Long-Distance Travel Mode Shifts Due to Automated Vehicles:
A Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis

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Abstract

In recent years vehicle automation technology has experienced rapid gains. Yet little research has been conducted on self-driving vehicles' potential impacts on long-distance personal travel, which represents a major area of travel growth in the United States. Automated vehicles (AVs) offer flexible trip time and origin-destination pairings at lower (perceived) travel tie costs; thus, they have the potential to dramatically change how travelers pursue long-distance tours.

By analyzing travel surveys and then developing a statewide simulation experiment of long-distance travel, this paper anticipates AVs' impacts on long-distance travel choices. The research explores Michigan State's 2009Long-Distance Travel Survey and estimates a long-distance trip generation model and modal-agnostic long-distance mode-choice model. These models were applied in a statewide simulation experiment in which AVs are introduced as a new mode with lower perceived travel time costs (via lowered values of travel time en route) and higher travel costs, (to reflect the initially high price of complete vehicle automation). This experiment highlights the potential shifts in mode choices across different trip distances and purposes. Specifically, for travel under 500 miles, AVs tend to draw from personal vehicles use and airlines equally. Airlines are estimated to remain preferred for distances over 500 miles (e.g. 43.6% of trips greater than 500 miles were by air, and 70.9% of trips greater than 1000 miles were by air). Additionally, at certain AV travel time valuations, travel cost is not a significant factor. As the perceived travel time benefits from hands-free travel rise, monetary costs become less important.

Keywords: long-distance travel, self-driving vehicles, autonomous vehicles, airline competition

Introduction

In recent years the technological state of vehicle automation has been experiencing rapid gains, and multiple auto manufacturers and technology providers appear set to introduce a self-driving vehicle by or before 2020 (Bierstadt et al. 2014). These developments will have profound impacts across the transportation system, for roadway safety, urban congestion, environmental implications, freight delivery, personal mobility, and travel behavior in general. One area of impact where little research has been conducted to date is on the potential impacts of vehicle automation on long-distance personal travel, which represents one of the largest areas of travel growth in the United States (US Travel Association 2015). Long-distance travel decisions, including the number of annual trips, timing of trips, destinations, durations, and travel parties are significantly more influenced by costs and travel time than daily travel (LaMondia *et al.* 2015) due to the increased time and cost investments inherent to this travel. As such, automated vehicles (AVs), which offer alternative travel time valuations and travel costs, have the potential to dramatically change how travelers pursue long-distance tours. For example, business travelers will be freed to work en-route to their destination, as they would on a plane, but with no airport access, egress, or wait times. Families and friends traveling together may be able to have quality interaction time while traveling at a reduced cost when compared to higher speed trains and airlines.

To assess the impact of these potential changes, this research investigation examines data obtained from the Michigan State 2009 Long-Distance Travel Survey in three specific ways: First, a household long-distance trip generation model was estimated and examined. Second, a household modal-agnostic long-distance travel mode choice model was estimated and examined, including consideration of households' sensitivity to travel time and costs. Third, the previous two models were applied to a statewide experiment in which AVs are introduced as a new mode with lower perceived travel time cost valuations, though at higher travel costs, to account for the price of automation technology. This experiment highlights the potential shift in mode choices (to now include AVs) across different trip distances and purposes. Observed AV trip records do not exist as this mode is not yet widely available, so the experiment incorporates the as-yet-unobserved AV mode choices via two main techniques. First, the model includes a single mode-utility function with parameter weights estimated from observable trip mode choices between personal vehicles and air travel. This model is then applied to also include likely AV trip characteristics (e.g. perceived cost and travel time). Second, a range of likely AV trip characteristics and their impacts on mode choices were studied to account for the lack of current knowledge on exactly how these vehicles will change perceived travel times and costs.

This paper is organized as follows: A background on vehicle automation and long-distance travel choices is provided in the next section, followed by a description of Michigan State's 2009 Long-Distance Travel Survey, and its supporting data. The trip generation and mode choice model specifications are then defined, followed by an application of these models and the results. Finally, conclusions from all analyses are presented.

Background

Emergence of Vehicle Automation Technology

Automated and connected vehicles offer greater efficiency and safety throughout the transportation system. The ability of these systems to greatly reduce human error while driving may lead to higher capacity traffic flows, fewer crashes, and increased freedom for drivers, as they are released from driving tasks and freed to perform other activities (see, e.g., Fagnant and Kockelman 2015c).

NHTSA (2013) describes five levels of automation ranging from absolute human control (Level 0) to absolute vehicle control (Level 4). This investigation is primarily concerned with Levels 3 and 4, where complete control of the vehicle is shifted from the driver to the vehicle in either some (Level 3) or all (Level 4) circumstances. These levels of vehicle automation have the greatest potential to impact long-distance travel behavior, since both will likely allow freedom from driving tasks during the majority of the trip. Stress and demands on the driver should be greatly reduced and drivers will be allowed to use their travel time more productively. These improvements can greatly decrease the perceived burden associated with driving, which could likely change modal travel choices. Essentially, longer trips may be taken by AV as the perceived burden falls.

