.e., transportation disadvantage). Additionally, SAVs are also expected to present a reduction of the cost for their service, which could benefit low income households since the cost of owning a vehicle is significant (Pettigrew et al., 2018). In general, lower income groups are more inclined to make fewer trips and travel shorter distances than higher income groups (Giuliano, 2005). AVs are expected to provide a reduction of the cost for their service, which could benefit low income households since the cost of owning a vehicles is significant (Pettigrew et al., 2018). However, low income households tend to travel long distances using public transportation more frequently to access the closest supermarket because of limited inexpensive transportation options. Shaheen (2018) concludes that people who are traveling using shared modes (such as public transportation) are more prone to use automated modes. Thus, it is hypothesized that transportation disadvantaged groups, which can tend to be people from lower income groups, may be considered early adopters of SAVs and hence, identifying the factors that are affecting the intention to switch from public transportation to SAVs can aid planning and policy makers to gain a better understanding on the public acceptance and ensure a smooth transition to the era of automation.

Nevertheless, the implications of SAVs for social equity are still under researched and uncertainty exists on the potential adoption and market penetration within transportation disadvantaged populations as well as on the factors that would affect their intention to switch from public transportation to SAVs.

Previous work (Milakis et al., 2017) has argued that equity must be prioritized in the way that AVs are deployed and regulated, and the potential social acceptance among different population groups, particularly the transportation disadvantaged, must be investigated (Cavoli et al., 2017; Ricci et al., 2018).

In view of the above, this study aims to assess to what extent transportation disadvantaged groups intend to adopt SAVs in two study areas (Indianapolis, IN and Chicago, IL) with different density and travel characteristics, as well as identify potential geographical areas where SAVs can be effectively deployed. Indianapolis is mainly an automobile-oriented area, where 82% of commuters drive alone to get to work, 2% of workers use public transportation, and 10% carpool to get to work and approximately 6% use other modes (e.g., walking or biking). On the other hand, Chicago has an advanced multimodal transportation system offering additional transportation modes alternatives. In particular, regarding to the 2017 NHTS, approximately 50% of people in Chicago use their private vehicles, around 8% carpool, approximately 28% use public transportation, and around 14% use other modes (e.g., walking or biking) for the commuting trips. Furthermore, more than 23% of the Chicago residents commute less than 5 minutes to work in comparison with 6.1% in Indianapolis. Indianapolis is also four times less densely populated than Chicago and exhibits below-average transit coverage (42%) compared to Chicago (79%) (U.S. Census Bureau., 2015).

Additionally, this report addresses the following questions Figure 1-1:

(i) What is the public acceptance in these two areas of study by identifying the population characteristics of those who would adopt AVs and exploring factors that affect the intention to switch from public transportation to ridesharing services operated through AVs?

(ii) What can policy makers do in order to ensure a smooth transition to AVs especially in transportation disadvantaged areas?

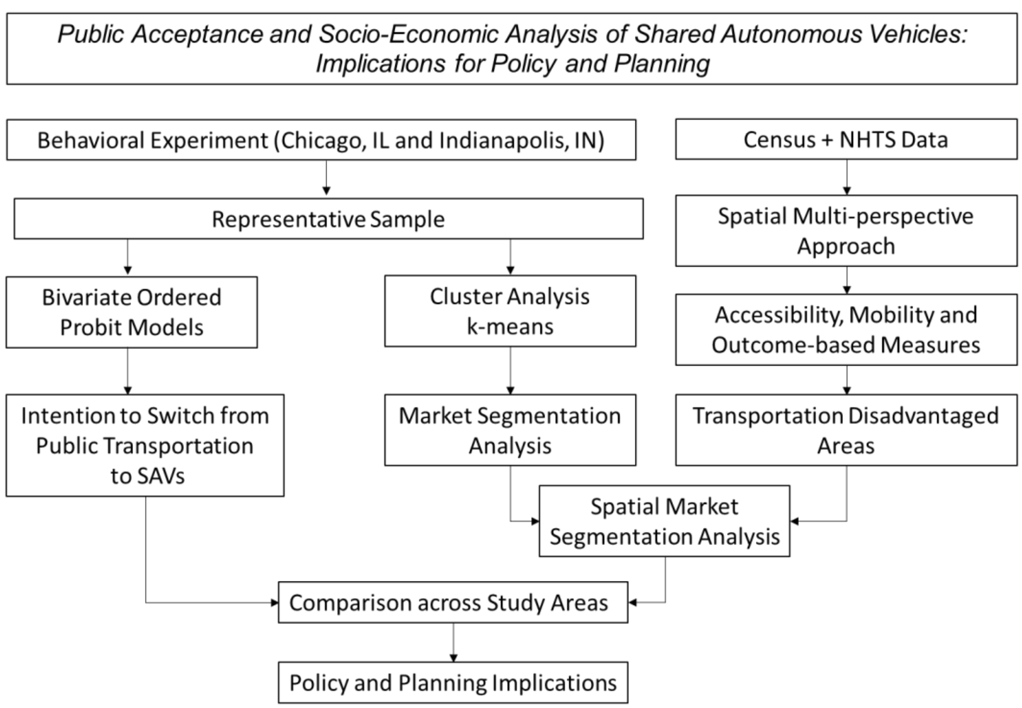

Figure 1-1 Project Framework - Public Acceptance and Socio-Economic Analysis of Shared Autonomous Vehicles: Implications for Policy and Planning

Thus, it is hypothesized that transportation disadvantaged groups, which can tend to be people from lower income groups, may be considered early adopters of SAVs and hence, identifying the factors that are affecting the intention to switch from public transportation to SAVs can aid planning and policy makers to gain a better understanding on the public acceptance and ensure a smooth transition to the era of automation.

To address our overall goal, a stated preference survey was prepared and distributed in Chicago, IL, and Indianapolis, IN. The survey instrument was designed based on the literature reported in (Gkartzonikas & Gkritza, 2019) and includes 5 sections. Respondents of the survey are people over 18 years old that reside in Chicago, IL or Indianapolis, IN; 400 completed responses were collected from each study area. The public acceptance of SAVs was assessed by conducting a market segmentation analysis (in a similar vein as performed in Gkritza et al., 2020) grouping the respondents into five adopter categories and specifically into innovators, early adopters, early majority, late majority, and laggards. Evaluating the factors that affect the intention to switch from public transportation to ridesharing services operated through AVs (SAVs) was achieved by estimating discrete ordered probability models. This analysis can provide information on the hypothesis that transportation disadvantaged groups may be early adopters of SAVs and can lead to policy and planning implications. Furthermore, a multi-spatial perspective approach proposed by Pyrialakou, (2016) which involved accessibility, mobility, and outcome-based measures, was employed to identify transportation disadvantaged areas. The results of the spatial analysis were integrated with the results of the AV market segmentation analysis for each area to assess to what extent transportation disadvantaged groups intend to adopt SAVs, as well as identify potential geographical areas where SAVs can be effectively deployed. This study is a first step to assess the potential for vehicle automation in diverse areas, and to plan for ways to effectively accommodate the demand from groups that are transportation disadvantaged. It provides a well-documented and easy-to-use framework that can support both planning and policy decisions in urban areas in an era of emergent automated transportation technologies by also considering the transportation disadvantaged areas. Transportation planners and engineers, urban planners, and original equipment manufacturers can use the results of this study to prepare for the deployment of SAVs by designing marketing strategies to improve people's perceptions of SAVs. This is an important step towards the global goal of achieving equitable access, wider social equity, social diversity, and accessibility for all (Curl et al., 2018).

2 Estimating Public Acceptance of SAVs

Understanding who are the potential users of AVs and how the users are classified into different categories based on the adoption of the technology could inform planning and policy decisions. This classification is achieved by using the components found as significant determinants of the behavioral intention to ride in AVs as inputs. Consequently, to profile each AV market segment, different socio-demographic variables and trip characteristics were considered attempting to provide insights about the market acceptance and adoption. It is also hypothesized that transportation disadvantaged groups may be considered early adopters of SAVs so the analysis also focuses on identifying the factors that could affect the intention to switch from public transportation to SAVs through a series of econometric models.

2.1 Survey Design and Data Collection

The survey instrument included five sections and it was based on the supporting literature summarized in (Gkartzonikas & Gkritza, 2019). The first section included questions pertaining to people's awareness of AVs, where those with a higher level of awareness might be people who use multiple modes of transportation for their trips and people who are considered innovators or early adopters. The second section included questions on travel characteristics, where respondents were asked to fill out a mini travel diary regarding the mode of transportation, they chose for different trip purposes and indicate whether they use carsharing and ridesharing services. The third section included attitudinal questions regarding AVs to capture the components discussed in the theoretical model. A 5-point Likert-type scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). The fourth section included a choice experiment to assess the impact of people's opinions regarding their preferred mode of transportation if AVs were implemented in the short and long run. Lastly, the fifth section included socio-demographic questions to relate the respondents' characteristics expressed in the previous sections to specific socio-demographic profiles (for additional information on the survey design and sampling methods used, please refer to Gkritza et al., 2020.) Note that for the purpose of this study, the fourth section of the survey was not considered in the analyses that follows.

The surveys were distributed online using Qualtrics in October-November 2017 (IRB Protocol Number: 1701018708) in Chicago and May 2018 (IRB Protocol number 1801020160) in Indianapolis. The target population of the surveys were adults residing in the metropolitan areas soliciting a total of 400 completed responses in each area to ensure a confidence level of 95% and a 5% of margin of error. 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 Bureau (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 summarizes statistics of socioeconomic and demographic variables.

Table 2-1 Summary Statistics of Selected Socio-economic and Demographic Variables

Variable	Description	Freq. (sample)	*Freq. (Census)	Freq. (sample)	*Freq. (Census)
		Chicago		Indianapolis	
Gender	Male	47%	47%	46%	46%
	Female	53%	53%	54%	54%
Age	18-24 years old	14%	14%	18%	18%
	25-34 years old	25%	25%	17%	17%
	35-44 years old	18%	18%	17%	17%
	45-54 years old	16%	16%	18%	18%
	55-64 years old	14%	14%	15%	15%
	65 plus years old	13%	13%	16%	16%
Education	High school graduate	21%	33%	19%	38%
	Technical training beyond high school	5%	6%	5%	5%
	Some college	28%	18%	27%	25%
	College graduate	34%	28%	34%	20%
	Graduate school	12%	15%	14%	12%
Income	Less than $25K	16%	31%	18%	26%
	$25K-$50K	28%	23%	25%	26%
	$50K-$75K	22%	17%	23%	18%
	$75K-$100K	15%	11%	17%	11%
	$100K-$150K	14%	10%	12%	11%
	Over $150K	5%	8%	5%	8%

*U.S. Census 2010 data Chicago-MSA, Illinois Indianapolis-MSA, Indiana. The same data were used to accomplish representative age and gender brackets (US Census Bureau, 2010).

2.2 Market Segmentation Analysis

2.2.1 Methodology

A market segmentation analysis is performed to understand who will adopt the technology first. This was achieved by conducting a cluster analysis. This methodology can investigate how homogenous the objects are and then can classify similar groups together that they are called clusters (Mooi & Sarstedt, 2011). The objects that belong to the same clusters have the maximum similarity among them and the maximum dissimilarity among objects that belong to different clusters. Specifically, the cluster analysis was conducted by identifying distinct market segments based on respondents' attitudes towards AV use, perceived behavioral control, self-efficacy, subjective norms, personal moral norms, compatibility, relative advantage, driving-related sensation seeking, affinity to innovativeness, and intention to ride in AVs. The k-means method was selected as the partitioning method since it is affected to a lesser extent by outliers and it is also the natural choice when dealing with ordered data (Mooi & Sarstedt, 2011). Using the k-means approach the within cluster variation is minimized. The k-means method requires a pre-defined number of clusters, which may increase subjectivity to the interpretation of the result. This is not considered a shortcoming since a well-established theory (Diffusion of Innovation, DoI) to capture the adopter categories is used. The respondents were classified using the five adopter categories established by Rogers, which include innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003). This categorization can help identify which socio-demographic groups share similar attitudes towards AVs and trip characteristics.

2.2.2 Results

The next step was to interpret the results by observing the mean values of each cluster, comparing each average score and label each cluster using Rogers' adopter levels (innovators, early adopters, early majority, late majority, laggards). The average scores of each cluster are shown in Appendix A Market Segmentation Analysisfor Chicago and Indianapolis. The scale followed is a 5-point Likert scale, where 1 represents the strongly disagree option (most negative) and 5 represents the strongly agree option (most positive). In general, innovators have the highest score on the majority of the factors, whereas laggards have the lowest score. Analysis of variance was conducted for the ten variables for each study area. The results indicated that the average scores for each variable are statistically different between the five clusters. Figure 2-1 illustrates the distribution of the population into each adopter category (cluster) for Chicago and Indianapolis, respectively.

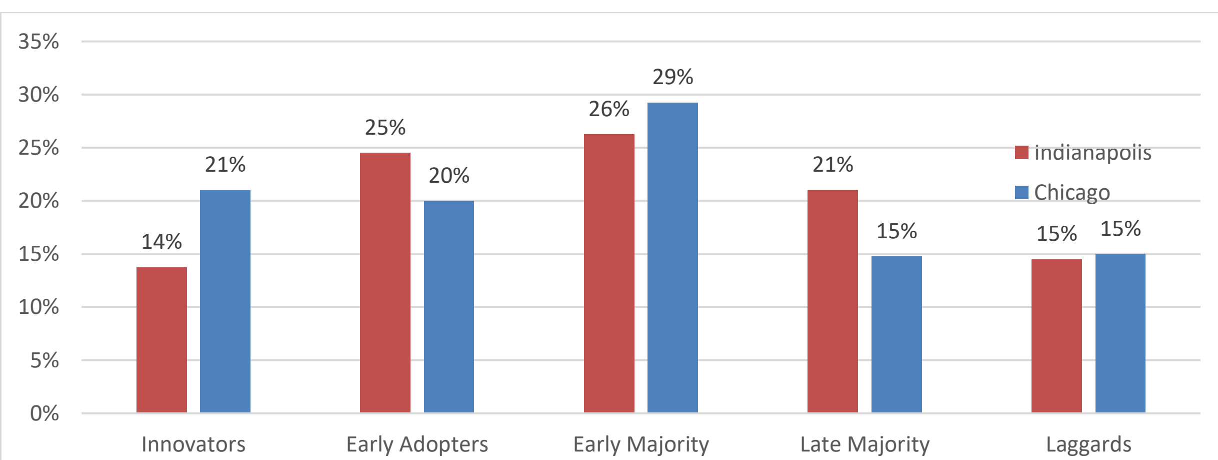

Figure 2-1 Distribution of Adopter Categories for Each Cluster - Chicago and Indianapolis

It was found that Chicago generally has a more innovative population, with a higher percentage in the first three categories (innovators, early adopters, and early majority categories). This percentage was 70% for Chicago compared with 65% for Indianapolis. Additionally, the percentage of the late majority category was higher in Indianapolis, while the laggard category makes up a similar proportion of each study area. These results are in line with expectations and the general knowledge about the study areas; that is, Chicago is a much larger and more modern area that its people rely on the multimodal nature of the services provided for their trips and is often seen as more technologically savvy and attractive to young people, compared to Indianapolis. Lastly, to profile each market segment, different socio-demographic variables and trip characteristics were used. Table 2-2 and Table 2-3 show the summary of the cluster characteristics for each category for Chicago and Indianapolis, respectively.

