ANTICIPATING CURRENT & COMING TECHNOLOGIES THAT IMPACT U.S. TRAVEL CHOICES

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ABSTRACT

A wide range of transportation technologies are on the horizon. Understanding the preferences for these technologies is important to ensure an efficient and equitable future transportation system. A survey was conducted in April 2021 of 998 Americans to examine preferences for a wide range of emerging and future transportation technologies. Americans are concerned about vehicle range and charging station availability for electric vehicles (EVs) and hesitant about autonomous vehicle (AV) safety. Opinions about many transportation technologies, such as vertical takeoff and landing (i.e., air taxis), shared parking, and air-drone delivery are mixed. These technologies are less familiar to the general population than EVs and AVs and continued tracking of preferences and research is necessary to inform policy analysis and forecasted demand. A 55% increase is estimated in the probability of an individual choosing a battery-electric vehicle (BEV) truck if its fuel economy increases by about 9%. This result supports a market for BEV trucks, such as those currently under development by many automakers.

The preference for vehicle autonomation appears to depend on the use case. Driving task automation tends to be preferred by residents of low-density, car-dependent areas where long commutes are common. In contrast, automated parking technologies tend to be favored by those living in denser communities. Intermittent bus lanes are strongly favored by those living in high population density areas, but not among those in areas with high shares of zero-vehicle households. These results provide indications of where to direct future research in the field.

Keywords: Transportation attitudes; transportation technology; autonomous vehicles; willingness-to-pay

INTRODUCTION

Numerous innovations are occurring in the transportation sector, with automation, electrification, and ride-hailing being among the most widely discussed technologies. Electrification is introducing new players in the original equipment manufacturer (OEM) market and forcing incumbents towards innovation. The development of mobile application-based transportation service providers (e.g., Uber, Lyft, and DiDi) provide a glimpse into a future city where households purchase transportation as a packaged service rather than to own and maintain their own vehicles. Automation of the driving task is now a question of when rather than if, providing a means of significantly reducing the cost of providing transportation services. There is also the possibility of urban air mobility (via vertical take-off and lift, for passengers and goods), alongside more mundane innovations (like dynamic bus priority lanes and (de)congestion pricing). Much uncertainty exists as to how these emerging and future technologies will affect travel. Impacts depend on rates of technology development, individual preferences and adoption rates, and policy directions taken by government actors. A multi-faceted research approach is required to capture the breadth of potential impacts from these technologies.

This paper summarizes the findings of one component of this research agenda - with a focus on the preferences of individuals. A survey was developed to collect a wide range of travel preferences from a representative sample of Americans. The survey contained a mix of attitudinal, willingness-to-pay, and situational questions related to a variety of transportation technologies.

Previous surveys have targeted specific technologies. A common focus in the transportation literature is the willingness to pay (WTP) for vehicle automation. These studies generally use survey results to forecast market penetration of autonomous vehicles (AVs) (Bansal et al., 2017; Harb et al., 2018; Wang et al., 2021) or mode choice with the introduction of AVs as a modal alternative (Gurumurthy & Kockelman, 2020). Similar research streams exist for electric vehicles (EVs) (Quarles & Kockelman, 2017) and ride-hailing adoption and mode choice (Alemi et al., 2018; Loa & Habib, 2021). Vertical takeoff and landing (VTOL) urban air mobility is also an emerging topic of interest in travel behavior research (Garrow et al., 2020; Wu & Zhang, 2021). There are advantages to such targeted treatments of future transportation technologies. It allows for a deep investigation of preferences and a wide range of questions to be included in the survey about the technology. Given the potential of mobility as a service (MaaS) and the large number of technologies on the horizon, it is equally important to obtain cross-cutting results for a single sample of individuals. In this way, the preferences for a given individual can be compared for multiple technologies rather than relying on comparisons across sociodemographic groups among multiple surveys. The survey described in this paper included questions about the above technologies (AVs both private and shared, EVs, ride-hailing, and VTOL), since they are likely to be important technologies in the coming decades. However, it included a wider range of technologies: bike-sharing, microtransit, personal rapid transit, vehicle-to-person communication systems, remote vehicle control equipment, automated parking, vehicle platooning technology, shared parking, air-based drone delivery, and congestion pricing. Questions also address home location and remote work, in light of the recent COVID-19 pandemic.