In recent years vehicle automation technology has experienced rapid gains, and partially- or fully-automated vehicle sales to the public appear imminent. Mercedes and BMW 2014 models both have automated steering, braking, and acceleration capabilities. Google has stated that it plans to have AVs on the market by 2018 and will likely be followed by 2020 by GM, Mercedes-Benz, Audi, Volvo, Nissan and BMW (Bierstadt et al. 2014). Moreover, AV legislation is proceeding apace, with California, Nevada, Michigan, Florida, and Washington, D.C. having enacted legislation addressing AVs as of May 2015 (Weiner et al. 2015). Litman et al. (2015) predicts AVs will comprise between 2 to 5 percent of all new vehicles sold in the 2020s, though these first vehicles to enter the market will likely come at a substantial price and only be available to the wealthy. Yet the pace of future market penetration remains quite uncertain. For example, Litman predicts the U.S. vehicle fleet to pass the 50% threshold sometime in the 2050s, while Bierstadt et al. (2014) anticipates a faster adoption rate, reaching the 50% market penetration mark between 2035 and 2050. Nevertheless, regardless of the pace of the transition, prognosticators agree that an automated driving future is coming, and that this will have direct and profound impacts on travel behavior and the transportation system.

Long-Distance Travel

The National Household Travel Survey (NHTS) defines long-distance travel as one-way trips longer than 50 miles from origin to destination (Gudzinas et al. 2012). Santos et al. (2011) summarizes the data from the 2009 NHTS in relation to past surveys and shows how the frequency and length of daily person trips has experienced minor fluctuations between 1990 and 2009 while remaining relatively constant. Thus as America's total population has grown, total trips and miles traveled has increased steadily in consort.

One important decision with respect to long-distance travel is mode choice, which makes these trips most receptive to automated vehicles. Most mode choice models currently in use are formulated as binary logit, multinomial logit, or nested logit discrete choice models, though some analysis work has utilized cross-tab and descriptive statistics to inform long-distance distribution estimations (Gudzinas et al. 2012). Gudzinas et al. (2012) surveyed much of the literature modeling long-distance travel using 2001 NHTS data, finding that these models performed very well when predicting long-distance travel by air or personal vehicle.

Cho et al. (2013) used a multinomial logit model to conduct a long-distance mode choice model. The model focused on making predications relevant to policy makers especially in regard to less prominent forms of travel such as high speed rail. Cho et al (2013) model was constructed using the 2009 NHTS data set, while developing synthetic travel times and costs for all modes of travel. Outwater et al. (2015) also recently developed a nationwide model for forecasting long-distance travel that included a joint destination-mode choice model. The model included time and cost factors for each mode as well as destination-specific characteristics, and the researchers found that coefficients on these parameters changed over trip distances.

An examination of Gudzinas et al. (2012)'s survey of long-distance travel models as well as Cho et al.'s (2013) work provides a representative array of long-distance travel used within the United States. These models examine travel modes including private vehicle, bus, plane, and train. Survey data and model results show that personal vehicles were by far the most popular travel choice, accounting for over ninety percent of long-distance trips (Cho et al. 2013). Air travel comprised 7% out of the remaining 10% of trips; with bus and train accounting for 2% and 1%, respectively.

Factors influencing long-distance travel mode include gender, age, income, household location trip distance and trip purpose. Those in higher income groups are much more likely to have a high value of travel time and are more likely to choose more expensive options that reduce travel time and increase comfort. Both studies found that as distance of trips increases so does the likelihood of traveling by air. Gudzinas et al. (2012) found that the characteristics of the traveler were much more significant than the characteristics of the trip when predicting mode choice; meaning, the factors that most determine mode choice are fixed attributes. Both studies showed that travelers are more likely to opt to use their personal vehicle if the trip is for pleasure rather than business.

Convergence

As AVs look to become a reality, the intercity travel market appears set to change and companies are reimagining the physical structure of vehicles to take advantage of this new technology. For example, Rinspeed has produced a concept car design with rear-facing bench-like seats set for viewing a large flat screen television. This and other designs may allow the rider to better relax, work, or otherwise take advantage of their travel time, rather than driving, and more extensive models could come to resemble a mobile office. Other models could even push the envelope further through the development of a driverless sleeper car, complete with a bed.

All of this plays into the fundamental tradeoff between air and auto travel. At its most basic form, long-distance travel is a tradeoff between time and cost, though as noted previously, a variety factors will result in certain modes being prioritized, or greater weights assigned towards time or cost considerations. Though there are fixed airport access and wait times, air travel is typically faster but more expensive than travel by car. However, AV travel may shift this balance by reducing the perceived cost of in-vehicle travel time, though at added costs of the technology.