Table 2-2 Summary of Cluster Characteristics – Chicago

	Innovators	**Early adopters**	**Early majority**	**Late majority**	**Laggards**
Level of awareness	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
Commuting patterns	40% use public transportation and walk to their commute trips as primary modes	20% use public transportation to their commute trips as primary modes	60% use their personal vehicles for their commute trips	80% use their personal vehicles for trips regardless the trip purpose	70% use their personal vehicles for trips regardless the trip purpose
Vehicle ownership	Half of them do not own a vehicle. 33% drove more than 15,000 miles last year (US avg)	20% of them do not own a vehicle. 40% have 1 vehicle in their household	45% do not own a vehicle. 33% drove between 5k-10k miles last year	55% have at least one vehicle in their household	35% do not own a personal vehicle
Use of ride-hailing services	60% use ride-hailing services for their trips (10% use ride-hailing services for social / recreational trips)	50% use ride-hailing services	40% use ride-hailing services	20% use ride-hailing services and none of them use car-sharing services	20% use ride-hailing services and 5% car-sharing services
Gender	60% are male	Equally split between male and female	60% are female	66% are male	75% are female
Age	60% are Millennials (<34 y.o.)	Most dominant category people 25-34 years old	Most dominant category people 35-44 years old	Most dominant category people 45-54 years old	50% are people over 55 years old and 25% over 65 years old
Employment status	Employment status	60% work full time	10% are currently unemployed	25% have retired	33% have retired
Income	Higher than average income – 40% earn below $50k	Higher than average income - most dominant categories are $25k-$50k and $100-$150k	Lower than average income – 25% earn under $25k	Highest average income – most dominant categories are $75k-$100k and $100k-$150k	Lowest average income – 50% earn $25k-$50k
Education level	75% college graduates or finished grad school	45% finished grad school	33% high school graduates	75% college graduates or finished grad school	45% college graduates

Table 2-3 Summary of Cluster Characteristics – Indianapolis

	Innovators	Early adopters	Early majority	Late majority	Laggards
Level of awareness	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
Commuting patterns	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
Vehicle ownership	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)
Use of ride-hailing services	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.
Gender	64% are male	54% are female	58% are female	64% are female	52% are female
Age	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
Employment status	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
Income	Higher than average income – $52k on average	Higher than average income – around $50k	Lowest average income – around $45k	Average income around $48k	Average income around $48k
Education level	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

In both study areas, the separation between the categories of highest innovation (innovators and early adopters) compared with categories of lower innovation (late majority and laggards) tends to fall primarily along lines of current modal preference and age-related characteristics. What appears to be the most predictive factor for AV interest is the current modal choice of the respondent. Members of the innovative groups are more likely to walk, bike, or use public transportation for commuting, and are less likely to own a personal vehicle than less innovative groups. Use of ride hailing and car sharing technology is much more typical in innovative groups and is very uncommon in late majority or laggard groups. This was the case for both study areas, though the trend was much more obvious in Chicago, likely due to the greater availability and usefulness/practicality of non-personal-vehicle modes. In Indianapolis, with a more homogeneous use of personal vehicle as mode of choice throughout innovation groups, the difference between these groups were not as defined, apart from at the edges (i.e., zero respondents in the Indianapolis Laggard group had used a car-sharing service).

Age-related trends are also observed in both study areas, with older and retired respondents much less likely to be interested in AV technology. Millennials working full time make up most of the Innovator group in both areas, though the difference between groups beyond that is less defined. Laggards have the highest rate of retirement and the highest average age in both study areas. Gender also appears to play a role, as does income and education. Innovative respondents were more likely to be male in Chicago, with 60% of the Innovators being male and 75% of the Laggards being female; a trend that was less clear in Indianapolis. Innovative groups also tended to have higher than average income within the respondent pool, and a higher education level. These trends are less strong in Indianapolis, where education and income levels in general tend to be lower. Lastly, the distribution of adopter categories for each ZIP code are shown spatially in Figure 2-2 and Figure 2-3 for Chicago and Indianapolis, respectively.

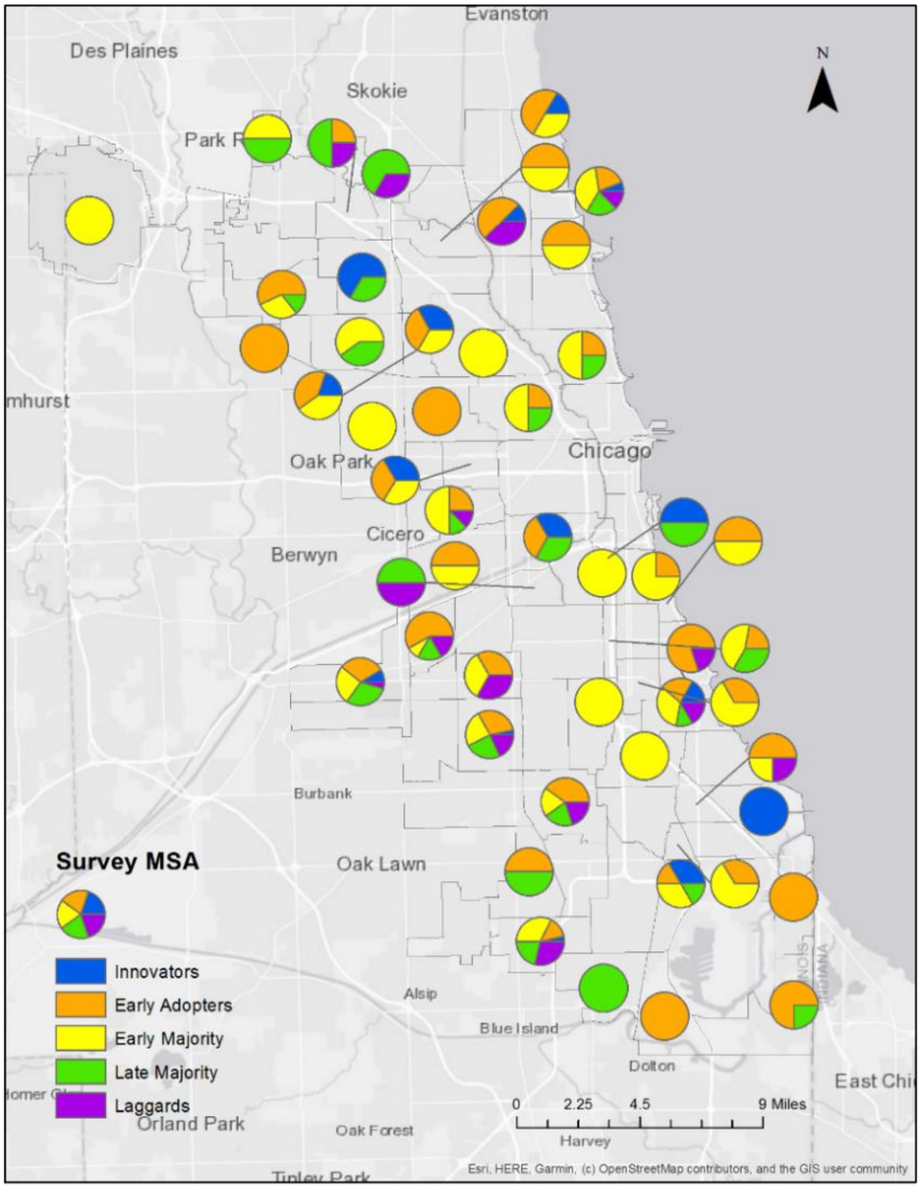

Figure 2-2 Distribution for Adopter Categories per ZIP Code - Chicago

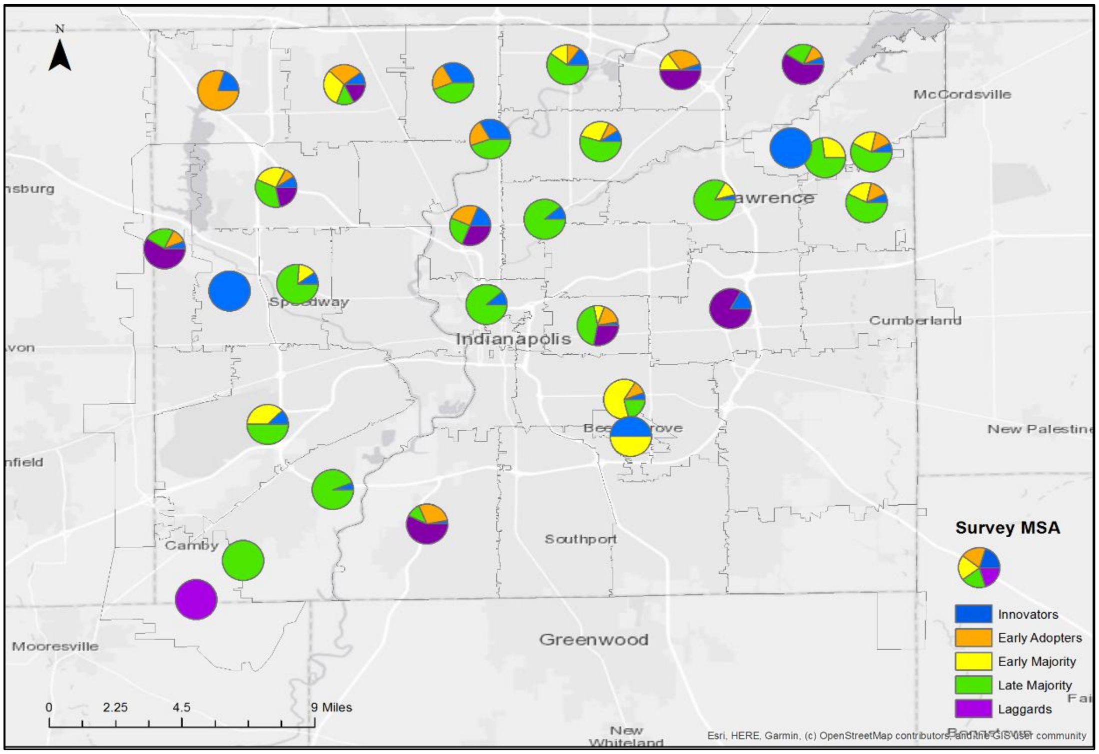

Figure 2-3 Distribution for Adopter Categories per ZIP Code – Indianapolis

2.3 Intention to Switch from Public Transportation to SAVs

2.3.1 Methodology

This study assessed the public acceptance and intention to switch from public transportation to ridesharing services operated through AVs in the short and long-run using data from surveys in Indianapolis and Chicago and via estimating discrete ordered probability models. Modeling consumers' behavioral responses and studying these relationships can facilitate this question for prediction and forecasting purposes, enabling effective policymaking. The most common modeling technique for assessing mode choice decisions is discrete choice (Brownstone & Train, 1998);(Mannering & Mahmassani, 1985). Bivariate ordered probit models were estimated to assess the likelihood of an individual shifts from public transportation in the short and long run. This model specification was selected because it takes into consideration the ordinal nature of the data as well as the cross-correlation between the questions on the short and long run (correlation coefficient of 0.70 and 0.73 for Indianapolis and Chicago, respectively). The combination of the evident cross-correlation, with the potential for unobserved factors related to both short- and long-term intentions, provide sufficient evidence that modeling both as a system may be most appropriate. For this analysis, 200 Halton draws were used, as suggested in previous work (Bhat, 2003). The variables related to respondents' opinions on AVs (willingness to be an early adopter, adherence to subjective norms, distrust of strangers, compatibility with the respondent's lifestyle, and safety concerns) could potentially be endogenous to the dependent variables. To account for this endogeneity, these variables were modeled using binary ordered probit models that include exogenous variables such as socio-economic, demographic, and transportation-related variables. The resulting probabilities were then used as model inputs to evaluate the intention to switch from public transportation to ridesharing services that use AVs in the short and long run.

2.3.2 Results

2.3.2.1 Descriptive Statistics/Trends

The dependent variables that evaluated the association between the intention to switch from public transportation to ridesharing services operated through AVs correspond to the following two questions in the survey: (a) 'I expect that I will be sometimes switching from public transportation in favor of using ridesharing services on autonomous vehicles in the near future', and (b) 'I expect that I will be sometimes switching from public transportation in favor of using ridesharing services on autonomous vehicles in the foreseeable future'. The available responses consisted of five options on a five-point Likert rating scale ranging from 1 (strongly disagree) to 5 (strongly agree). Figure 2-4 and Figure 2-5 illustrate the descriptive statistics of the aforementioned dependent variables for each area.

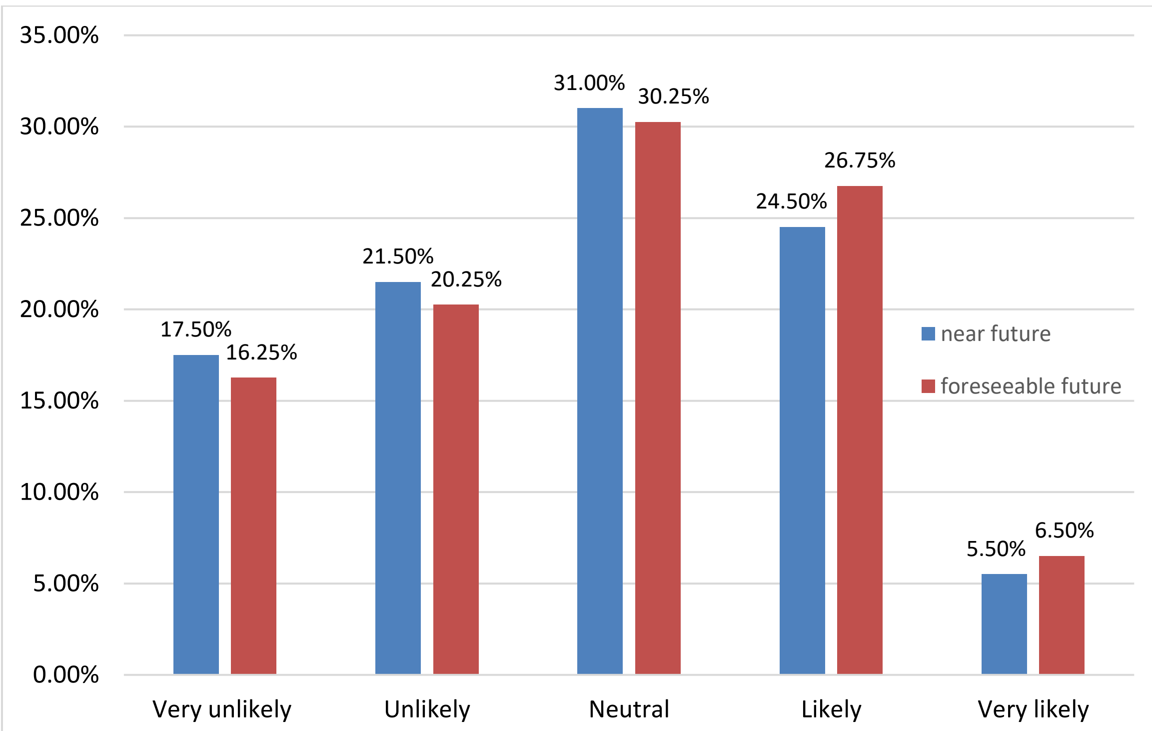

Figure 2-4 Summary Statistics of Dependent Variables - Chicago

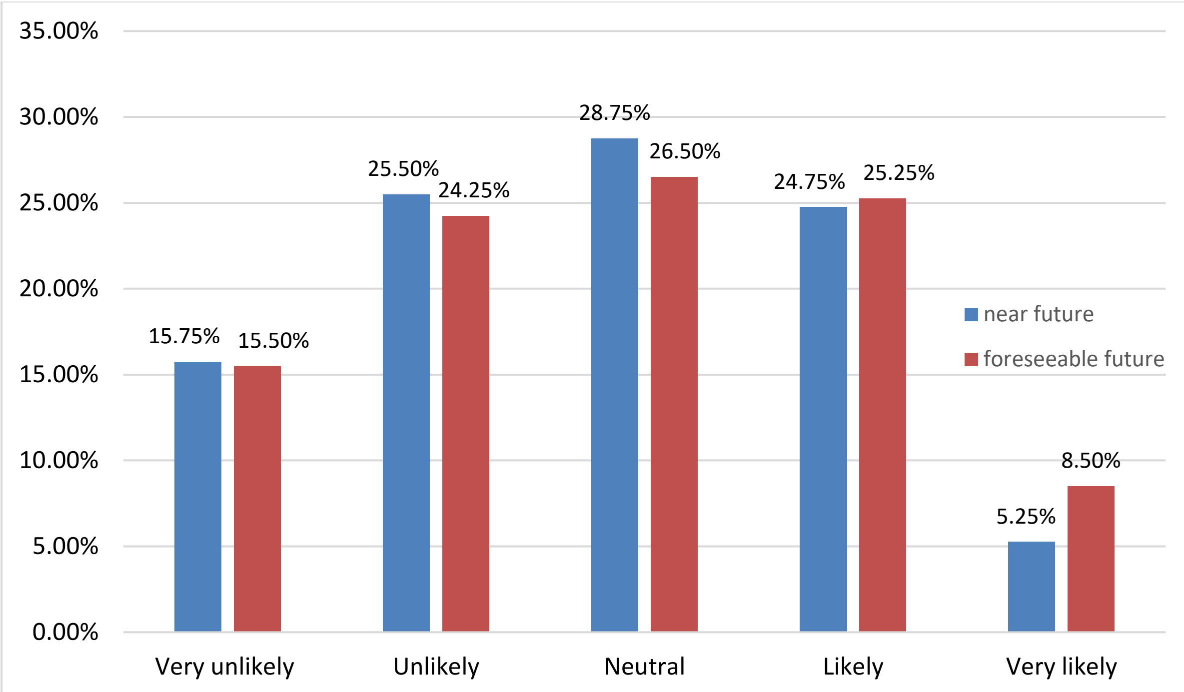

Figure 2-5 Summary Statistics of Dependent Variables - Indianapolis

2.3.2.2 Estimation Results

The estimation results for the questions related to the intention to switch from public transportation to ridesharing services that use AVs in the short and long run are presented Appendix B Bivariate Order Probit Modelfor Chicago and Indianapolis, respectively. A summary table (see Table 2-4) compares the sign (positive or negative) that each variable has for all the models. The results can help elucidate the factors that drive the intention to switch from public transportation to ridesharing services operated through AVs. This can be achieved by assessing the factors that lead people to switch from public transportation to SAVs (which is also a shared transportation mode). The cross-equation correlation coefficient was found to be statistically significant ($p < 0.001$), validating the assumption that modeling the correlated dependent variables as a system is an appropriate modeling technique. Results found in Chicago and Indianapolis seem to show similar trends across all the categories of variables (related to awareness, travel characteristics, perceptions/opinions/attitudes, mode choice, socio-demographics) that affect the intention to switch. The main differences between both models were mostly related to the socio-demographic variables, a finding that indicates the need of the market segmentation analysis in order to get a better understanding regarding the profiles and market segments of each study area.