Given the scope of the survey, only a subset of the results is presented in this paper. The survey instrument is first described, along with question classifications, and sampling frame. A weighting strategy corrects for sample vs population differences in demographics, and population-corrected summary statistics are compared to related results from a 2017 survey (Quarles et al., 2017). Attitudinal results are then discussed. The paper includes the results from several models, with detailed discussion provided for two predictive models, for next-vehicle choice behavior and willingness to pay for AV technologies, before concluding.

SURVEY DESIGN AND DATA PROCESSING

This section outlines the design and processing of the survey instrument. It defines the quota variables used to ensure the sample matched the population and the post-stratification process to adjust the sample distribution across a wider range of control dimensions.

Questionnaire Design and Data Acquisition

The survey was administered to a sample of 998 respondents (after filtering for incomplete responses) representing a cross-section of Americans. Quotas were set during survey collection to maintain consistency with key demographic variables: gender, age (6 categories), educational attainment (4 categories), and geographic region (4 categories). These quotas were used as tracking guidelines rather than hard limits to avoid overfitting and under-sampling of other key variables. The survey was designed in Qualtrics and the survey panel was obtained from a professional survey vender (Dynata). The survey includes 81 questions (with some questions not being presented to respondents based on survey logic) and has the following structure:

- **Screening**: Respondents were first screened to ensure they were 18 years of age or older. Additionally, persons over the age of 74 were not included in the survey frame given the long-time horizon of some survey questions. It was assumed that the preferences of persons aged 65 to 74 are representative of those who will be 75 years of age or older when many of these technologies enter the market (perhaps 10-30 years from today).
- **"Brain check"**: A set of definitions of internal combustion engine (ICE), hybrid electric (HEV), and plug-in hybrid electric (PHEV) vehicles was provided, along with a corresponding set of figures, and respondents were asked to match the definitions with the figures (see Figure 1). This question checks for respondent attention and ensures a reasonable baseline level of knowledge about currently available transportation powertrains to accurately complete the survey.

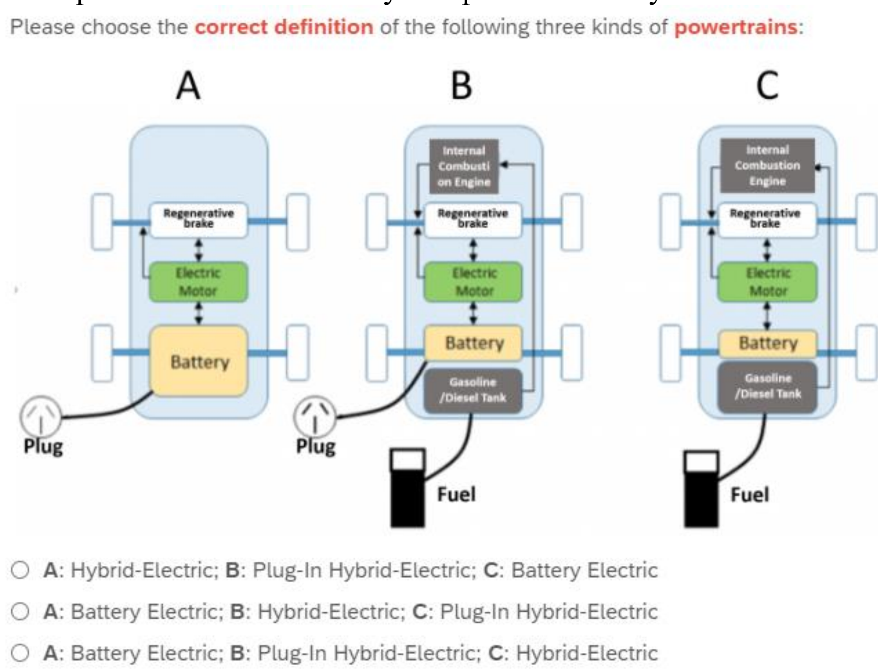

Figure 1. "Brain Check" Question to Check for Respondent Attention and Knowledge

- **Attitudes to new travel technologies:** Current and future vehicle ownership, EVs, AVs, bike-sharing, microtransit, ride-sharing, shared autonomous vehicles (SAVs), vehicle-to-person (V2P) communication systems, remote control driving, automated guided vehicle (AGV) parking, vehicle platooning, vertical take-off and landing (VTOL) aircraft, peer-to-peer (P2P) parking, bus lane with priority, drone delivery, personal rapid transit, congestion pricing, and remote work.