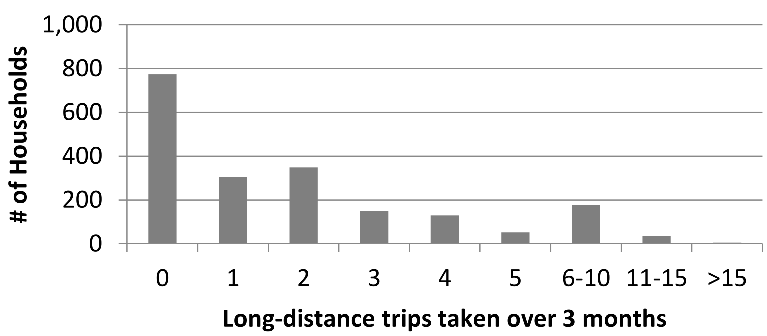
MacKenzie et al (2014) estimates current generalized travel costs at $1.16 per mile (including time, ownership, fuel, maintenance, insurance, etc.), $0.50 of which is attributable to the costs of the driver's time. Using long-run elasticity value ranges between -1.0 and -2.0, a 50% to 80% reduced value of in-vehicle travel time, and other benefits stemming from vehicle automation, MacKenzie et al. (2014) estimated that AVs could end up increasing light duty vehicle travel between 30% and 160%. In contrast, Gucwa's (2014) San Francisco Bay Area simulations show that overall personal travel could increase by a much smaller 4-8%, with travel time valuations falling by up to 50% from current levels. Yet whichever prognostication ends up holding true, both agree that AVs will result in more personal travel. Moreover, both works indicate that in addition to seeing a mode shift between air and rail, travelers may also opt to take increasingly long and more frequent long-distance trips. Tempering this view, without a reduction in roadway congestion there are likely limitations to how much long-distance travel may rise, particularly for regular long-distance commuters. Laberteaux's (2014) research shows that average daily travel budgets have remained at a relatively constant 1 to 1.5 hours, across cultures, economic circumstances, and decades. While it is possible that these travel time budgets could grow since drivers would be freed from the task of driving, the magnitude of this phenomenon remains quite uncertain given historical consistency.

Moreover, it is possible that intercity travel could be further impacted through the presence of shared AV (SAV) fleets. At the local travel level, SAVs could connect travelers to and from airports and rail stations, while at the intercity travel level they could represent another travel modal option if a household vehicle is unavailable. Fagnant and Kockelman (2015a, 2015b) simulated this first general context using SAVs across the Austin, TX network, serving a portion of all trips within a 12 x 24 mile area. Meanwhile, Chen et al. (2015) simulated SAV fleet operations for an idealized region, including mode choices for trips up to 70+ miles in length. This second context was found to sometimes stress a trip-based carsharing system, higher prices were charged for trips that required more empty-vehicle travel to reach the trip-maker's starting point.

The 2009 Michigan Long-Distance Travel Survey and Supporting Data

This research work relied on three primary datasets: the 2009 Michigan Long-Distance Travel Survey (MLDTS, Abt SRBI 2010), the 2010 Michigan statewide model long-distance trip forecasts (Abt SRBI 2010), and long-distance travel mode characteristic skims between National Use Microdata Areas (NUMAs) created by Resource Systems Group (RSG) Inc. (Outwater *et al. 2015*). These mode characteristic skims include the cost and travel times of the shortest path driving and the median flight itinerary between each origin-destination pair. Each dataset provided unique information that, only when combined, provided all the necessary information to complete the experiment in the state.

First, the Michigan Long-Distance Travel Survey was collected in 2009 in tandem with the Travel Counts Household Travel Survey. The survey included 4330 records of long-distance trips completed over a 3 month period (although the 3 month period varied across the year by respondent). This dataset was geocoded into ArcGIS and each origin and destination was mapped based on latitude and longitude. The dataset was cleaned, removing unidentified destinations, destinations outside the United States, incomplete trip records, and duplicate records for individuals in the same household on the same long-distance trip. Additionally, trips that used rail, bus or ferry modes were removed due to the lack of mode characteristic data for many origin-destination pairs (i.e. rail/bus/ferry were not an option for the majority of destinations) and the small number of records using these modes in the dataset (2.3%). After cleaning, the trip dataset included 2,574 unique long-distance trips, with corresponding respondent, household, origin, and destination information. These trips were completed by 1,975 unique households, which took 2.05 trips on average (with a 2.77 trip standard deviation). Five households took more than 15 trips over the 3-month period, with one household making 22 trips. Trip distances averaged roughly 230 miles, with a 200 mile standard deviation (though exact trip distances greater than 1000 miles were unknown). The distributions of trips taken per household and trip distances are shown in Figure 1.



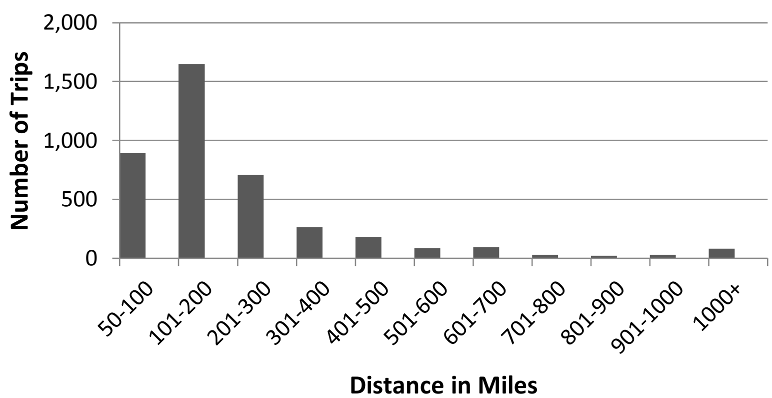


Figure 1: Distributions of Michigan State's Year 2009 Trip Counts and Distances in Michigan (Over a 3-month period)

Of the surveyed households, 30% were single persons, 40% consisted of two individuals, 13% had three persons and the remaining 17% had 4 or more people. Households averaged 1.82 vehicles, with 0.98 workers. Population density among the surveyed households averaged 0.23 households per acre, with a 0.37 standard deviation, and varying from 1.71 in Wayne County (Detroit plus some of the surrounding suburbs) to just 0.0038 in Ontonagon County in Michigan's Upper Peninsula. 26% of households were located in areas where over 40% of annual household incomes were less than $30,000, while 40% of households were located in areas where over 40% of annual household incomes were $60,000 or more.