Table 2-4 Comparison of the Variable Signs for the Bivariate Ordered Probit Models for Chicago and Indianapolis

Variable	Chicago		Indianapolis	
	Short-term Intention to Switch	Long-term Intention to Switch	Short-term Intention to Switch	Long-term Intention to Switch
	Estimated Parameter (p-value)	Estimated Parameter (p-value)	Estimated Parameter (p-value)	Estimated Parameter (p-value)
Awareness				
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no)	+	+	+	+
Travel characteristics variables				
Respondents who indicated that they have a car-sharing account (1: yes, 0: no)	ns	+	+	+
Respondents who indicated that they drive less than 15,000 miles per year (1: yes, 0: no)	ns	ns	ns	+
Respondents who indicated that they drive less than 20,000 miles per year (1: yes, 0: no)	ns	+	ns	ns
Perceptions / Opinions / Attitudes				
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**	+	+	+	+
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**	+	+	+	+
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**	ns	-	-	-
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)	+	ns	+	ns
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	-	ns	-	-
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	+	+	+	+
Socio-demographics				
Respondents who are between 18 and 34 years old (1: yes, 0: no)	+	+	ns	ns
Respondents who are between 25 and 34 years old (1: yes, 0: no)	ns	ns	+	+
Respondents who are over 55 years old (1: yes, 0: no)	ns	ns	-	-
Respondents who indicated that they are students (1: yes, 0: no)	ns	+	Ns	ns
Respondents who have annual income less than $50,000 (1: yes, 0: no)	ns	ns	+	+

*ns indicates no statistical significance (p>0.10)

The intention to switch from public transportation to ridesharing services operated through AVs seems to be associated with factors similar to those that affect private vehicle ownership decisions. The results indicate that the greater the level of awareness of AVs, the stronger the intention to switch. Additionally, people who have a car-sharing account and therefore may have higher exposure ridesharing services seem to be more willing to opt in to using SAVs in the foreseeable future. The literature shows similar results, where it has been found that people with prior experience with vehicle sharing services (e.g., car-sharing or ridesharing) are more eager to use SAVs (Shaheen, 2018). Similarly, it was found that people who drive more than the average U.S. driver, in particular, more than 20,000 miles per year, are less willing to switch to AVs, a result in line with the findings of Haboucha, Ishaq, & Shiftan, (2017).

Early adopters (those with an affinity to innovativeness) and respondents who tend to be influenced by their social circles (those who adhere to subjective norms) have a stronger intention to switch to the use of SAVs. However, people who have safety concerns about AV technology seem less likely to switch, a finding that is also supported by the literature (Kyriakidis et al., 2015; Schoettle & Sivak, 2014). Mode choice-related factors such as the importance that respondents gave to the reliability, safety, and flexibility of different mode alternatives were found to be key determinants of the intention to switch, especially in the short term. In particular, reliability and flexibility were positively associated with the intention to switch, while safety was negatively associated. The former factors are linked with a stronger intention to switch, possibly because SAVs are perceived to be more reliable than public transportation, especially in terms of less waiting time, but SAVs are also perceived to be more flexible than public transportation, which operates on fixed routes. However, safety is related to a weaker intention to switch because SAVs are sometimes perceived as less safe than public transportation, especially as this emerging technology is first introduced. Such factors were found in the literature to be important to mode choice decisions, especially in the context of public transportation (Beck & Rose, 2016; Tyrinopoulos & Antoniou, 2008).

Regarding socio-demographic variables, younger respondents (between 18 and 34 years old) and students seem to be eager to substitute SAVs for public transportation, regardless the time period. In general, Millennials have a more positive perception of AVs and are one of the largest user groups of car-sharing and ridesharing services (Shaheen, 2018). However, older respondents (over 55 years old) were found to be negatively associated with the intention to switch in Indianapolis. Lastly, respondents with a reported income less than $50,000 in Indianapolis seem to be unlikely to postpone the purchase of a non-AV when AVs become commercially available.

3 Identifying Transport Need/Disadvantaged Areas

3.1 Methodology

In order to measure the implications that the new technology would bring to disadvantaged populations, it is first necessary to know the spatial location of those groups. For that end, three approaches (accessibility-, mobility-, and outcome-focused) are used in this analysis to explore the transport disadvantage of an individual, group, or area. These approaches have pros and cons, and therefore studies frequently combine measures based on more than one approach. Pyrialakou, Gkritza, & Fricker, (2016) stated that there is a significant lack of U.S. data related to the transport disadvantage of specific sociodemographic groups that can support a further investigation into transport need. The measures explored herein use socioeconomic and demographic data from the 2017 American Community Surveys (ACS), as well as the 2017 National Household Travel Survey, aggregated at the block groups census level (2010 block groups delineation). In addition, geocoded data related to the existing transportation systems and available opportunities is used.

3.1.1 Accessibility-based Measure

The accessibility levels are explored by spatially distributing opportunities/attractions (e.g., hospitals, schools, libraries, park/recreational facilities) in Indianapolis, IN and in Chicago, IL, which are joined with current transportation infrastructure to identify areas with high or low levels of accessibility to those opportunities. To perform this analysis, ArcGIS was used. The opportunities considered for the analysis, as suggested by Pyrialakou et al., (2016), and their sources, are listed in Table 3-1. Firstly, distance from each opportunity to the Census Block Group (CBG) was calculated using point distance. After that, different multi-ring buffers (i.e., different distances are used to delimit an area) were used to define the areas with different accessibility levels (Table 3-2 and 3-3).

Table 3-1 Opportunities Considered in the Accessibility-based Measure

Data	Chicago	Source	Indy	Source
Bus Stops	2017	CTA	2018	IndyGo
Large Hospital	2016	Chicago JSON	2012	Indiana Department of Homeland Security
Public Schools	2015	Chicago JSON	2013	Indiana Department of Education
Recreational facilities	2012	Chicago JSON	2012	Indiana Department of Natural Resources
Museums	2018	Google Earth	2015	Indiana Geological Survey
Public libraries	2018	Google Earth	2012	Indiana State Library
Rail Stations	2017	CTA	2018	Amtrak
NHTS	2017	FHWA	2017	FHWA
Block Group Census	2010	US Census Bureau	2010	US Census Bureau

The criteria used to identify areas with low, medium, and high accessibility changed for each study area due to different transportation characteristics. For instance, Chicago's average travel speed by driving was considered 23.7 mph and Indianapolis' average travel speed by driving was 37.5 mph. For transit, the average speeds for Chicago and Indianapolis were 9.03 mph and 25.5 mph, respectively (IndyGo Transit System, 2015). Finally, the walking speed was assumed 3 mph.

Table 3-2 Opportunities Considered in the Analysis- Chicago

			Travel time (min)			Accessibility levels	
	Distance (miles)	Walking	Transit	Driving	Low	Medium	High
Large hospital	1.19	24	8	3		✓	✓
Schools	0.09	2	1				✓
Recreational facilities	0.11	2	1				✓
Museums	2.05	41	14	5		✓	✓
Public libraries	1.56	31	10	4		✓	✓
Transportation Stations							
Bus Stop	0.03	1					✓

Table 3-3 Opportunities Considered in the Analysis - Indianapolis

			Travel time (min)			Accessibility levels	
	Distance (miles)	Walking	Transit	Driving	Low	Medium	High
Large hospital	2.01	40	10	3		✓	✓
Schools	0.17	3	1				✓
Recreational facilities	0.10	2					✓
Museums	3.66	73	18	6		✓	✓
Public libraries	0.97	19	5	2		✓	✓
Transportation Stations							
Bus Stop	0.27	5					✓

Considering the values presented in Table 3-2 and 3-3, an area can be described as having (1) low accessibility levels, if none of the opportunities considered can be reached within the travel time chosen (neither by walking, transit, nor by automobile); (2) medium accessibility levels, if schools and recreational facilities cannot be reached within the travel time chosen by walking or transit, but the rest of the opportunities considered can be reached by automobile; and (3) high accessibility levels, if all opportunities considered can be reached within the travel time chosen and the travel mode assumed. These characteristics were similar to the ones considered by Pyrialakou et al., (2016).

3.1.2 Mobility-based Measure

Mobility refers to the movement of people (and/or goods) and the ability of people to travel between places. This measure attempts to capture the easiness of people to travel between activity sites. Since the objective of this report is to identify disadvantaged areas, the use of survey data for certain disadvantaged groups is considered in this index. Disadvantaged population are argued to influence in a certain extent whether an area is considered transportation disadvantaged. The index accounts for eight population groups identified in the literature that are expected to have relatively low mobility levels:
Three groups due to age or physical factors:

- Persons below 14 years old
- Persons above 65 years old

- Disabled persons

Five groups that have a high probability of experiencing a lack of mobility choices based on age, income levels, or the absence of personal vehicle:

- Unemployed
- Not in the labor force
- Persons below the poverty line
- Households with zero vehicles
- Single-parent family with working parent and children under 18 years old

Based on these eight population groups, eight separate mobility measures are estimated (one for each group). Each measure is estimated as a relative ratio, within the corresponding disadvantaged group, with the BG census data from the ACS. The 2017 estimates were used for this analysis (U.S. Census Bureau, 2017). Subsequently, the sum of the normalized values of the measures is calculated. Finally, the need index consists of the normalized sum on a scale of 0 to 100, with 0 denoting a very low transport need and 100 a very high transport need in the area. The need index accounts for all eight measures using equal weights. Step-by-step sample calculations for a tract are presented below (Pyrialakou et al., 2016):

1. For the eight measures, obtain the number of individuals (or households) in each population category that live within the CBG, n.
2. For each measure, calculate the relative measure based on:

$$m_{ij} = \frac{p_{ij}}{\sum_1^n p_{ij}} * 100\% \qquad \text{Equation 3.1}$$

3. Calculate the normalized values for each relative measure using:

$$rm_{ij} = \frac{(m_{ij} - m_{ij}^{min})}{(m_{ij}^{max} - m_{ij}^{min})} \qquad \text{Equation 3.2}$$

Where m_{ij}^{min} is the minimum and m_{ij}^{max} is the maximum value within group j

4. Calculate the sum of the eight normalized relative measures estimated in step 2 using equal weights:

$$NI_{ij}^{raw} = \sum_{j=1}^{8} w_{ij} * rm_{ij} \qquad \text{Equation 3.3}$$

5. Calculate the need index as the normalized value of the sum of the eight normalized relative measures using:

$$NI_i = \frac{(NI_i^{raw} - NI_i^{raw,min})}{(NI_i^{raw,max} - NI_i^{raw,min})} \qquad \text{Equation 3.4}$$

Different weights can be used in step 4. However, this research considers all groups are of equal importance in this analysis since there is not enough literature to justify different weights across groups.

3.1.3 Outcome-based Measure

The final measure of the need assessment is the outcome-based approach. In order to perform this analysis, individual-level data is needed using activity diaries or similar methods, which is currently available through NHTS data. Considering this as a limited sample, the 2017 data set consists of 118,208,251 households. Therefore, an aggregation of responses at any spatial level is not an insignificant matter. For that reason, the Bureau of Transportation Statistics (BTS) has developed the 2017 Transferability Statistics intended to provide estimates of average household person trips, vehicle trips, person miles, and vehicle miles traveled at the census tract level (NHTS, 2017).

This analysis uses the daily person miles estimated by BTS using three-person households owning one vehicle for Chicago and two-person households using two vehicles in Indianapolis. The estimates of person-miles were chosen as the closest indicator of the average trip length that individuals living in each area are traveling for day-to-day activities. It is speculated that this indicator would be highly related with accessibility of an area; the fewer the opportunities in proximity to an area, the greater the trip lengths would need to be in order for people to reach different types of opportunities (Pyrialakou et al., 2016). However, this measure approximates the trip length and does not provide information regarding the number of daily trips, which can be seen as a limitation of the data used.

By combining the results of the three previous measures, the need gap can be acknowledged. This gap is commonly identified by comparing the transportation supply and transportation need of an area. In this analysis, it is proposed that the levels of accessibility should also be taken into consideration. Specifically, this need gap hopes to highlight areas with high and very high transport need joined with low accessibility levels.

3.2 Results

3.2.1 Accessibility-based Approach

Figure 3-1 illustrates the results of the accessibility analysis for Chicago. Areas with low, medium, and high accessibility are recognized. In addition, census block groups that are completely within low-accessibility areas are represented with a lighter grey color. The results show that a large part of Chicago is characterized by low accessibility levels. Approximately 79% of the metropolitan area presents very low accessibility, 7% present low accessibility, 13% presents medium accessibility and only 1% presents high accessibility. As expected, high accessibility is seen close to the downtown area, where ‘The Loop’ and other transit facilities are located as well as diversity in the land use.

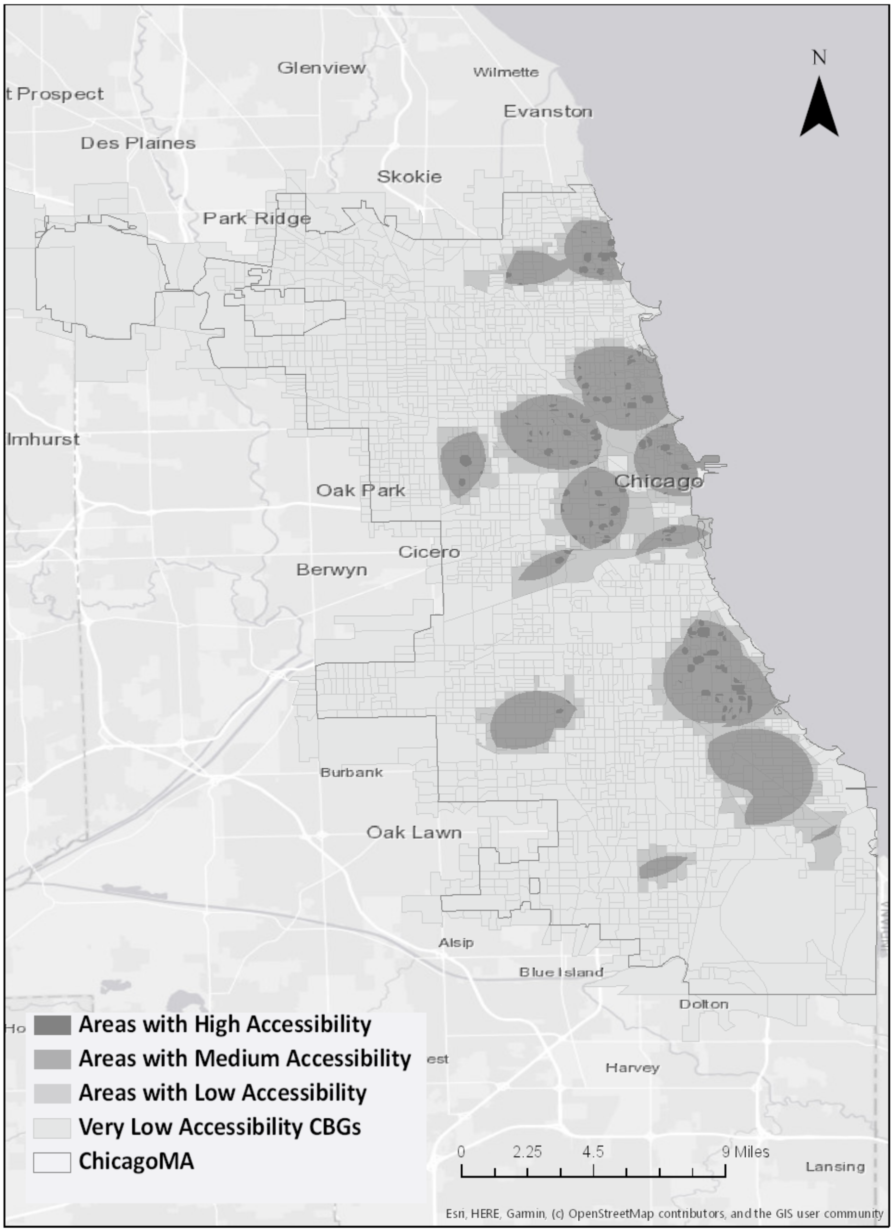

Figure 3-1 Accessibility Analysis by CBG- Chicago

A similar trend is seen in Figure 3-2 for Indianapolis. The lighter grey color represents low accessibility census block groups. According to the analysis, 89% of Indianapolis (Marion County area) is classified as to have very low accessibility, while 1% presents high accessibility. Similarly, downtown area is where most of the CBGs classified as a high and medium accessibility are located. This area is also located close to the interstate ring that surround Indy downtown and provides access to different areas.