- **Willingness to pay (WTP):** for shared mobility and self-driving vehicles.
- **Location change:** timing and influence of transportation technologies on the decision.
- **Demographics:** personal and household demographics of respondents.

Data Cleaning and Sample Weighting

Additional post-stratification weighting was applied to the collected sample to match a larger set of demographic and other variables. 2015-2019 American Community Survey (ACS) public-use microsample (PUMS) data were used to construct combinations of marginal and partial joint distributions. An iterative proportion fitting (IPF) approach was used to match survey responses to control totals from the ACS. The choice of weighting variable was based on a combination of literature sources (Malatest & DMG, 2018; Mohadjer et al., 2001; Roth et al., 2017), previous work by the research team (Bansal et al., 2017; Gurumurthy & Kockelman, 2020; Quarles & Kockelman, 2017; Zhou & Kockelman, 2011), and the variables in the survey for which the team could obtain reliable control totals from external surveys. The following set of weights was used in the IPF procedure:

Weight 1

- Geographic division: New England; Middle Atlantic; East North Central; West North Central; South Atlantic; East South Central; West South Central; Mountain; and Pacific.

Weight 2

- Household size: 1; 2; 3; 4; and 5+
- Employment status: employed, working 40 or more hours per week (including self-employed); employed, working 1-39 hours per week; student, working part-time; student, not working; not employed, looking for work; not employed, not looking for work; and retired.
- Household vehicles: 0; 1; 2; 3; and 4+

Weight 3

- Educational attainment: less than high school; high school; some college; associate or technical degree; bachelor's degree; master's degree or higher.
- Household (pre-tax) income: Less than \$10,000; \$10,000 to \$19,999; \$20,000 to \$29,999; \$30,000 to \$39,999; \$40,000 to \$49,999; \$50,000 to \$59,999; \$60,000 to \$74,999; \$75,000 to \$99,999; \$100,000 to \$124,999; \$125,000 to \$149,999; \$150,000 to \$199,999; \$200,000 or more.

Weight 4

- Age and gender: 18 to 24; 25 to 34; 35 to 44; 45 to 54; 55 to 64; and 65 to 74 (in combination with male or female).
- Marital status: single; married; divorced or separated; and widowed.

The levels for many of these dimensions are more disaggregate than in previous work because they are constructed from the control totals from the PUMS sample rather than existing variable distribution tables. Overall, the initial distributions were close to the final distributions, suggesting that minimal weighting was required to match the population. The survey oversampled male respondents and respondents aged 65 to 74 but under-sampled respondents aged 55 to 64 and those with a high school degree or equivalent.

Geocoding and Referencing Survey to External Datasets

Model estimation requires additional data on the demographic of sub-regions of the United States, land use and built environment characteristics, and other relevant explanatory variables. The EPA Smart Location database provides a wide range of these variables for block groups (Ramsey and Bell, 2014). A zipcode question was included in the survey that asked for the full zipcode+4 of respondents' home locations. The online geocodio tool was used to obtain longitude and latitude coordinates for these zip+4 data (Dotsquare LLC, 2021). There is no single point for zip+4 codes, so geocodio randomly assigns among the list of buildings in a given zip+4 code. Despite the inclusion in the survey of a link to lookup zip+4 codes, many respondents provided only their 5-digit zipcode. However, the survey metadata included an IP address longitude and latitude. These coordinates will be more detailed than a 5-digit zipcode; however, some respondents may complete the survey at a different location than their home. In the case that a respondent did not provide their zip+4 code, the IP address was used only if its coordinates lay within the stated 5-digit home zipcode. Otherwise, the centroid coordinates for the 5-digit zip code were used to associate the survey record with EPA smart location data.