The survey records were then matched based on latitude/longitude points with data from the 2010 Michigan statewide model zones, and long-distance travel mode characteristic skims between NUMAs. Specifically, home zone characteristics, including population density, income levels, education levels, etc., from the statewide model TAZs were added to each trip record. This was performed since some information regarding individual household characteristics (e.g., income, employment type) was not present at the trip level, and was therefore proxied through shared TAZ similarities. Additionally, based on each specific origin and destination zone pair in each trip record, imputed mode data was added based on the NUMA traffic skims. This mode data, which included travel costs, travel times, transfers, wait times, etc., was generated using published cost records between airports and traffic simulations between zone centroids for the entire country by Resource Systems Group, Inc. as part of their effort to develop a framework for long-distance travel forecasting. Table 1 depicts summary characteristics across the sampled traveler population.

Table 1: Traveler Summary Trip Characteristics

	Average	**Std. Dev**	**Min.**	**Max**
Household Size	2.16	1.03	1	4
# of Household Workers	0.98	0.88	0	3
# of Household Vehicles	1.82	0.84	0	3
# Long-Distance Trips	2.05	2.77	0	22
TAZ Percent Employment in Manufacturing	0.08	0.11	0	0.74
TAZ Percent Employment in Service	0.35	0.15	0	0.88
TAZ Percent Employment in Retail	0.14	0.08	0	0.64
TAZ Percent Employment in Education	0.05	0.05	0	0.64
TAZ Percent Employment in Other Professions	0.39	0.16	0.03	0.95
TAZ Percentage of Households with Income < $30k	0.32	0.13	0.06	0.87
TAZ Percentage of Households with Income $30-60k	0.31	0.07	0.09	0.60
TAZ Percentage of Households with Income > $60k	0.37	0.15	0	0.81
County Employment Rate (Jobs / Household)	0.88	1.14	0.02	16.37
County Population Density (Households / Acre)	0.23	0.37	0.0038	1.71

It is important to note that there are some spatial assumptions attached to both sets of zones. There are 2307 disaggregate in-state TAZs for which information was first matched, so the regional characteristics are specific to the small areas surrounding each household. However, while the NUMA dataset included 35,102 zones for the entire United States, Michigan was only represented by 204 zones. Trips matched to this second dataset included slightly more geographic aggregation, but recorded trip distances were, on average, only 9.5% smaller than the NUMA based trip characteristics.

Model Estimation and Specifications

Trip Generation

A trip generation model was developed using a version of the Michigan travel survey aggregated by household ID in order to estimate the number and length of long-distance trips made by households throughout the state. This was conducted by developing a negative binomial model to estimate the number of trips that a given household would make over a three-month period (the duration of the travel survey), then applying the model across Michigan's 3.87 million households, spread over the 2,307 transportation analysis zones (TAZs). A trip distance distribution model for long-distance trips was also explored, though it was discarded due to poor model fit.

A negative binomial was chosen to estimate the number of long-distance household trips, due to the discrete nature of long-distance trip-making, and because of the presence of over-dispersion in the dataset. The potential impact of a number of variables was assessed, including household-specific characteristics including number of household members and number of workers, as well as TAZ-linked variables including origin location (from across Michigan's seven sampling count regions), percentage employment in manufacturing, service, and education sectors, employment density, household density, and percentage of households with annual incomes above $60,000 and below $30,000. Stata (v. 12.1) statistical software was used, with a stepwise elimination methodology utilized to pare down the model until all remaining coefficients were statistically significant at the 5% level or greater. The resulting model is shown in Table 2.

Table 2: Results of Negative Binomial Long-Distance Trip Generation Model

	Coefficient	z-stat
Household Size	0.405	12.71
# of Household Workers	0.086	2.27
# of Household Vehicles	0.289	6.99
Southwest Michigan (Sampling Region 5)	-0.317	-3.88
TAZ Percent Employment in Education	-1.903	-3.39
TAZ Percentage of Households with Income Greater than $60k	0.588	2.98
County Population Density (Households / Acre)	-0.293	-3.42
Constant	-0.993	-9.34
α (Over-Dispersion)	0.855	
N_{obs} = 1973, Log likelihood = -3538.56, LR $\chi^2(7)$= 491.31 (0.0000)		

These model results may be interpreted such that household size, the number of workers in a given household, the number of vehicles owned by the household and the share of higher income households in the household's TAZ are all correlated with increased trip-making. In contrast, households in TAZs with strong employment in the education sector is associated with lower trip-making rates, as is higher county population density and origin from the survey's Region 5, spanning much of the Michigan Lower Peninsula's southwest quadrant. While there was some expected correlation among a few of the variables (e.g., household size, household workers and household vehicles), the degree of correlation remained below 0.6 in all instances, the resulting coefficients were all statistically significant, and made intuitive sense in terms of their impact on long distance trips made. Therefore, any possible multicollinearity issues in this model were not deemed to be substantial. Model residuals were also examined against all seven variables included in the negative binomial regression model, with no apparent model assumption violations or other causes for concern.