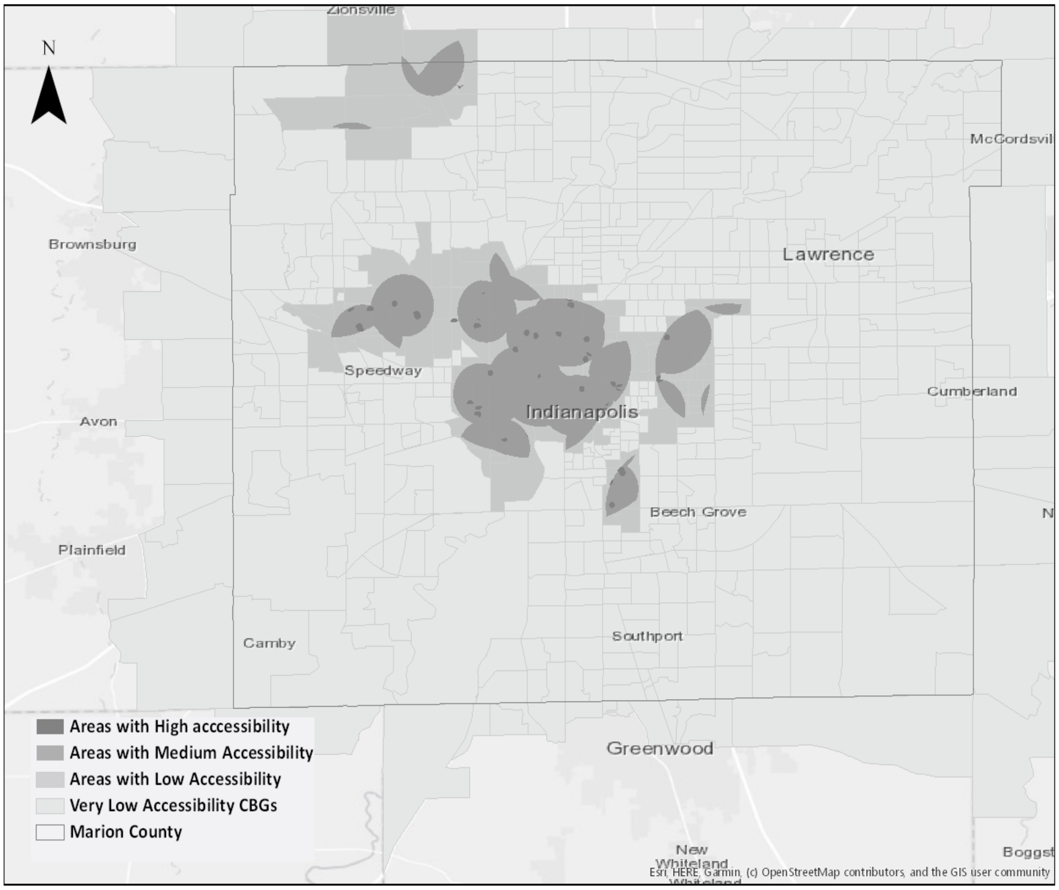

Figure 3-2 Accessibility Analysis by CBG- Indianapolis

3.2.2 Mobility-based Measure

Figure 3-3 and Figure 3-4 present the findings of the transportation need index for Chicago and Indianapolis, respectively. The cut-off points for the transportation need index of this application are based on equal intervals (very low is 0-20, low is 21-40, average is 41-60, high is 61-80, and very high is 81-100), as suggested by Pyrialakou (2016). It is worth to mention that contrary to the previous measure, a high need index represents an area in disadvantage.

Chicago presents a high number of CBGs classified as very low need, which covers 54% of the area of analysis. CBGs classified as low need are 35% of the area of analysis. Moderate need only covers 6% of the area. High and very high need are 1% and 3% of the area of analysis, respectively. As it can be seen in Figure 3-3, the low indexes are located close to downtown. The biggest area that registered to be in need is in the south part of Chicago.

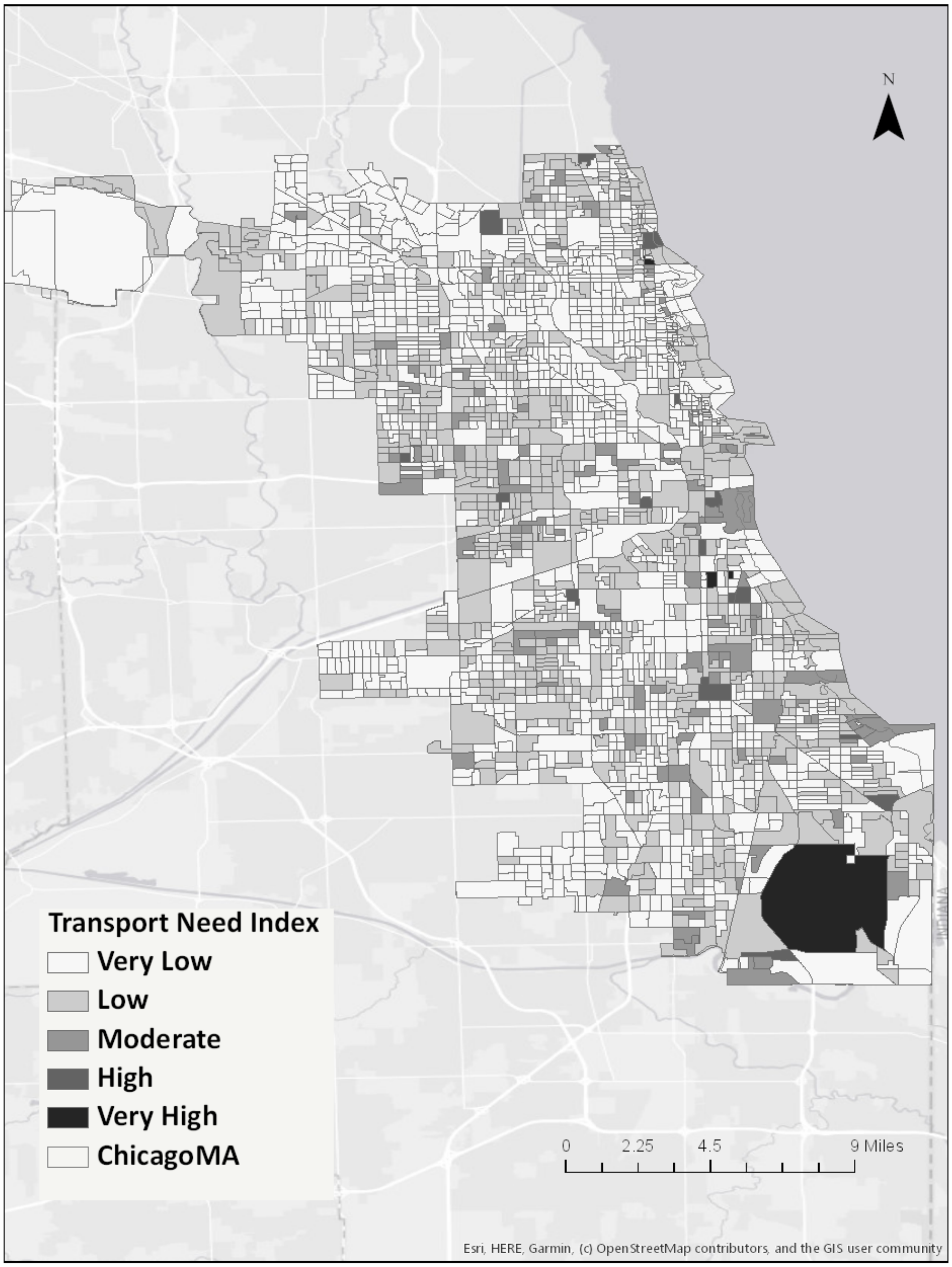

Figure 3-3 Mobility Analysis by CBG- Chicago

On the other hand, Indianapolis results show that only 37% of its area is classified in very low need, while 50% resulted to be in low need. 7% of the Indianapolis area resulted to be in moderate need. Only 1% of the area resulted to be in high need while 5% of the area resulted to be in very high transportation need. It is worth to mention that the transportation index presented herein has been constructed as a relative transportation need within an area, so it aims to identify areas that can be prioritizing to provide public transportation.

To explore the spatial autocorrelation of transportation needs and recognize any spatial patterns that might occur in the study areas, the Moran's I coefficient is estimated following Anselin, (2010) methodology. To calculate the global value of Moran's I coefficient, the *Spatial Autocorrelation* tool in ArcGIS was used. In addition, the *Cluster and Outlier Analysis* tool was used to calculate the local Moran's I values and identify any spatial patterns, such as areas where CBGs of high transport need or low transport need are concentrated, and/or any outliers, such as areas of low (or high) transport need where a high (or low) transport need CBGs are located. A first-order queen contiguity row-standardized weight matrix was chosen. This matrix identifies all the direct neighboring CBGs for each CBG, or CBGs sharing boundaries and/or nodes. The matrix was created using GeoDA and then used it in the spatial analysis performed within ArcGIS.

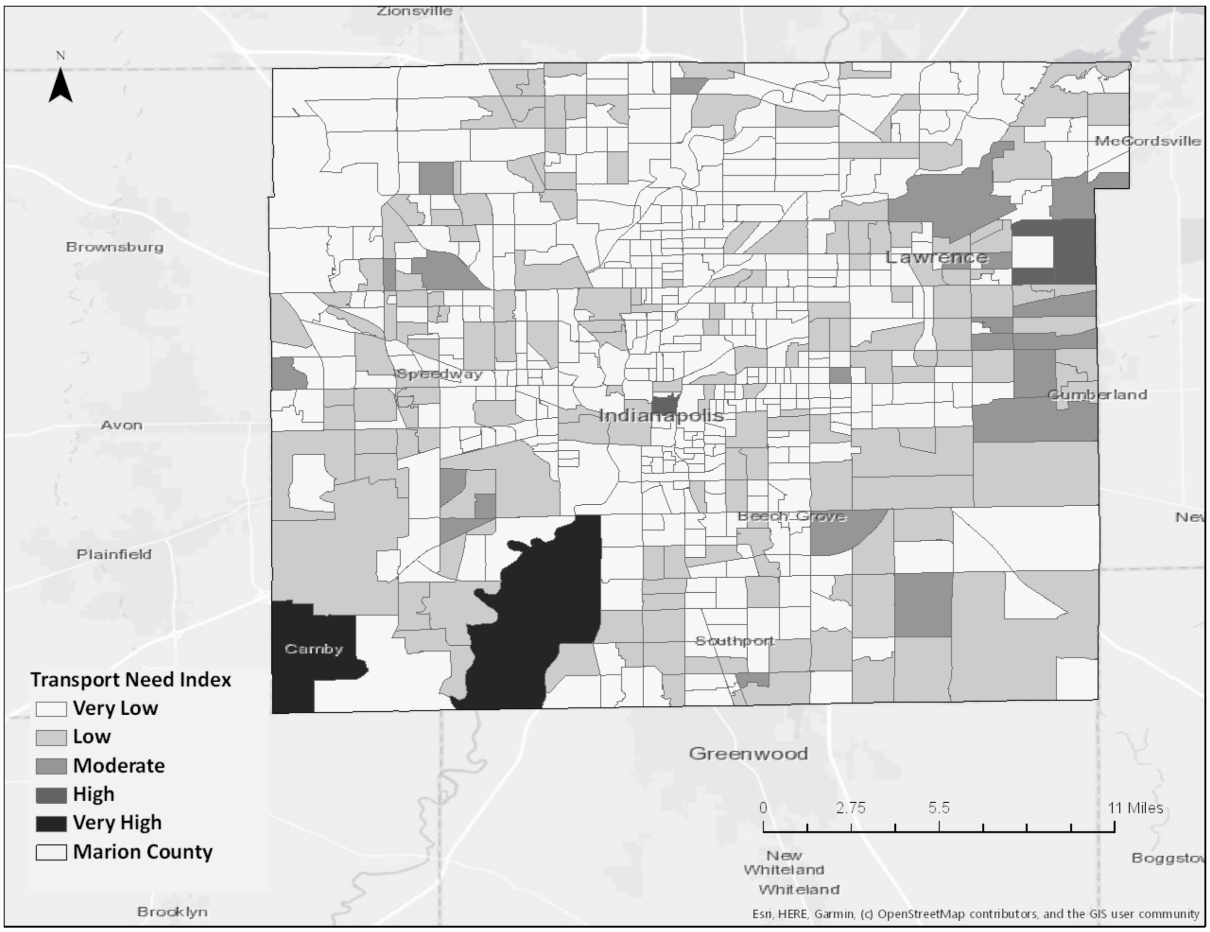

Figure 3-4 Mobility Analysis by CBG- Indianapolis

For Chicago, Moran's I was found to be 0.18067, significant at a 1% level (z-score of 13.51). The positive value of Moran's I suggests that CBGs with high transport need and CBGs with low transport need are clustered. For Chicago, the null hypothesis of complete spatial randomness is rejected, and it suggests that the transportation need is spatially distributed in a non-random way. Figure 3-5 shows the results of the local Moran's I analysis for Chicago. Most of the study area resulted to have a non-significant Moran's I (at the 0.05 significance level). However, some cluster of high transportation need were identified in the south area of Chicago and some other in the west side of the study area.