One of the decisions that is of interest from the survey results is the next vehicle preference. Based on the survey data, the following 16 vehicle types were defined as the full factorial combination of four vehicle classes (coupe, sedan ICE, SUV/minivan, & pickup truck) and four powertrain classes (ICE, BEV, HEV, & PHEV). As a backend database to its fuel economy website, the EPA provides a rich dataset of vehicle attributes including fuel economy, charging time for plugin electric vehicles (PEVs), tailpipe emissions, fuel costs, luggage volume, and savings/expenditures over five years relative to an average car. The survey data include whether the next vehicle purchase will be a new or used vehicle. As such, vehicle data from the EPA database was aggregated into "new" (assumed as vehicle model years 2020, 2021, and 2022) and "used" (assumed as vehicle model years between 2009 to 2019, inclusive). Edmonds statistics suggest an average used vehicle age of 3.5-4.4 years, so averaging over a 10-year range seems reasonable (Edmunds, 2019).

In addition to vehicle characteristics, price is an important variable to include in the model. A web scraping of all Kelley Blue Book listings was tested as of May 2021; but it proved too difficult, given the setup of their vehicle listings. Instead, January 2021 Kelley Blue Book statistics for sales price by vehicle class and total sales were used to obtain weighted average prices for each of the 16 vehicle types. In some cases (HEV, PHEV, and BEV SUV/minivan and pickup trucks), prices were not reported for the vehicle category, or it does not exist yet. In these cases, prices for several models or the expected price were taken as representative of the market (Car & Driver, 2020; Car Cody, 2021; Ford Motor Company, 2021a; Phil Long Ford of Chapel Hills, 2021).

Figure 2 shows the distribution of responses across the United States. The survey provides a good spatial distribution of responses. While there are no responses geocoded to either Alaska or Maine, there is one respondent in each case who reports it as their home state. For both respondents, their reported zip code and the IP address coordinates in the survey metadata place them in a different state than that indicated in the home state question. Given that the survey was conducted in April and the fact that both are northern states, it is likely the case that these respondents completed the survey at a winter residence.

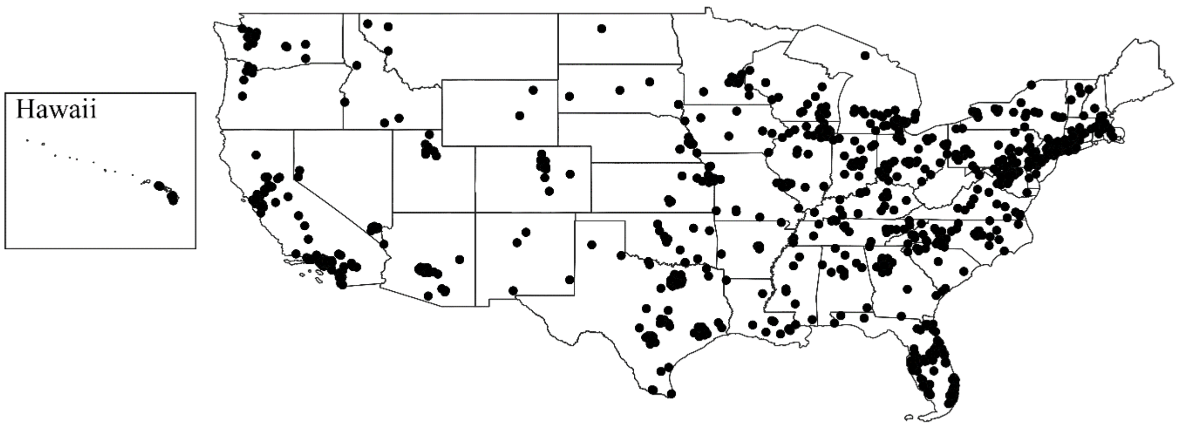

Figure 2. Distribution of Survey Responses

SUMMARY STATISTICS

This section provides general statistics derived from the survey results. In many cases, comparison is made with a previous survey conducted by the research team in 2017 (Quarles & Kockelman, 2017). Vehicle ownership and purchase statistics are presented first. Attitudinal results are then given based on a large set of questions about future transportation technologies.

Vehicle Ownership and Purchase

Most respondents own gasoline-powered sedans, minivans, SUVs, or CUVs. However, the distribution is quite different for their anticipated next vehicle (see Table 1). A higher share of respondents expects their next vehicle to be a pickup truck or coupe - a shift towards the higher and lower ends of the vehicle class distribution. Most respondents intend to purchase a gasoline- or diesel-powered vehicle but a significant portion of respondents intend to switch to battery or plug-in electric vehicles (an increase of ~18 percentage points over 2017 results). There is a marked decline in the percent of respondents who intend to purchase gasoline- or diesel-powered vehicles. The largest increase is for BEVs (12.7 percentage points), which is a promising trend for the adoption of lower emissions vehicles.