A secondary trip distance model was explored using both a linear and a log-linear model formulation in order to determine the distribution of long-distance trip lengths. Correlations among long-distance observations due to multiple trips stemming from the same household were addressed through use of clustering (1,201 households were responsible for making 4,044 trips). This was conducted through Stata's embedded clustering linear regression option (see, e.g., UCLA SCG 2006), which may be used to account for such correlations, and adjusts regression standard errors and outputs based on the number of non-correlated observations (i.e., unique travelers). The same variables related to household, TAZ, and county-wide characteristics that were used in the negative binomial trip generation model were also used as inputs into the linear and log-linear regression models to estimate trip distance distributions. However, while a few variables exhibited statistical significance in impacting trip distance predictions (including regional differences, county-wide service sector employment, and county-wide household density), both models exhibited R^2 values less than 0.03. This indicates that these distance-related statistical regression models performed quite poorly, and therefore the distribution of trip lengths among all sampled trips was assumed instead, and that distribution was later applied uniformly across all generated trips, as described subsequently in the Statewide Mode Shift Experiment section of this paper.

Mode Choice

The mode choice model was estimated using a modal-agnostic binary logistic regression on the Michigan long-distance travel survey data. This means that a single utility function was estimated that can be applied to each mode individually and applied to the probability calculation for mode preference. No observed long-distance trip records or stated preference surveys were available to estimate a model that included AV-specific parameters. As such, it is assumed that individuals consider perceived travel times, costs, and other factors similarly, regardless of mode. However, as detailed in the simulation section below, the costs and travel times of AVs are calculated to incorporate how individuals perceive time in an AV or cost of an AV differently than driving a personal vehicle.

The dataset (of the 2574 unique long-distance trip records) included two unique mode choices: personal vehicle (95.2% of trips) and air travel (4.8% of trips). Such a model allows for the introduction of additional modes (in this case an AV option) and still weights choices appropriately (Horowitz 1993). A variety of interactions between mode characteristics (e.g. cost, travel time, transfers) and trip/traveler characteristics (e.g. purposes, travel party size, household size, income, prior travel) were considered during the estimation process. The mlogit package within R statistical tool was used to estimate the model through maximum likelihood estimation and a stepwise elimination methodology was also applied here. The final model had a log likelihood of -411.71 and a log likelihood ratio test chi-square statistic of 164.71, highlights the model is significantly better than the constant-only specification, at any level of significance

Table 3 details the interactions that are most significant to mode preference. Not surprisingly, the coefficients for cost and travel times are all negative, implying that modes with shorter travel times and lower costs are generally preferred. Interestingly, cost is only a major concern for those households with incomes less than $50,000. The impact of travel times varies by trip purpose, with households being most concerned about travel times when completing a work trip. The utility for a long-distance travel mode decreases as the travel time increases, although individuals' sensitivity to this decreases from travel for work, to vacation/relaxation, and to visiting friends or relatives respectively. Each of these trip purpose factors are relative to travel for personal activities (e.g. recreation) or personal business (e.g. religious). It is important to also recognize that transfers and wait times for the air mode were not significant, perhaps because they are already built into the travel time component.

Table 3: Parameter Estimates for Binary Logistic Regression of Long-Distance Mode Choices

	Coefficient	t-stat
Intercept	-3.6268	-25.41
Cost x …		
…Income Less than $50k	-0.0026	-2.89
Travel Time x …		
…Travel for Visiting Friends or Relatives (VFR)	-0.0022	-4.36
…Travel for Work	-0.0042	-9.87
…Travel for Vacation/Relaxation	-0.0031	-8.42
N_{obs} = 2574, Log likelihood = -411.71, Pseudo R^2 = 0.167		

Individuals' sensitivity to cost and travel time when selecting between modes with the addition of AVs as a new travel mode was also considered. Twenty-four combinations of time and cost were imputed for theoretical AV modes for each trip in the dataset for this comparison. Each case calculated AV characteristics based on known personal vehicle trip characteristics to identify potential ways in which AVs would be introduced into the roadway fleet (i.e. lower costs and less burdensome perceived travel times). For example, one comparison assumed that AVs were 25% more expensive than personal vehicle modes and travelers would perceive their travel time to be just 75% as burdensome as person vehicle travel time using other modes, on a per-hour basis. Overall mode shares were calculated for each assumed relationship and presented in Figure 2. Each line on the graph represents a given AV perceived travel time relative to the time it would take to personally drive to the destination on a scale from 1 (which indicates no difference in time) to 0.5 (which indicates it feels like the AV travel time was half that of driving oneself). These ranges are consistent with Gucwa's (2014) methodological assumptions regarding the relative burden of in-vehicle travel time likely for automated vehicles as compared to manually-driven autos. Each point on the lines represents a given AV cost relative to the cost it would take to personally drive to the destination on a scale from 1 (which indicates no difference in cost) to 2 (which indicates the cost of AV travel is double that of driving oneself).