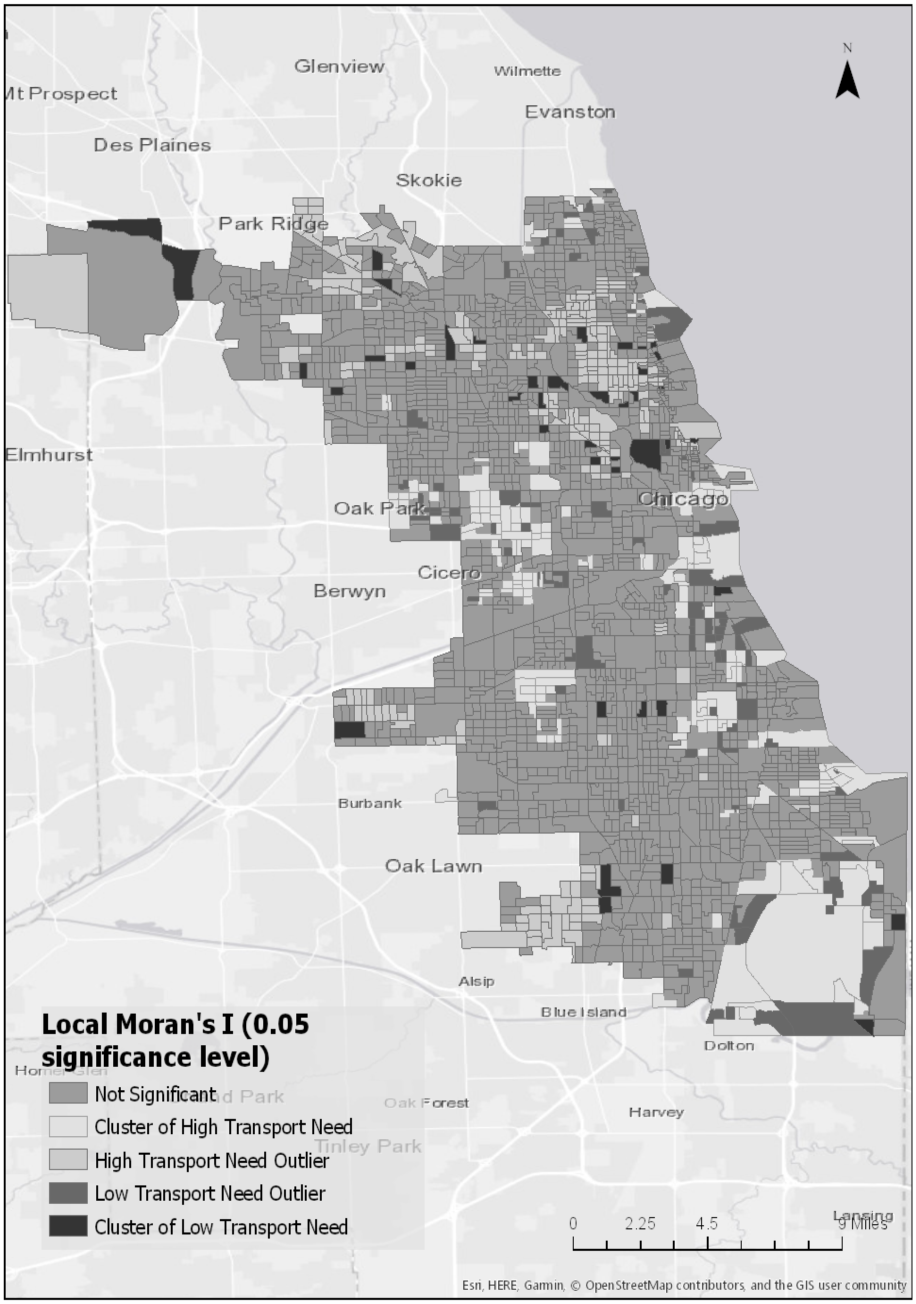

Figure 3-5 Results of the Cluster and Outlier Analysis Using Local Moran's I - Chicago

For Indianapolis, Moran's I was found to be 0.18205, significant at a 1% level (z-score of 13.67). The positive value of Moran's I suggests that CBGs with high transport need and CBGs with low transport need are clustered. For Indianapolis, the null hypothesis of complete spatial randomness is rejected, and it suggests that the transportation need is spatially distributed in a non-random way. Figure 3-6 shows the results of the local Moran's I analysis for Indianapolis. Similar to the findings in Chicago, most of the study area resulted in a non-significant Moran's I (at the 0.05 significance level). However, some cluster of high transportation need were identified in the southwest area of Indianapolis and some other in the east side of the study area.

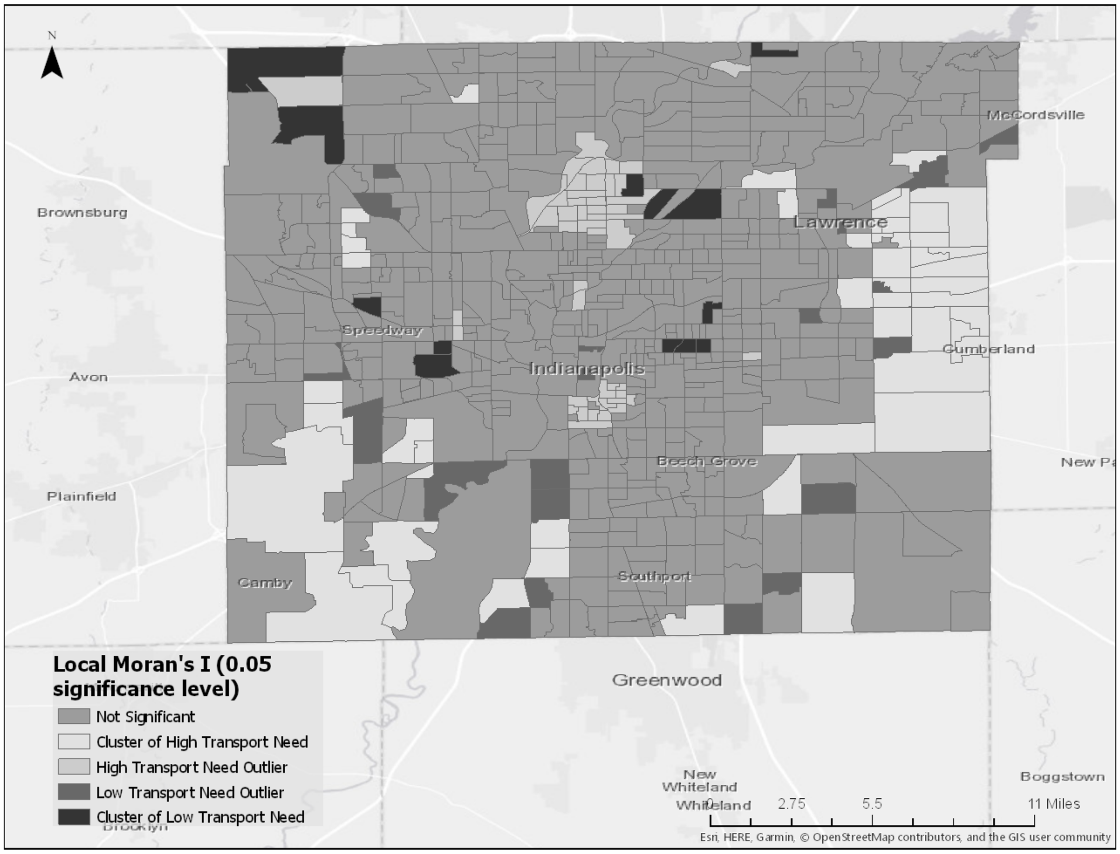

Figure 3-6 Results of the Cluster and Outlier Analysis Using Local Moran's I - Indianapolis

3.2.3 Outcome-based Measure

Figure 3-7 shows the results of the outcome-based analysis at the CBG level for Chicago. The analysis shows that closer to the downtown area, lower trip lengths (0-8.85 miles) are exhibited. It seems that CBGs located near the main roads in Chicago exhibit, in general, higher trip lengths. That finding might indicate that people chose their household location considering that they would have a higher access to automobile-oriented facilities such as highways. However, different areas within Chicago resulted in the lower classification of trip length, which might be associated to the diversity of jobs and opportunities in those areas.

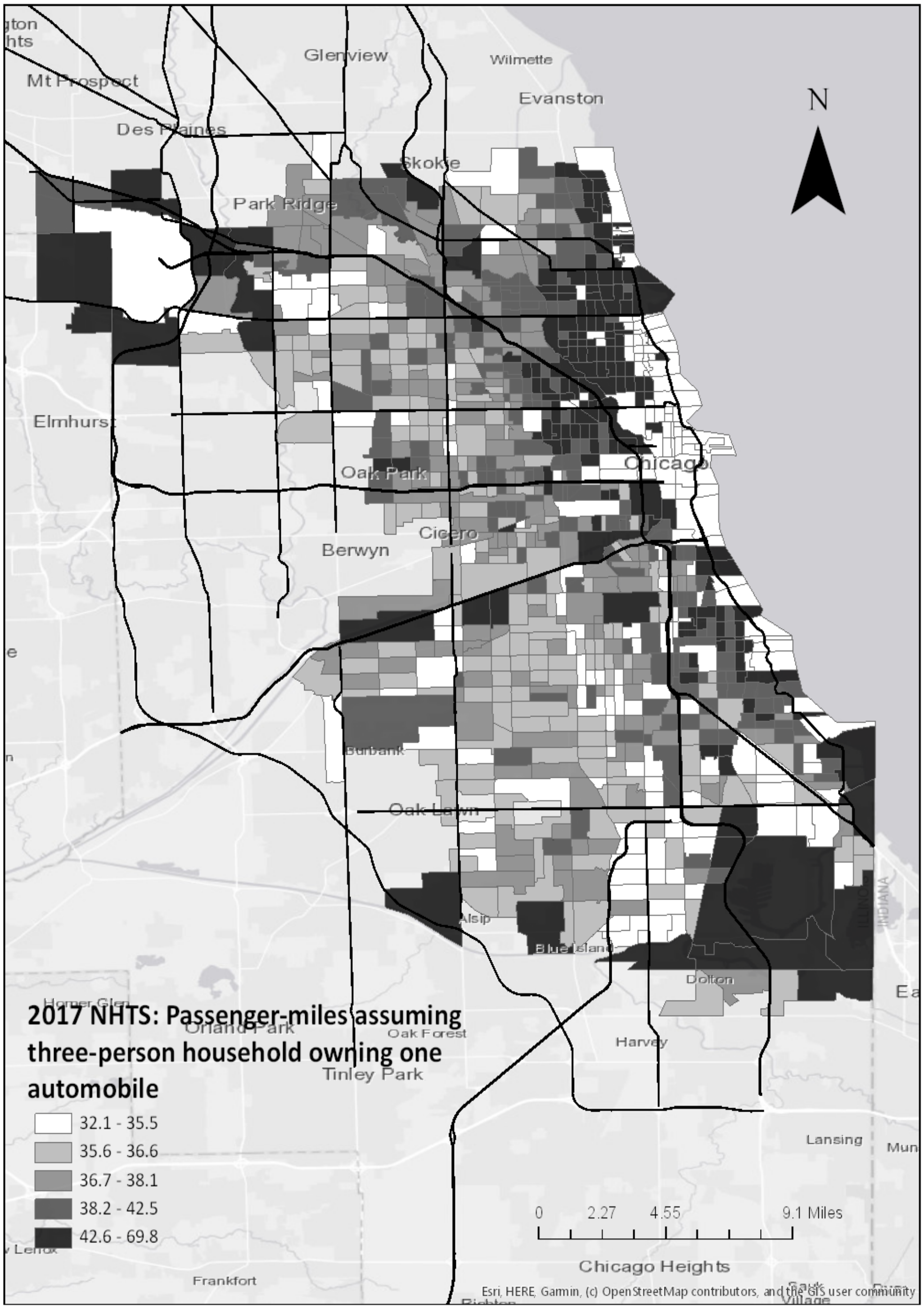

Figure 3-7 Outcome-Based Analysis Results by CBG - Chicago

Figure 3-8 shows the outcome-based analysis results for Indianapolis. In this case, CBGs with the lowest number of trip length were found outside the downtown area. Like Chicago, CBGs located closer to the main roads of the study area exhibit a high trip length, in general, than the ones slightly further away. Additionally, areas located in the border of Indianapolis also exhibit high trip length.

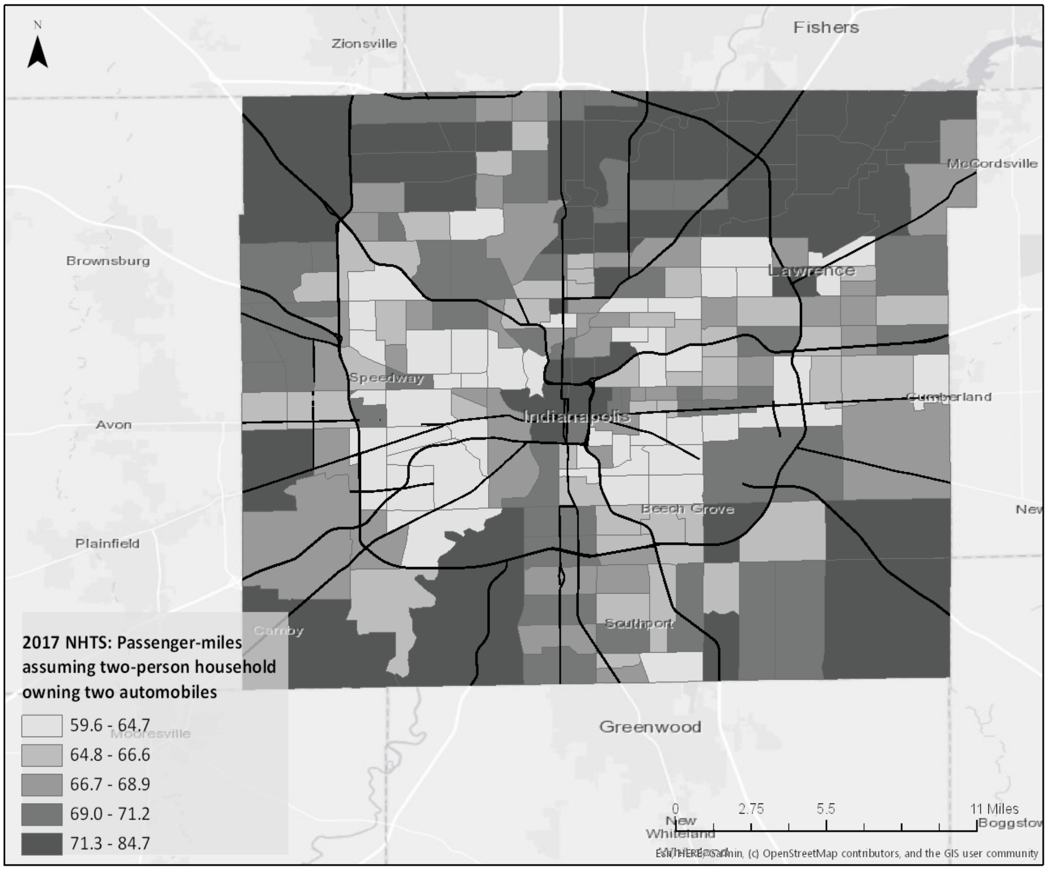

Figure 3-8 Outcome-Based Analysis Results by CBG - Indianapolis

3.2.4 Needs Gap Assessment

In order to identify the areas that are highly disadvantaged, areas that have been identified to be in high and very high need (based on the transportation index), CBGs that presented very low accessibility (based on accessibility-based measured), and CBGs with high trip length were combined spatially by using ArcGIS. The results of this assessment for Chicago and Indianapolis is presented in Figure 3-9 and Figure 3-10, respectively.

As Figure 3-9 illustrates, Chicago presented areas in need in different parts of the study area. The biggest area resulted to be closer to the south part of Chicago, which was also highlighted in previous analysis. The CBGs identified as need gaps represent 4% of Chicago (Grey in Figure 3-9) and are within highly transport disadvantaged areas (Pink in Figure 3-9). Those areas represent 12% of the Chicago. In those highly transport disadvantaged areas, 22% of habitants are under the age of 14, 14% are above 65 years old, 14% are classified as disabled according to the ACS, and 5% were unemployed. Most importantly, 42% of households in those areas do not own a car and 35% are single-parent family with working parent and children under 18 years old. Therefore, there is a need for strategies oriented towards providing equal services to those disadvantaged groups identified in Chicago.