Table 1. Type of Vehicle for Next Acquisition Among Those Intending to Purchase a Vehicle in the Future (Population Weighted)

	2017	2021	Change (2021-2017)

Gasoline or Diesel-powered Sedan	35.9%	13.2%	-22.7%
Gasoline or Diesel-powered Coupe, or Compact Car	9.9%	9.1%	-0.8%
Gasoline or Diesel-powered Minivan, SUV, or CUV	28.3%	25.0%	-3.3%
Gasoline or Diesel-powered Pickup Truck	8.4%	10.3%	1.9%
Hybrid Electric Vehicle (HEV)	13.0%	15.2%	2.2%
Battery Electric Vehicle (BEV)	2.5%	15.2%	12.7%
Plug-in Hybrid-Electric Vehicle (PHEV)	2.1%	7.4%	5.3%

Note: Vehicle class was not asked in the 2017 survey for HEV, PHEV, & BEV

Attitudinal Analysis

The following section is divided into four subsections covering attitudes regarding new travel modes, attitudes regarding new travel technologies, willingness to pay for new travel modes and technologies, and changes in home location preferences. In some cases, additional concerns were imputed from the "other" option based on text responses. However, it should be noted that the totals for these responses are likely low and may have been selected by other respondents if presented in the survey. Descriptive results are presented through a combination of tables and figures, with quantitative modeling being reserved for the next section. Note: results for attitudinal analysis do not necessarily sum to 100% since respondents were allowed to select multiple options.

Attitudes regarding New Travel Modes

Charging concerns are a dominant force in hesitancy about EV adoption (see Table 3). Most respondents worry that EVs will have insufficient battery capacity for their daily travel and there are not enough charging stations. These are not new concerns, and the solution is likely as much informational as technological (Plug'N Drive, 2017). A 2016 study found that 87% of daily travel could be accomplished by EV (Needell et al., 2016), with vehicle range only increasing since then. Among the motivations for EV adoption are environmental concerns (air pollution and fossil fuel consumption) and lower fuel costs. However, a non-negligible segment of respondents (26%) stated they are not interested in purchasing an EV.

Table 2. Concerns and Motivations for EV Choice

Concerns	Percentage
Limited battery capacity	65.0%
Only a few charging stations	52.6%
Long charging times	36.8%
Smaller horsepower	22.5%
Lower price-performance ratio	26.8%
Environmental damage[*]	0.5%
Battery safety[*]	0.06%
Increased electricity demand[*]	0.06%

No concerns	11.9%
Motivations	
Reduce air pollution	38.9%
Electricity costs a lot less than gasoline	36.9%
Higher levels of comfort	28.8%
Reduce fossil fuel consumption	28.1%
Like emerging technology	15.2%
Other	1.2%
Would not consider it	26.0%

* Ascertained from notes relayed in “other” option.

In the case of AVs, there is a bifurcation in the perception of safety among respondents (see Table 3). Roughly 61% of respondents expressed concern about AVs causing traffic crashes, while 25% of respondents indicate increases safety as a motivation to use AVs. The ability of AVs to handle unusual situations (e.g., construction and snow cover) is also a major concern among respondents. A high percent (41.1%) of respondents were unwilling to consider travel by AV.

Table 3. Concerns and Motivations for AV Choice

Concerns	**Percentage**
Cause traffic crashes	61.4%
Cannot navigate under construction or covered by snow/ice	49.3%
Higher purchase cost	48.5%
Unclear responsibility between the vehicle and in-vehicle passengers when involved in a crash	44.3%
Technology dependence or fear of hacking*	0.4%
I like driving*	0.01%
No concerns	7.9%
Motivations	
Safety	25.4%
Allow younger teens, disabled, and elderly persons to travel by themselves	24.2%
Be able to work or sleep	22.8%
Do not have a driver's license	9.8%
Other	1.8%
Would not consider it	41.1%

* Ascertained from notes relayed in “other” option.