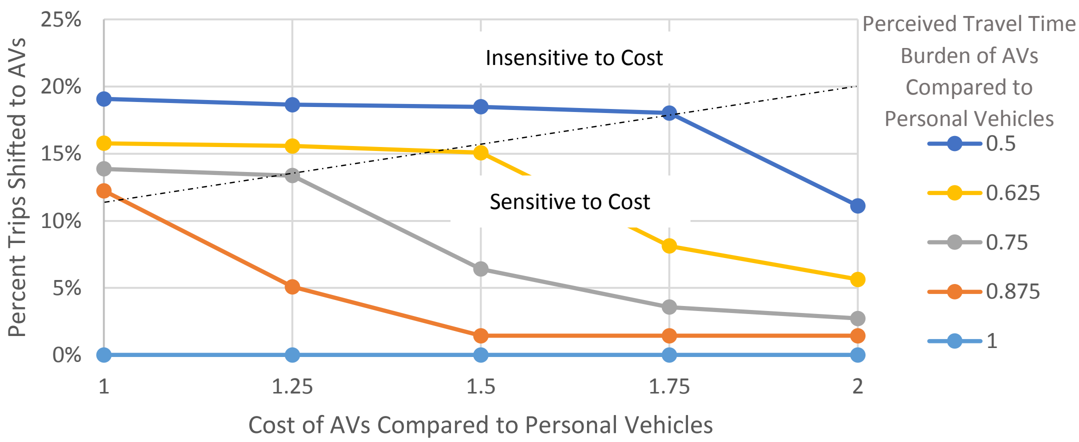


Figure 2:Long-Distance Mode Choice's Sensitivity to Travel Costs and Times

In general, as AVs' costs and perceived travel time burdens increase, relative to personal vehicles, the likelihood of the population embracing automated vehicles decreases. However, travel time and cost together seem to influence the adoption of AVs for long-distance travel. A line is drawn to show that at certain travel time valuations, cost is not a significant factor; the more the perceived benefit on travel time by AV, the less important cost becomes. In fact, if travel time valuations are perceived to be half (0.5) of the time it would take to drive oneself, costs of AVs can be as much as 75% greater than driving oneself before they start to affect preferences for AVs.

Statewide Mode Shift Simulation Experiment

Three cross tabulations and distributions of the state population and long distance trip characteristics were developed to assist in the experiment. First, the probabilities of each long-distance trip of falling into 11 different distance-bands (50-100 miles, 101-200 miles, …, greater than 1000 miles) were calculated using the state travel survey observed sample. A factor analysis of trip distance indicated that these distances were not dependent on any household or trip characteristics and were assumed to be random across trips. Second, a cross tabulation on the four trip purpose (work-related, vacation/relaxation, visiting friends and relatives (VFR), and personal activities) probabilities by household characteristics (household size, number of young/old children, and income above/below $50k) and trip distance was calculated, again with the state travel survey observed sample. In this distribution, if a household with the specific set of characteristics did not exist in the survey, purpose probabilities were assigned based on average values from the trips in that distance band. Third, the NUMA travel cost and time skims were combined with the travel survey to calculate the average cost and time for long distance trips based on distance and purpose.

To begin the experiment, a synthetic population was created across Michigan's 2,307 TAZs, with distributions of household sizes in each TAZ (containing one, two, three, or four + persons) obtained from the Michigan statewide travel survey. Since vehicle and worker information was not present in the regional TAZ dataset, random draws were taken across the sampled households contained in the travel survey, while matching sampling region and household size. This was conducted in order to seed each TAZ-household size pair with given vehicle ownership and characteristics. The trip generation model was then applied to each household in the synthetic population, which resulted in an estimated total of 8.12 million long-distance trips produced, over a 3-month period across all of Michigan.

Data from the American Community Survey (US Census Bureau 2015) regarding family makeup was then used to distribute these 8.12 million trips by various household compositions in order to apply the mode choice model developed earlier. This was conducted by examining distributions of family structure across Michigan, for single-member households, as well as two-parent and single-parent families. Resulting distributions examined trips generated according to accounted for family size (1 – 4+), low or high income (less than or greater than $50,000), presence of children aged birth – 5, and presence of children aged 6 – 17.

Each long-distance trip in the simulation was then randomly assigned one of the 11 trip distance categories based on the distributions identified previously. A monte-carlo simulation was then used to identify each trip's purpose from one of the four main categories based on the prior assigned distance and household characteristics. Finally, households were assigned the average trip cost and travel time for personal vehicle and air travel based on its distance and purpose from the distribution defined in the first step.

At this stage, all 8.12 million long-distance trips had a defined household, distance traveled, purpose, and set of travel costs and times by the two main modes. In order to set a baseline, the logistic mode choice model was applied to each household trip to determine the most likely mode each would choose. The results from this model, separated by distance band, can be seen in the "current mode choices" component of Figure 4. Personal vehicles are the dominant mode for trips less than 200 miles from the home, air travel become competitive with personal vehicles for travel between 201 and 500 miles from home, and air travel tends to be the preferred mode for trips 500 miles or more away from home.

The experiment assumed conservative characteristics for automated vehicles being introduced: the cost to take an automated vehicle on any of the 8.12 million trips would be double the cost of taking a personal vehicle and the perceived travel time of using an automated vehicle would only be three-quarters of the perceived travel time when taking a personal vehicle.

These values were simulated for all the trips and applied into the logistic mode choice model to determine how mode choices would shift. The results on mode choices can be seen in the "Introduction of AVs to Mode Choices" component of Figure 3. Across the different distance bands, automated vehicles became a preferred option for many trips. Especially noteworthy is the relationship that AVs have with personal vehicles, almost matching those mode choices evenly. Air travel maintains its relationship relative to personal vehicles but also sees many travelers switch to AVs. Rail and buses were not included in the simulation because 1) many of the origin-destination pairs did not support these modes and, as a result, no trip characteristic data was available and 2) very few observed trip records included these modes. Additionally, while theoretical high speed rail could be included in the experiment, it was decided to focus on AVs.