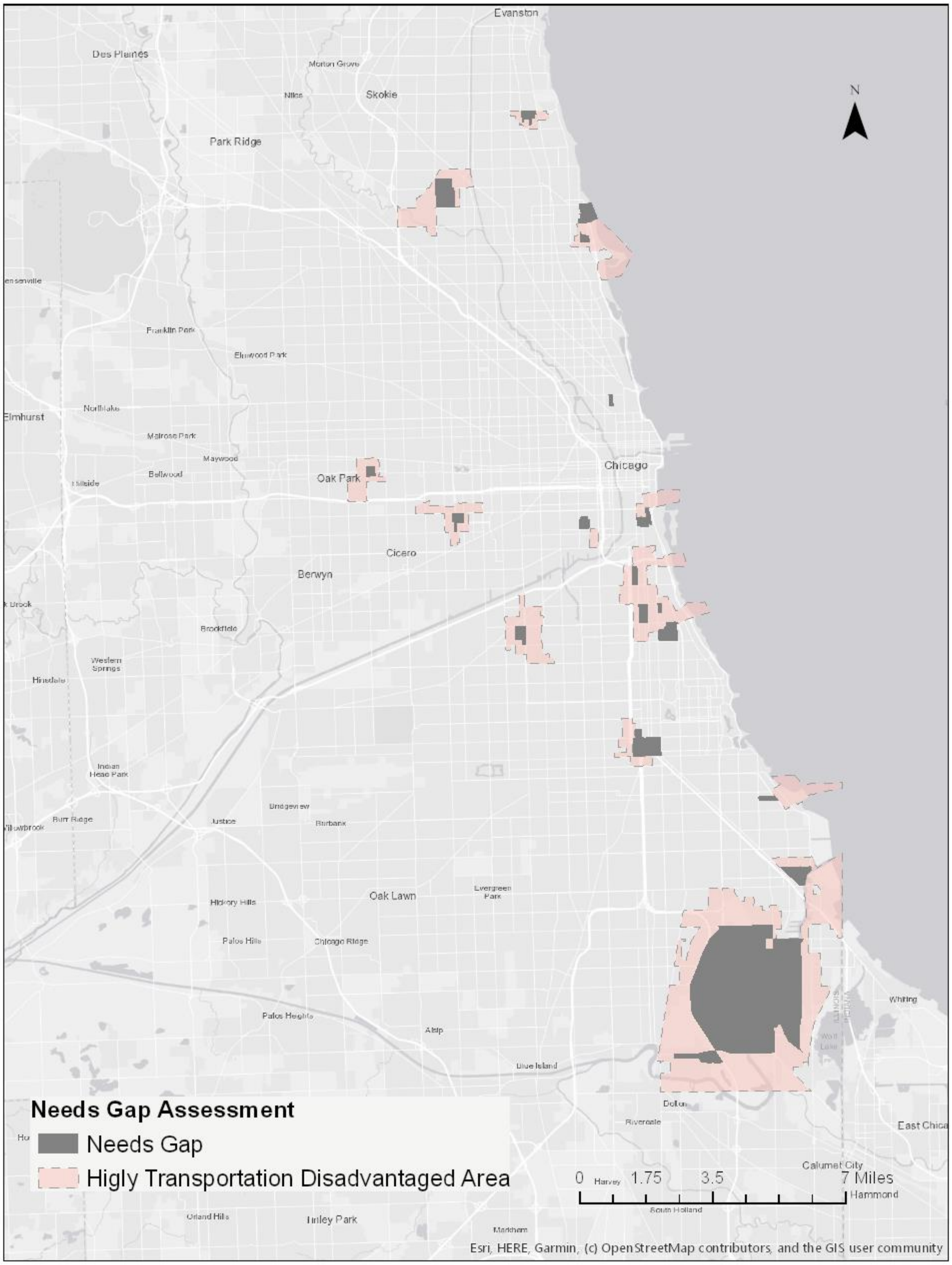

Figure 3-9 Results of the Need Gap Assessment CBGs-Chicago

A similar analysis was carried out for Indianapolis as Figure 3-10 illustrates. Indianapolis presented areas in need in the south-west and north-east. The CBGS identified as need gaps represent 6% of the study area(Grey in Figure 3-10) and are within highly transport disadvantaged areas (Pink in Figure 3-10). Those areas represent 16% of the Indianapolis area. In those highly transport disadvantaged areas, 6% of habitants are under the poverty line, 12% are above 65 years old, 11% are classified as disabled according to the ACS, and 4% were unemployed. Most importantly, 51% of households in those areas do not own a car and 26% are single-parent families with a working parent and children under 18 years old. The results in Indianapolis area seems to be highly driven by the inaccessibility to transit, since both areas lack transit service. In those underserved areas, options such as SAVs could provide opportunities to enhance the mobility.

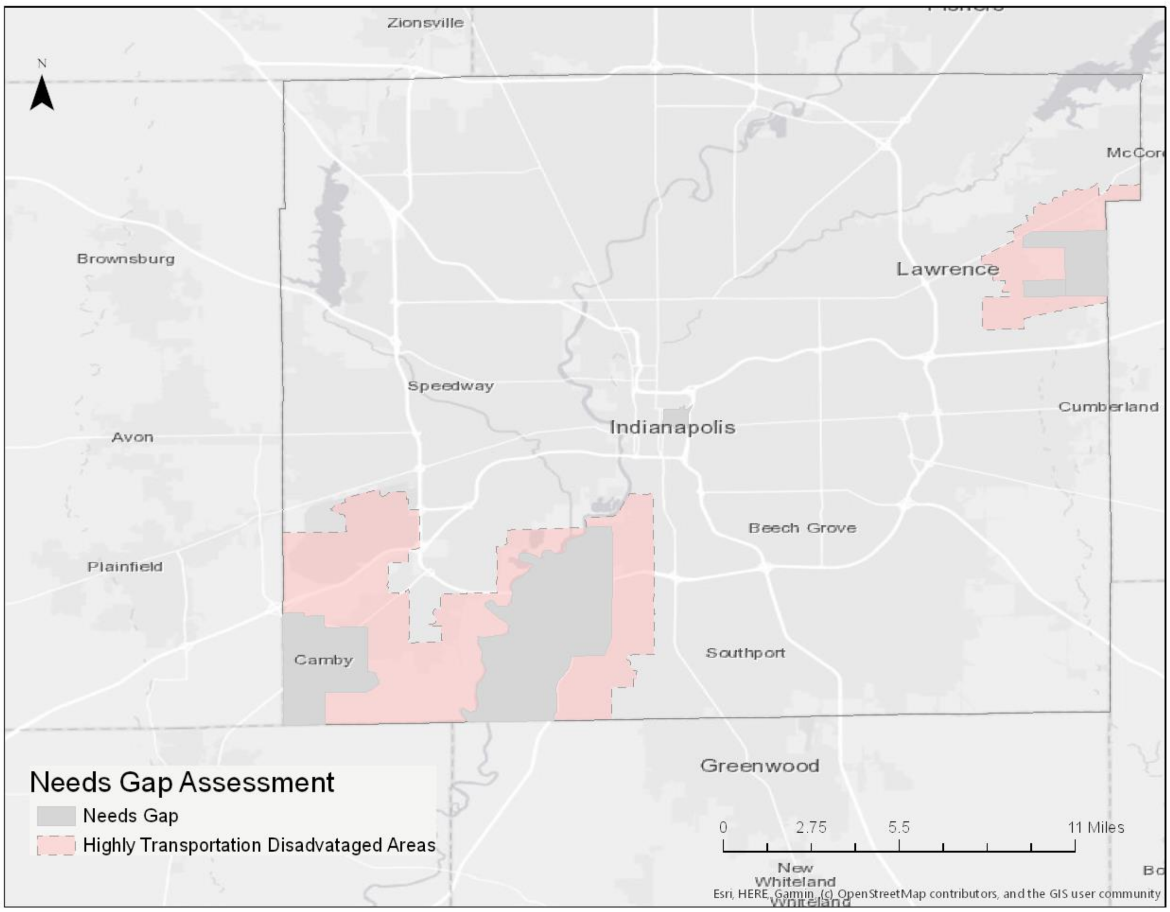

Figure 3-10 Results of the Need Gap Assessment CBGs-Indianapolis

4 Exploratory Spatial Analysis of Public Acceptance in Transportation Disadvantaged Areas

This section describes the spatial analysis that was conducted to assess public acceptance towards SAVs in the transportation disadvantaged areas in Indianapolis and Chicago. The geographical unit of measurement herein is the ZIP code area. This geographical unit approach is not inferring that people behave similarly within the ZIP code area, but rather defines a small enough geographical unit in which public information could be available to use as inputs and ultimately, to compare the resulting outputs from the spatial analysis with the findings from the survey.

4.1 Preliminary Analyses

As Established by W. Tobler's statement, known as the First Law of Geography, geographical entities tend to be rather similar the closer they are located (Tobler, 1970). This principle is considered to identify the analysis methods presented in this section. Fundamentally, site features are related with the actual geographical features of places but also with socioeconomic settings; thus, a spatial analysis is the appropriate method to reveal the spatial patterns of the willingness to shift to ridesharing services (SAVs) over the study areas. This method involves collating the socioeconomic characteristics and information about commuting behaviors (using information from the survey) as inputs and comparing the corresponding spatial outputs with the level of adoption in each study area. First, spatial autocorrelation was considered under two different approaches: univariate analysis and multivariate analysis. The univariate spatial autocorrelation was explored by Local Anselin-Moran's I method and for Getis Ord Gi*. Anselin-Moran's Local I was first calculated to assess spatial autocorrelation using ArcGIS 10.7. This method aims to evaluate whether a correlation exists between the analyzed geographical entities in terms of a specific associated attribute. This evaluation is done by a cluster process in which the model groups the entities on whether they show positive correlation, negative correlation or do not show any significant correlation between them (Anselin, 2010). The input was defined as the mean value obtained from the survey questions associated with the intention to ride SAVs at the ZIP code level. The analysis results did not provide enough evidence to infer any statistically significant conclusions because the responses over 40 ZIP code areas did not provide a large enough sample to predict the attitude towards SAVs (Figure 4-1).

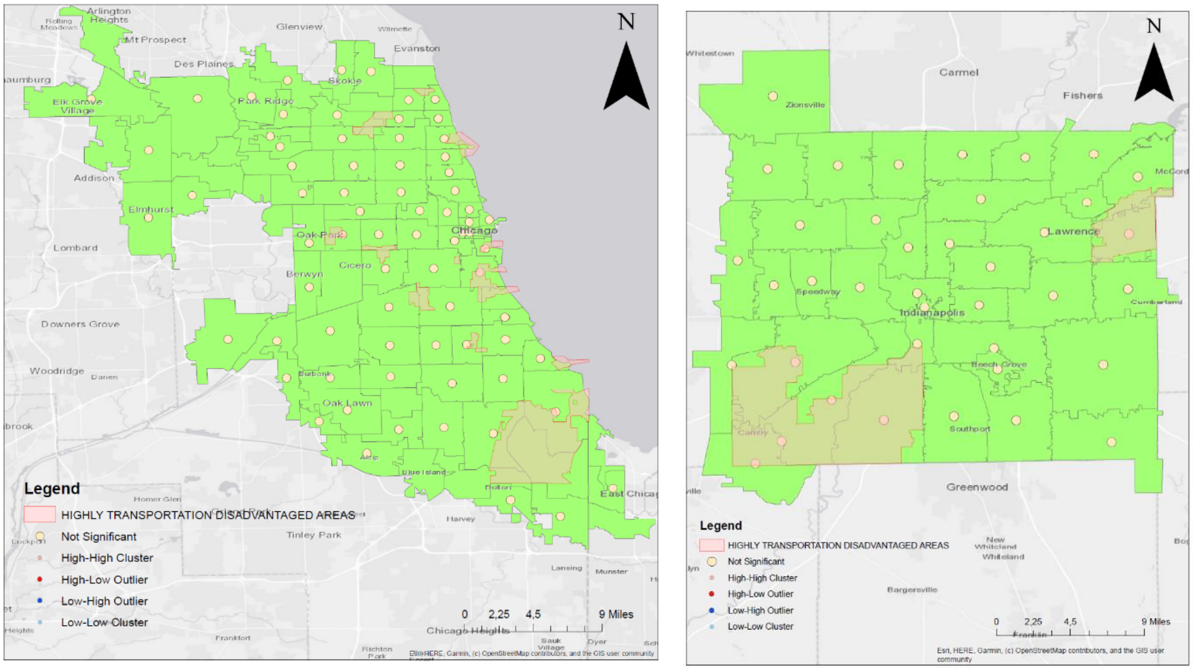

Figure 4-1 Anselin Local Moran's I Analysis for Chicago and Indianapolis

Other methods such as incremental spatial autocorrelation and high/low clustering (Getis-Ord Gi* statistic) did not yield statistically significant results either. As shown in Figure 4-2, it is not possible to discern any spatial correlation in terms of public acceptance of SAVs in the transportation disadvantaged areas by the univariate spatial autocorrelation. These results worked as guidance to continuing the next stage by developing the multivariate spatial analysis using K-means cluster method.

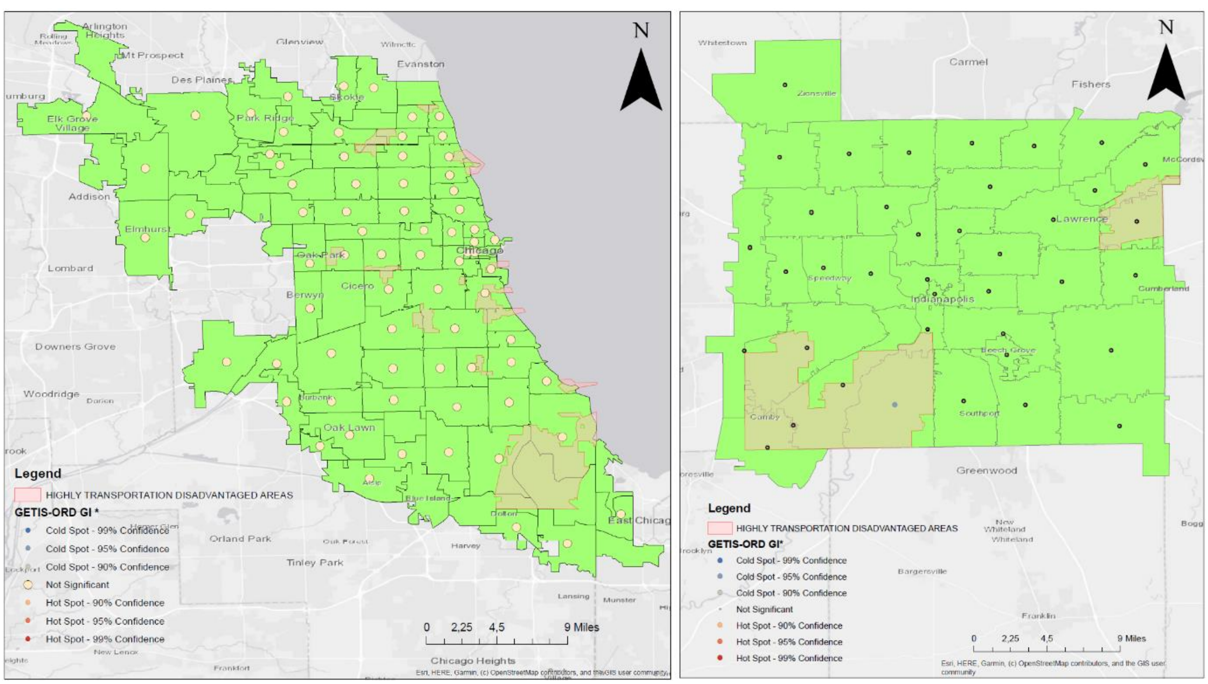

Figure 4-2 Getis Ord G* Analysis at Chicago and Indianapolis

4.2 Spatial Market Segmentation Analysis

A spatial market segmentation analysis was conducted using the k-means cluster in order to be consistent with the a-spatial procedure adopted and described in subsection 2.2. The inputs included ten indices that were defined as the mean value obtained from the survey questions associated with the broad attitude towards SAV vehicles, as explained in Gkartzonikas & Gkritza, (2019). This methodology generates accurate results when the input data is ordinal, thus using the indices responses to perform the spatial segmentation analysis is a good assumption. Five clusters with no spatial constraints and equally weighted input indices were identified as shown in Figure 4-3 and 4-4.

Figure 4-3 presents the results for Chicago. As it can be seen, the majority of the highly transportation disadvantaged areas (HTDA) are located in ZIP Codes were respondents resulted to be classified as late majority or laggards. Fewer HTDA were located in ZIP codes classified as Innovators or Early Adopters. Some of the areas that were classified as HTDA were not represented by a response in the survey. Since the survey was collected online, access to internet in those areas that are disadvantaged might have been an issue.