Table 4 emphasizes how travelers shifted from each mode to automated vehicles across different trip distance bands. For travel under 500 miles, automated vehicles tend to draw from personal vehicles and airlines equally (although the shortest distances less than 200 miles see the strongest draw up to 36.7% for AVs from personal vehicles). Travel beyond 500 miles away from the home has a consistent 20% draw from personal vehicles, but this shift drops off for air travel dramatically, getting down to about 10%. Clearly, airlines are still the preferred mode for the longest travel distances. A similar table that considered shifts by trip purpose was also considered, but the results showed that shifts to AVs were relatively consistent across all trip purposes.

Table 4: Changes in Trip Volume by Different Modes after the Introduction of AVs

	Change in Trip Volume by…	
Distance of LD Trip	Personal Vehicle	Airline
50 to 100 miles	-36.7%	-34.9%
101 to 200 miles	-34.4%	-33.4%
201 to 300 miles	-30.7%	-30.2%
301 to 400 miles	-28.0%	-26.5%
401 to 500 miles	-26.2%	-25.1%
501 to 600 miles	-21.9%	-18.5%
601 to 700 miles	-21.7%	-16.2%
701 to 800 miles	-24.2%	-19.9%
801 to 900 miles	-24.1%	-11.4%
901 to 1000 miles	-20.2%	-9.3%
1000 miles or more	-22.9%	-10.4%

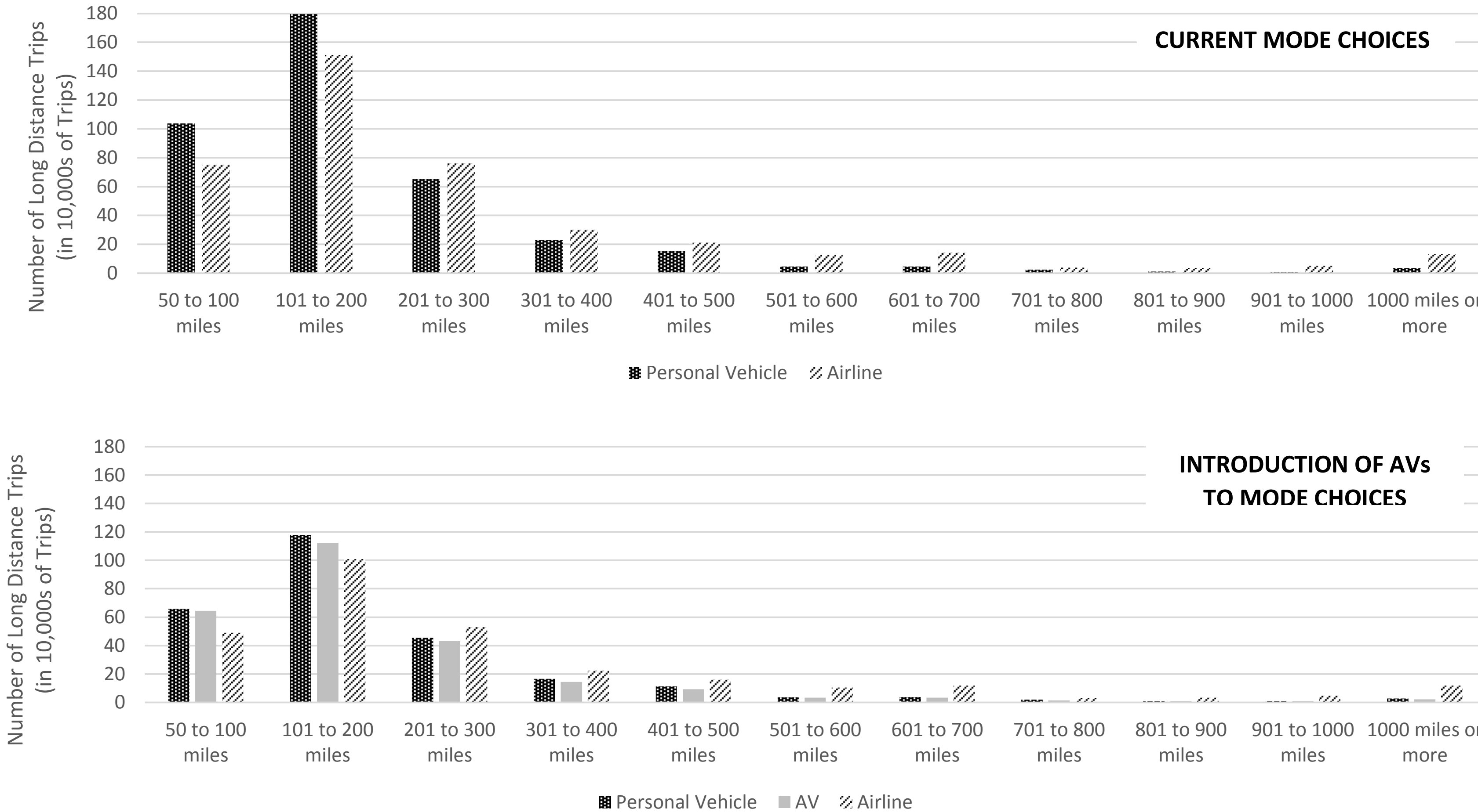


Figure 3: Simulated Michigan LD Trip Mode Choices Before/After Automated Vehicles are Introduced