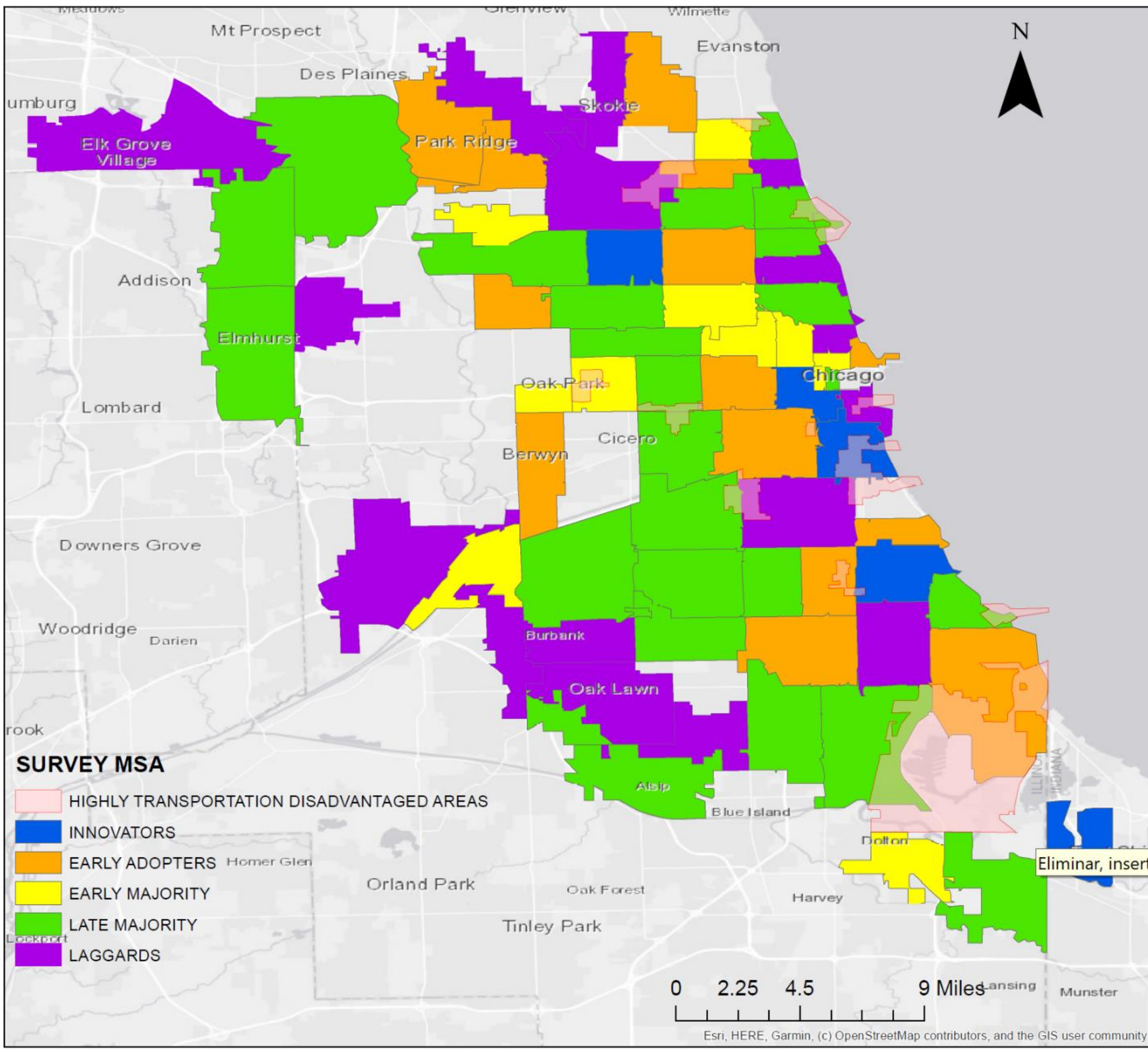

Figure 4-3 Spatial Market Segmentation – Chicago

Figure 4-4 presents the results for Indianapolis. In this study area, the majority of HTDA areas are in ZIP codes where responses are classified as innovators or early adopters. A lower percentage of HTDA was classified as late majority. Neither HTDA in Indianapolis involved ZIP codes with high percentage of early majority or laggards.

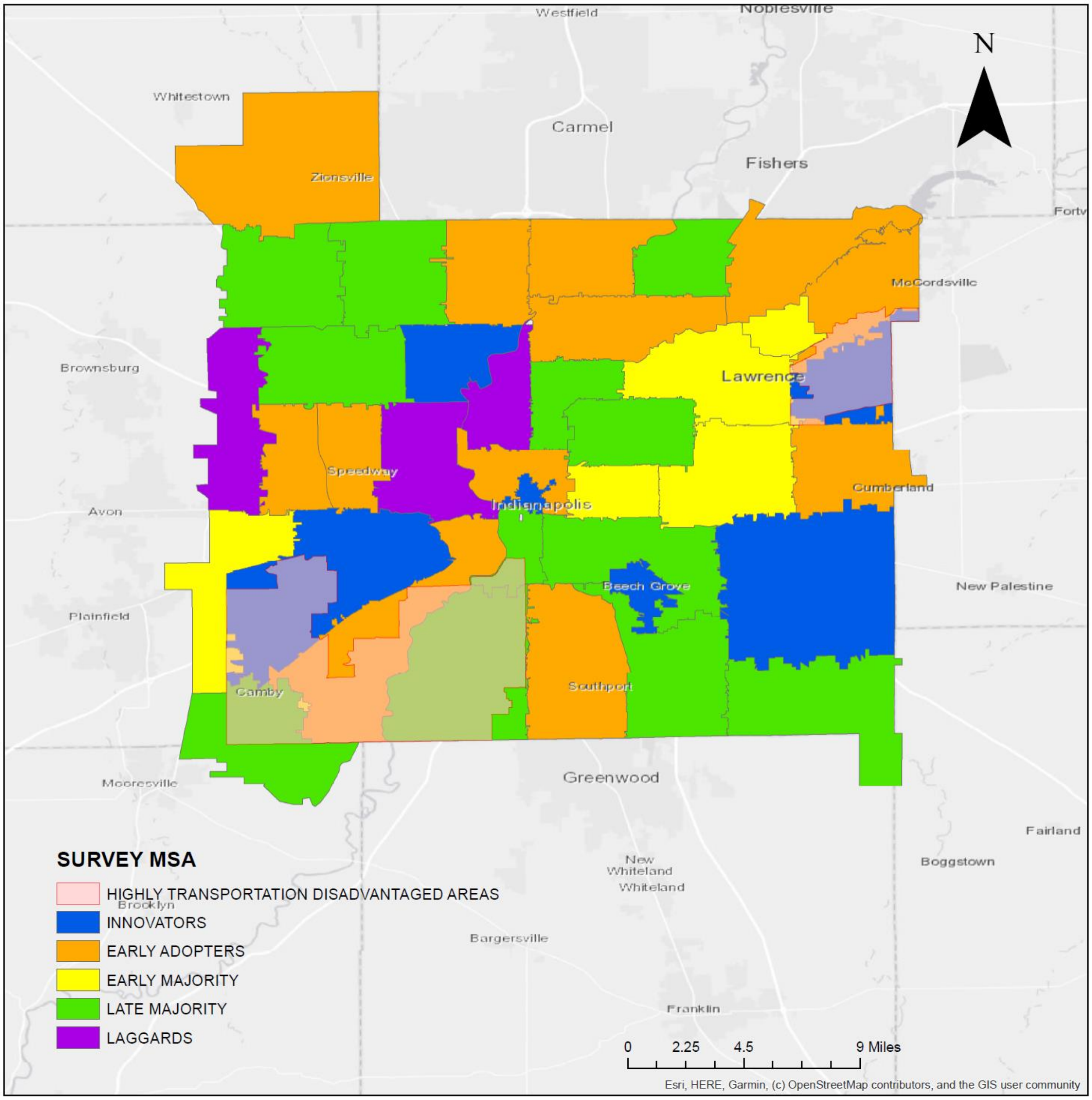

Figure 4-4 Spatial Market Segmentation – Indianapolis

5 Discussion

5.1 Comparison of Findings Across the Two Study Areas

This study evaluated the public acceptance of SAVs in two study areas with a focus on transportation disadvantaged areas. In particular, the public acceptance was assessed by identifying who will adopt the technology first and characteristics that describe the adopter categories, and by exploring the factors affecting the intention to switch from public transportation to ridesharing services operated through AVs. This analysis was performed by using data of a stated preference survey distributed online to adults residing in two study areas - Chicago, IL, and Indianapolis, IN – and collecting 400 completed responses from each area. Furthermore, this study conducted a spatial multi-perspective approach using accessibility, mobility, and outcome-based measures to identify transportation need gaps of transportation disadvantaged areas. Then, the results of the market segmentation analysis and the spatial multi-perspective approach were integrated to identify level of adoption for each transportation disadvantaged area. This section attempts to summarize the findings of each analysis performed under this study, followed by a comparison across both study areas and a list of practical policy and planning implications.

The market segmentation analysis classified the respondents into five adopter categories (innovators, early adopters, early majority, late majority, laggards). Regardless of the study area, it was found that people classified as innovators or early adopters are more likely to use other modes for commuting than their private vehicles (e.g., walking, biking, or public transportation), and they own or have access to fewer vehicles compared to their counterparts. Furthermore, these adopter groups are more likely to be members of ride-hailing and car-sharing services, younger individuals, people who work full time, and people with higher incomes and levels of education. Most innovators were found to have a higher education and income level in Chicago compared to the corresponding group in Indianapolis. Moreover, this study attempted to elucidate and assess the factors that drive the intention to switch from public transportation to ridesharing services operated through AVs (which is also a shared transportation mode). Results found in Chicago and Indianapolis seem to show similar trends across all the categories of variables that affect the intention to switch. The main differences between the results across the two study areas were mostly related to the socio-demographic variables, a finding that indicates the need of the market segmentation analysis in order to get a better understanding regarding the profiles and market segments of each study area.

The identification of transportation disadvantaged areas showed some similar patterns in both study areas. For instance, the accessibility measure showed that 79% of Chicago is classified as having low accessibility to opportunities compared to 89% of Indianapolis. As expected, the areas closest to the downtown and surrounded by highways for each study area seem to have high level of accessibility to opportunities. The results showcased by the mobility measure revealed that 54% of Chicago has a very low need of transportation, while 37% of the Indianapolis area was classified as having low mobility need. Note that this measure considers the socio-demographic characteristics of the census block groups. The spatial autocorrelation analysis showed that both Indianapolis and Chicago transportation need areas were not randomly distributed in the space. This finding highlights the lack of mobility infrastructure such as pedestrian features, connectivity to public transit, and walkable areas. Finally, the outcome-based measure results showed that in both study areas, people in CBGs located near to the main roads incur higher trip lengths. Although the patterns observed were similar in both study areas, the spatial distribution of the transportation disadvantaged areas varied. For Chicago, it was found that the highly transportation disadvantaged areas (HTDAs) were scattered through the area (representing 12% of the metropolitan area), while Indianapolis had two clear areas (in the northeast and southwest) that were classified as transportation disadvantaged (representing 16% of the metropolitan area).

The results of the spatial market segmentation analysis showed that most of the respondents located in areas classified as transportation disadvantaged are clustered as early adopters and innovators in both Chicago and Indianapolis. Early adopters are the second category in the diffusion of innovation theory and are known to be opinion leaders and embrace change opportunities. Since this group is characterized by promoting technology among peers and others, the presence of this group among transportation disadvantaged areas might be able to motivate others to also adopt the technology. Since SAVs are expected to provide more mobility and accessibility to disadvantaged groups such as the elderly, children, and disabled, the provision of such a service could fulfill the existing transportation needs in the identified areas. Proper market campaigns are recommended to increase public awareness of SAVs.

5.2 Policy Implications

The findings presented in this study provide insights into perceptions of and attitudes toward SAVs that can help transportation and urban planners, as well as original equipment manufacturers and ridesharing service companies, to prepare for the deployment of SAVs. Marketing strategies and educational sessions should be targeted and location-specific so as to increase public awareness and acceptance of AVs by conveying the benefits of and concerns regarding AVs. This can be especially effective in the case of Indianapolis, where respondents had a lower level of affinity of innovativeness and they might be less aware of the technology and have more trust concerns than respondents in Chicago that had a higher number of innovators and early adopters. Some other strategies mentioned in the literature for ridesharing service companies are: reduce service fees to be reachable for transportation disadvantaged populations; provide pre-tax commuter benefits; subsidize part of the trips; and provide different means to access the service (i.e., not only through a mobile app but also kiosk or cards sold in convenience stores, especially for the elderly) (Harper et al., 2016; Shaheen et al., 2017).

Physical access also has become an important topic to close the gap between transportation disadvantaged areas and transportation, as shown in the results of the accessibility analysis presented in this report. In this vein, policy makers should promote change in the design of the street that guarantee the service could be reached not only by young people but also the elderly. Delimited curbs and pick up areas accessible to wheelchair and other disabled travelers should be ensured. Additionally, it would be necessary to serve the population in different accessible vehicles, which would expand the service to users with special needs. In order to bring awareness of all the benefits of AV technology addressed in the literature, policy makers should implement AV information dissemination campaigning that motivates laggards and convinces early adopters of those benefits.

Furthermore, the spatial market segmentation analysis for the transportation disadvantaged areas suggested that residents of highly transportation disadvantaged areas in Chicago are mostly in the late majority or laggard adopter categories. However, there are areas, mainly closer to downtown Chicago, that include innovators and early adopters. For the respondents that are classified as late adopters or laggards, policy makers could promote campaigns including the use of celebrity endorsers, online content marketing and videos of AV travel experiences, pop-up AV information centers, and general direct marketing communications. Those experiences could make these populations fully aware of the technology benefits (Bennett et al., 2019). On another hand, the results for Indianapolis indicate that both innovators and early adopters reside in the transportation disadvantaged areas. This represents a great opportunity to promote higher awareness of the possible benefits that SAVs could bring to those communities and ensure a smooth deployment of the technology.

Lastly, the findings of the analysis evaluating factors of the intention to switch from public transportation to ridesharing services operated through AVs suggest that there is a need for wider testing of this technology in urban areas coupled with targeted marketing campaigns. For example, Waymo's Early Rider program, which offers ride-hailing services operated through AVs in test cities such as Phoenix, Arizona, can communicate and demonstrate the benefits that AV technology can bring through first-hand experience. In this way, the perceived benefits could be made to outweigh the perceived risks, thereby removing a psychological barrier to the adoption of AVs. Until psychological barriers are removed, it seems unlikely that conventional automobiles will lose their dominant market share. Similarly, public transit owners do not need to fear the loss of their ridership to SAVs, at least in the short term. Nevertheless, identifying strategies to supplement traditional transit services with SAVs (e.g., as feeder modes for first/last-mile trips) and providing premium on-demand services with a lower capacity than conventional buses but with greater flexibility and comfort can enhance the attractiveness of public transit.

5.3 Limitations and Recommendations for Future Research

This study has some limitations, many of which provide opportunities for further research. This study is a cross-sectional study and not a longitudinal study, which means that the results reflect only the current situation and do not capture changes in public opinion over time, which would be worth exploring by future studies. Furthermore, the analysis was based on the data of a stated preference survey that is subject to its limitations because the questions are hypothetical in nature. Different remedies were used to account for the limitations such as different techniques on data preparation and analysis; for example, removal of incomplete responses, cases of over-coverage, passive responses, and rigorous econometric modeling. Furthermore, the analysis pertaining to the intention to switch from public transportation to ridesharing services operated through AVs could be explored to target captive public transportation users and not the general population.

Additionally, in order to identify the transportation disadvantaged areas, census block groups were used as units of analysis. From that, we are assuming that the residents of those block groups are homogenous in socio-economic characteristics, which it is a limitation of this study. Further characteristics like 'unbanked' population (i.e., population that does not have access to bank accounts), percentage of actual access to internet/smartphones, and ridesharing/carsharing experiences were not considered in this analysis due to unavailability of data. These data could enrich the analysis by including populations that would be limited in the access to this new technology.

Moreover, the analysis performed to identify the spatial level of adoption in both study areas did not provide significant differences. This might be due to the responses were grouped by ZIP codes, which is a larger geographic unit compared with others such as individual records or census block groups. In order to identify a spatial market segmentation, researchers could use socio-demographics as a key link with the survey data. For that, techniques such as propensity score matching, which permits using observational data instead of exclusively using experimental data, would allow to match the commuting behavior reflected in the survey with larger socioeconomic data, such as the census data. This can serve as a means of assigning adopter categories to each ZIP code.

6 Synopsis of Performance Indicators

6.1 Part I

The research from this advanced research project was disseminated to over 175 people from industry, government, and academia. The research was presented at several conferences, including the 2020 Transportation Research Board Annual Meeting in Washington, DC, the 2021 CCAT Annual Symposium in Ann Arbor, the 2019 International Conference on Transportation and Development in Alexandria, the 2019 ITE Great Lakes District Annual Meeting in Indianapolis, the 2019 Purdue Road School in West Lafayette, the 2019 Next Generation Transportation Systems Conference, West Lafayette, and the 2019 ITE (Purdue Chapter) Annual Dinner. This project supported 2 doctoral students. The outputs, outcomes, and impacts are described in the following sections.

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) one transportation-related advanced degree programs utilized grant funds during the reporting period – 2 doctoral level programs, (d) 3 students supported by this grant received degrees – 1 undergraduate degree and 2 doctoral degrees. Some of these students were also partially supported by another CCAT project.

6.2 Part II

Research Performance Indicators: 7 conference articles and 1 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 that were produced by this research project.

Leadership Development Performance Indicators: This research project generated 3 media engagements, 7 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 (CE 561), a mandatory graduate level course at Purdue University's transportation engineering program.

Technology Transfer Performance Indicators: Regarding this CCAT research project, there were 3 media stories referencing the research or other related activities. Also, there was 1 press release and 200 website hits.

Collaboration Performance Indicators: There was collaboration with other agencies as 1 agency provided matching funds.