While the results shown in Figure 4 and Table 4 illuminate a dramatic potential for mode shift towards AVs as they become a reality, it is important to acknowledge the limitations of this experiment. In reality, air travel is virtually non-existent for journeys under 100 miles and uncommon for trips under 200 miles. The simulations shown here did not account for travel to and from airports but not the wait time through security of the transfer time if an air trip had multiple legs With just seven airports in Michigan that serve more than 50,000 annual enplanements, and a land area of over 56,000 square miles, little if any time could be saved by air travel for most shorter trips, with the result being higher costs and possibly higher travel times as too. Future work could address this issue through the development of a destination choice model, which could be used to account for airport locations in relation to traveler origin and destinations, and therefore more accurately estimate air travel times. Additionally, this work did not account for changes in trip-making rates or changes in trip distance distributions (e.g., Gucwa 2014, MacKenzie 2014) and it is likely that travelers would take more frequent and longer trips as well due to the introduction of AVs. Future work could explore these aspects of AVs' impact on long-distance travel as well.

Conclusions

In recent years vehicle automation technology has experienced rapid gains, and partially- or fully-automated vehicle sales to the public appear imminent. One area of impact where little research has been conducted to date is on the potential impacts of vehicle automation on long-distance personal travel, which represents one of the largest areas of travel growth in the United States. Long-distance travel decisions, including the number of annual trips, timing of trips, destinations, durations, and travel parties are significantly more influenced by costs and travel time than daily travel, due to the increased time and cost investments inherent to this travel. As such, automated vehicles (AVs), which offer alternative travel time valuations and travel costs, have the potential to dramatically change how travelers pursue long-distance tours.

This paper analyzes the impact of introducing automated vehicles on long-distance travel mode choices through analyzing travel surveys and developing a statewide simulation experiment of long-distance travel. This research investigation explores the 2009 Michigan Long-Distance Travel Survey and estimates a long-distance trip generation model as well as a modal-agnostic long-distance mode choice model. Both models emphasize the complexity of long-distance travel decisions related to travel times and costs. For example, larger household sizes, workers and income lead to more long-distance trips, but also affect the mode choices for these trips. Trip purpose and income dominate the mode choice decision-making process.

These models were applied in a statewide simulation experiment in which AVs are introduced as a new mode with lower perceived travel time cost valuations, though at higher travel costs, to account for the price of automation technology. This experiment highlights the potential shift in in mode choices (to now include AVs) across different trip distances and purposes. Specifically, for travel under 500 miles, automated vehicles tend to draw from personal vehicles and airlines equally (although the shortest distances less than 200 miles see the strongest draw up to 36.7% for AVs from personal vehicles). Travel beyond 500 miles away from the home has a consistent 20% draw from personal vehicles, but this shift drops off for air travel dramatically. Airlines are still the preferred mode for the longest travel distances. Additionally, as AVs' costs increases and the perceived travel time benefits relative to conventional personal vehicles decreases, the likelihood of the population embracing automated vehicles decreases. However, at certain travel time valuations, cost is not a significant factor; the more the perceived benefit on travel time by AV, the less important cost becomes.

There are many opportunities to further determine how AVs (and other emerging modes such as high speed rail) will affect long-distance travel. This experiment incorporates perceived changes in travel times and cost within AV trip characteristics but assumes that individuals weight cost and travel times similarly regardless of mode. One alternative that removes this assumption would be to develop a stated mode preference survey that included AVs. Such a survey might consider an individual's recent long distance trip and ask if they would consider taking an AV, with a series of options that vary the costs and potential accommodations within the AV. For example, the ability to do work at a desk or interact with family around a table within an AV would be useful to quantify in terms of mode choices. The level of automation would also be a useful characteristic to examine. A multinomial logit regression could then be estimated to include AV-specific coefficients as data would be available for this mode.

While this work provides a preliminary investigation into AVs' potential impacts of on long-distance travel, they may inevitably change long-distance travel behavior and operations in other ways. For example, since AVs may allow travel time to be used more productively, travelers riding in them may strongly desire smoother rides with less sudden acceleration and deceleration. LeVine et al. (2015) examine these implications of the tradeoffs between rates of acceleration and deceleration and traveler comfort, as well as the resulting impacts on traffic operations. While this would have little impact on the intercity portion of a journey, it could create meaningful impacts when departing from the traveler's origin city and arriving at their destination.

Additionally, fully-automated vehicles could give rise to new frameworks such as the Shared Autonomous Vehicle (SAV), or on-demand driverless shuttle or taxi. These services could dramatically reduce costs associated with the first- and last-mile portions of an airport trip, whether replacing fares from human-driven taxis (Fagnant and Kockelman 2014, 2015a, 2015b), or airport parking costs. Moreover, SAVs could help improve travel local travel options at the destination city and lower costs for air travelers, many of whom may previously have relied on taxis or car rentals.

One final consideration is the possibility of AVs extending the hours that people are willing to travel. AVs may allow passengers to sleep en-route to their destination, which perhaps could be facilitated by a purpose-built driverless sleeper car. This framework in particular could be well suited towards enhancing AVs' attractiveness for long-distance travel.

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