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

7 Outputs, Outcomes, and Impacts

7.1 Outputs

7.1.2 Publications and Conference Proceedings

The results of this work have been presented in different conferences/venues 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
- Lisa L. Losada-Rojas and Konstantina Gkritza, 'Public Acceptance and Socio- Economic Analysis of Shared Autonomous Vehicles: Implications for Policy and Planning', 2021 CCAT Global Symposium. Online
- Lisa L. Losada-Rojas, Christos Gkartzonikas, Konstantina Gkritza, 'Market Acceptance of Autonomous Vehicles in Transportation Disadvantaged Areas: Implications for Policy and Planning, 99th Transportation Research Board. Washington D.C. January 12-16, 2020.
- Christos Gkartzonikas, Konstantina Gkritza, 'Potential Implications of Autonomous Vehicles on Personal Vehicle Ownership and Demand for Public Transit'. International Conference on Transportation and Development. Alexandria, Virginia. June 9-12, 2019.
- Lisa L. Losada-Rojas, Christos Gkartzonikas, Konstantina Gkritza, 'Assessing the Socio-Economic Implications Related to The Emergence of Shared Autonomous Vehicles' International Conference on Transportation and Development. Alexandria, Virginia. June 9-12, 2019.
- Lisa L. Losada-Rojas, Christos Gkartzonikas, Konstantina Gkritza 'Public Acceptance of Autonomous Vehicles Across Transportation Disadvantaged Areas in Indianapolis, CCAT Next-generation Transportation Systems conference, May 31, 2019.
- Christos Gkartzonikas, Lisa L. Losada-Rojas, Konstantina Gkritza, 'Assessing the Socio-Economic Implications Related to The Emergence of Shared Autonomous Vehicles: The Tale of Two Midwestern Cities' ITE Great Lakes District Annual Meeting 2019, May 2019.
- Lisa L. Losada-Rojas, Christos Gkartzonikas, Konstantina Gkritza 'Assessing the Socio-Economic Implications Related to The Emergence of Shared Autonomous Vehicles: The Tale of Two Midwestern Cities' 105th Purdue Road School Transportation Conference and Expo. West Lafayette, IN. March, 2019.

7.1.2 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
- A brochure was created to share the results of this project at the *Accessibility and Mobility for All Summit*, USDOT on October 29th, 2019. The brochure can be found at the following link*:* https://engineering.purdue.edu/STSRG/research/CCAT/Public%20Acceptance%20and%20Socio-Economic%20Analysis%20Project%20Brochure
- Database for highly transportation disadvantaged areas was created in both Chicago, IL and Indianapolis, IN.
- Fall 2018 & Fall 2019 & Fall 2020: CE 299 Smart Mobility, Lecture on Estimating Transportation Demand for Conventional and Emerging Modes.

7.2 Outcomes

- Increased understanding and awareness of autonomous vehicles' public acceptance, especially by those highly transportation disadvantaged.
- The spatial autocorrelation analysis showed that both Indianapolis and Chicago transportation need areas were not randomly distributed in the space.

7.3 Impacts

- Provide insights into perceptions of and attitudes toward Shared Autonomous Vehicles (SAVs) that can help the transportation and urban planners, original equipment manufacturers, and ridesharing service companies prepare for the deployment of SAVs.
- Identifying strategies to supplement traditional transit services with SAVs (e.g., as feeder modes for first/last-mile trips) and providing premium on-demand services with a lower capacity than conventional buses but with greater flexibility and comfort can enhance the attractiveness of public transit service.

7.4 Technology Transfer

- Not Applicable.

7.5 Challenges and lessons learned

- The analysis about the intention to switch from public transportation to ridesharing services operated through AVs could be explored to target captive public transportation users and not the general population.
- Characteristics like 'unbanked' population (i.e., the population that does not have access to bank accounts), percentage of actual access to internet/smartphones, and ridesharing/carsharing experiences were not considered in this analysis due to unavailability of data. Those are also important to consider when studying transportation disadvantaged populations.

List of Acronyms

ACS	American Community Survey
AV	Autonomous Vehicles
BTS	Bureau of Transportation Statistics
CBG	Census Block Group
CCAT	Center for Connected and Automated Transportation
CTA	Chicago Transit Authority
FHWA	Federal Highway Administration
HTDA	Highly Transportation Disadvantaged Areas
IRB	Institutional Review Board
MSA	Metropolitan Statistical Area
SAV	Shared Autonomous Vehicles
VMT	Vehicles Miles of Travel

References

Anselin, L. (2010). Local Indicators of Spatial Association-LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Beck, M. J., & Rose, J. M. (2016). The best of times and the worst of times: A new best–worst measure of attitudes toward public transport experiences. *Transportation Research Part A: Policy and Practice*, *86*, 108–123. https://doi.org/10.1016/j.tra.2016.02.002

Bennett, R., Vijaygopal, R., & Kottasz, R. (2019). Attitudes towards autonomous vehicles among people with physical disabilities. *Transportation Research Part A: Policy and Practice*, *127*, 1–17. https://doi.org/10.1016/j.tra.2019.07.002

Bhat, C. R. (2003). Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transportation Research Part B: Methodological*, *37*(9), 837–855. https://doi.org/10.1016/S0191-2615(02)00090-5

Brownstone, D., & Train, K. (1998). Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics*, *89*(1–2), 109–129.

Burns, L. D., Jordan, W. C., & Scarborough, B. A. (2013). *Transforming Personal Mobility*. The Earth Institute, Columbia University. http://sustainablemobility.ei.columbia.edu/files/2012/12/Transforming-Personal-Mobility-Jan-27-20132.pdf

Cavoli, C., Phillips, B., Cohen, T., & Jones, P. (2017). *Social and behavioural questions associated with Automated Vehicles: A Literature Review* (p. 124). Department of Transport.

Curl, A., Fitt, H., Dionisio-McHugh, R., Ahuriri-Driscoll, A., Fletcher, A., & Slaughter, H. (2018). *Autonomous vehicles and future urban environments: Exploring changing travel behaviours, built environments, and implications for wellbeing in an ageing society* (p. 43) [National Science Challenge 11: Building Better Homes, Towns and Cities.]. http://buildingbetter.nz/resources/publications.html

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1–13. https://doi.org/10.1016/j.trc.2013.12.001

Fagnant, D. J., & Kockelman, K. M. (2018). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, *45*(1), 143–158. https://doi.org/10.1007/s11116-016-9729-z

Giuliano, G. (2005). Low Income, Public Transit, and Mobility. *Transportation Research Record: Journal of the Transportation Research Board*, *1927*(1), 63–70. https://doi.org/10.1177/0361198105192700108

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 323–337. https://doi.org/10.1016/j.trc.2018.12.003

Gkritza, K., Gkartzonikas, C., Losada-Rojas, L. L., & Zhang, Z. (2020). *Behavioral Intention to Ride in an AV and Implications on Mode Choice Decisions, Energy Use and Emissions* (Forthcoming). Center for Connected and Automated Transportation.

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49. https://doi.org/10.1016/j.trc.2017.01.010

Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies*, *72*, 1–9. https://doi.org/10.1016/j.trc.2016.09.003

Hulse, L. M., Xie, H., & Galea, E. R. (2018). Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. *Safety Science*, *102*, 1–13. https://doi.org/10.1016/j.ssci.2017.10.001

IndyGo Transit System. (2015). *Comprehensive Operational Analysis (No. Part 2)* (p. 32). Indianapolis Public Transportation Corporation. https://www.indygo.net/wp-content/uploads/2019/06/2010-Final-Report-Part-2.pdf

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 127–140. https://doi.org/10.1016/j.trf.2015.04.014

Litman, T. (2017). *Public Transportation's Impact on Rural and Small Towns*. 48.

Mannering, F., & Mahmassani, H. (1985). Consumer valuation of foreign and domestic vehicle attributes: Econometric analysis and implications for auto demand. *Transportation Research Part A: General*, *19*(3), 243–251. https://doi.org/10.1016/0191-2607(85)90013-5

Martínez-Díaz, M., & Soriguera, F. (2018). Autonomous vehicles: Theoretical and practical challenges. *Transportation Research Procedia*, *33*, 275–282. https://doi.org/10.1016/j.trpro.2018.10.103

Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Autonomous vehicles: The next jump in accessibilities? *Research in Transportation Economics*, *62*, 80–91. https://doi.org/10.1016/j.retrec.2017.03.005

Milakis, D., van Arem, B., & van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, *21*(4), 324–348. https://doi.org/10.1080/15472450.2017.1291351

MIT Energy Initiative. (2019). *Insights into Future Mobility* (p. 220). MIT. http://energy.mit.edu/research/mobilityofthefuture/

Mooi, E., & Sarstedt, M. (2011). *A Concise Guide to Market Research*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-12541-6

Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C: Emerging Technologies*, *111*, 255–293. https://doi.org/10.1016/j.trc.2019.12.008

NHTS. (2017). *National Household Travel Survey*. https://nhts.ornl.gov/

Pettigrew, S., Fritschi, L., & Norman, R. (2018). The Potential Implications of Autonomous Vehicles in and around the Workplace. *International Journal of Environmental Research and Public Health*, *15*(9), 1876. https://doi.org/10.3390/ijerph15091876

Pyrialakou, V. D. (2016). *Assessing Public Transportation Options for Intercity Travel in U.S. Rural and Small Urban Areas: A Multimodal, Multiobjective, and People-Oriented Evaluation. PhD thesis.*

Pyrialakou, V. D., Gkritza, K., & Fricker, J. D. (2016). Accessibility, mobility, and realized travel behavior: Assessing transport disadvantage from a policy perspective. *Journal of Transport Geography*, *51*, 252–269. https://doi.org/10.1016/j.jtrangeo.2016.02.001

Ricci, A., Technical Activities Division, Transportation Research Board, & National Academies of Sciences, Engineering, and Medicine. (2018). *Socioeconomic Impacts of Automated and Connected Vehicles*. Transportation Research Board. https://doi.org/10.17226/25359

Rogers, E. M. (2003). *Diffusion of innovations* (Fifth edition, Free Press trade paperback edition). Free Press.

Schoettle, B., & Sivak, M. (2014). A survey of public opinion about connected vehicles in the U.S., the U.K., and Australia. *2014 International Conference on Connected Vehicles and Expo (ICCVE)*, 687–692. https://doi.org/10.1109/ICCVE.2014.7297637

Shaheen, S. (2018). *Shared Mobility Policies for California* (p.). Institute of Transportation Studies, Berkeley. https://doi.org/10.7922/G2VX0DP9

Shaheen, S., Cohen, A., & Yelchuru, B. (2017). *Travel Behavior: Shared Mobility and Transportation Equity* (PL-18-007; p. 66). Federal Highway Administration.

Sinha, K. C., & Labi, S. (2007). *Transportation decision making: Principles of project evaluation and programming*. John Wiley.

Tyrinopoulos, Y., & Antoniou, C. (2008). Public transit user satisfaction: Variability and policy implications. *Transport Policy*, *15*(4), 260–272. https://doi.org/10.1016/j.tranpol.2008.06.002

US Census Bureau. (2010). *Core Based Statistical Areas and Related Statistical Areas*. https://www.census.gov/geo/reference/gtc/gtc_cbsa.html

U.S. Census Bureau. (2015). *American FactFinder—Results*. American FactFinder. https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_15_1YR_S0801&prodType=table

U.S. Census Bureau. (2017). *2017 American Community Survey*. The United States Census Bureau. https://www.census.gov/programs-surveys/acs/news/data-releases/2017/release.html

Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, *86*, 1–18. https://doi.org/10.1016/j.tra.2015.12.001

Zmud, J., Sener, I., & Wagner, J. (2016). *Consumer Acceptance and Travel Behavior Impacts of Automated Vehicles*.

Appendix

Appendix A Market Segmentation Analysis

Table A1 Average scores of each cluster – Chicago

	Attitudes	Driving Related Sensation Seeking	Perceived Behavioral Control	Intention Ride	Early Adopters	Subjective Norms	Compatibility	Personal Moral Norms	Self-Efficacy	Relative Advantage
Innovators	4.04	3.52	3.99	3.94	4.10	3.89	3.91	3.82	4.11	3.88
Early Adopters	4.35	2.05	3.49	3.55	3.38	3.53	3.95	3.59	3.98	3.78
Early Majority	2.95	2.55	2.95	2.79	3.11	3.01	3.04	3.05	3.06	3.03
Late Majority	2.35	2.35	3.28	2.24	3.19	2.60	2.23	1.89	3.53	2.68
Laggards	1.49	2.03	1.89	1.43	2.57	2.19	1.58	1.74	2.08	2.15

Table A2 Average scores of each cluster – Indianapolis

	Attitudes	Driving Related Sensation Seeking	Perceived Behavioral Control	Intention Ride	Early Adopters	Subjective Norms	Compatibility	Personal Moral Norms	Self-Efficacy	Relative Advantage
Innovators	4.55	3.46	4.41	4.28	4.3	4.07	4.25	4.15	4.40	4.08
Early Adopters	4.08	2.26	3.55	3.52	3.40	3.36	3.71	3.61	3.91	3.71
Early Majority	3.20	2.63	3.23	2.89	3.30	3.04	2.95	2.84	3.46	3.23
Late Majority	2.08	2.19	2.92	2.00	3.00	2.58	2.12	2.18	3.03	2.66
Laggards	1.34	2.22	1.88	1.38	2.80	1.88	1.44	1.41	2.06	2.07

Appendix B Bivariate Order Probit Model

Table B1 Bivariate Ordered Probit Model – Chicago

Variable	Short-term Intention to Switch	Long-term Intention to Switch
	Estimated Parameter (p-value)	Estimated Parameter (p-value)
Constant	-1.344 (<0.001)	-0.721 (0.098)
Awareness		
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no)	0.058 (0.082)	0.062 (0.076)
Travel characteristics variables		
Respondents who indicated that they have a car-sharing account (1: yes, 0: no)	-	0.276 (0.057)
Respondents who indicated that they drive less than 20,000 miles per year (1: yes, 0: no)	-	0.252 (0.064)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**	0.288 (<0.001)	0.212 (0.010)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**	0.727 (<0.001)	0.640 (<0.001)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**	-	-0.201 (<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)	0.076 (0.099)	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	-0.167 (0.008)	-
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	0.132 (0.029)	0.108 (0.037)
Socio-demographics		
Respondents who are between 18 and 34 years old (1: yes, 0: no)	0.271 (0.032)	0.363 (0.007)
Respondents who indicated that they are students (1: yes, 0: no)	-	0.458 (0.019)
Threshold parameters		
Threshold 1	0.871 (<0.001)	0.913 (<0.001)
Threshold 2	1.868 (<0.001)	1.916 (<0.001)
Threshold 3	3.254 (<0.001)	3.220 (<0.001)
Cross-equation correlation coefficient (rho)	0.739 (<0.001)	
Pseudo R-squared	0.102	
Log-likelihood function	-635.87	
Restricted log-likelihood	-571.34	

** Predicted probabilities calculated using an estimated binary probit model

Table B2 Bivariate Ordered Probit Model – Indianapolis

Variable	Short-term Intention to Switch	Long-term Intention to Switch
	Estimated Parameter (p-value)	Estimated Parameter (p-value)
Constant	-0.817 (<0.001)	-0.594 (0.037)
Awareness		
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no)	0.127 (0.029)	0.108 (0.025)
Travel characteristics variables		
Respondents who indicated that they have a car-sharing account (1: yes, 0: no)	0.167 (0.018)	0.221 (0.020)
Respondents who indicated that they drive less than 15,000 miles per year (1: yes, 0: no)	-	0.197 (0.042)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**	0.184 (<0.001)	0.242 (<0.001)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**	0.284 (<0.001)	0.367 (<0.001)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**	-0.217 (0.013)	-0.194 (0.018)
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)	0.106 (0.067)	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	-0.154 (<0.001)	-0.171 (<0.001)
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	0.207 (0.021)	0.238 (0.019)
Socio-demographics		
Respondents who are between 25 and 34 years old (1: yes, 0: no)	0.149 (0.068)	0.162 (0.089)
Respondents who are over 55 years old (1: yes, 0: no)	-0.294 (0.024)	-0.367 (0.037)
Respondents who have annual income less than $50,000 (1: yes, 0: no)	0.328 (0.052)	0.379 (0.058)
Threshold parameters		
Threshold 1	0.792 (<0.001)	0.808 (<0.001)
Threshold 2	1.674 (<0.001)	1.842 (<0.001)
Threshold 3	3.018 (<0.001)	3.147 (<0.001)
Cross-equation correlation coefficient (rho)	0.628 (<0.001)	
Pseudo R-squared	0.157	
Log-likelihood function	-651.32	
Restricted log-likelihood	-548.91	

** Predicted probabilities calculated using an estimated binary probit model (see the Methods section).