Attitudes Regarding New Technologies

Respondents were asked a series of situational questions to assess their willingness to use various transportation technologies. All figures are based on population-weighted survey data. In the case of VTOL, about 36% of respondents expressed interest in using the service if it was twice the price of a taxi but halved the travel time (see Figure 3). This result indicates that such a service would be feasible, but it would likely serve a higher income niche market.

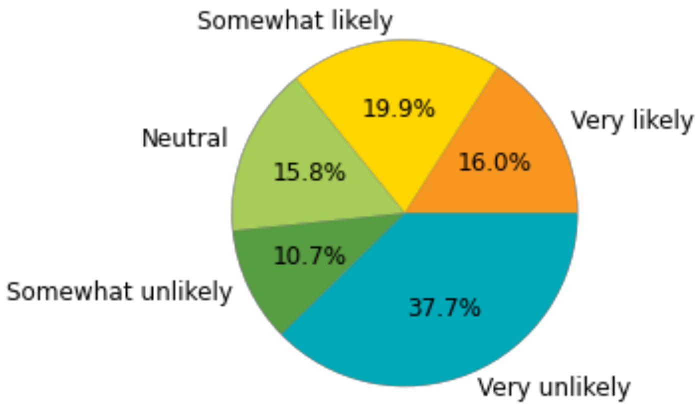

Figure 3. Willingness-To-Pay for EVTOL

Respondents were asked about both their WTP to share parking at their home (as a supplier - see Figure 4) and their travel destination (as a consumer - see Figure 5). In both cases, shared parking was assumed to offer a monetary benefit to the respondent. For shared parking at the destination, respondents were asked to assume they had a 50% chance of finding a shared space at $2/hour vs. a dedicated space at $4/hour. As with VTOL, responses were mixed to these questions, likely because the technologies are unfamiliar. If respondents had a wider exposure to shared parking systems, the distribution of responses would likely be more polarized (whether positive or negative).

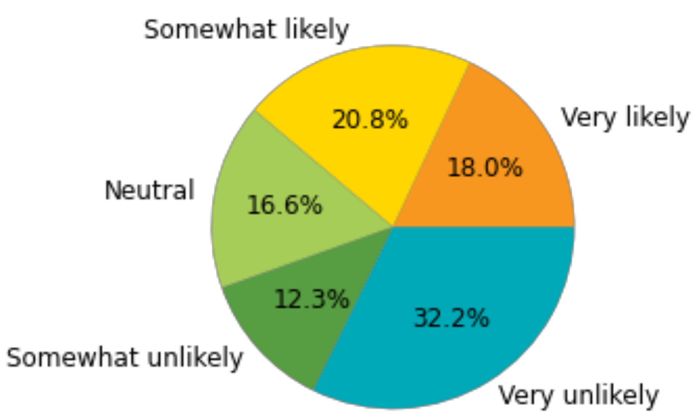

Figure 4. Willingness-To-Share Parking Space at Home

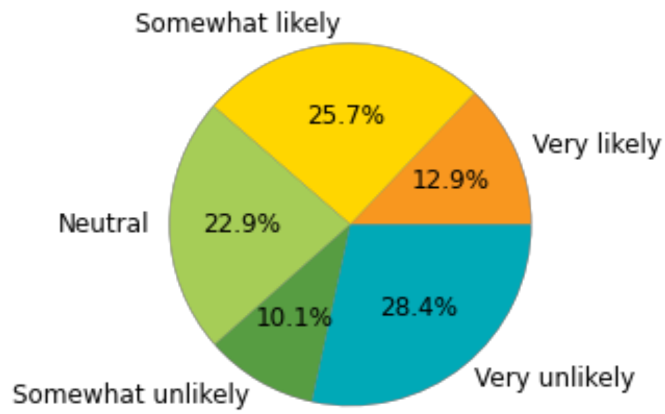

Figure 5. Willingness-To-Pay for Shared Parking at Destination

Another air-based technology on the horizon is drone delivery. Respondents were asked about both their willingness to use such a service (Figure 6) and their willingness to accept their neighbor's use of it (Figure 7). The delivery service would cost twice as much as traditional delivery but reduce the delivery time by half. Again, respondents expressed a mix of responses. There appears to be a higher willingness to accept the use of drones by neighbors relative to personal use. The difference in responses could be attributed to a common concern about privacy but a lack of cost in the second instance.

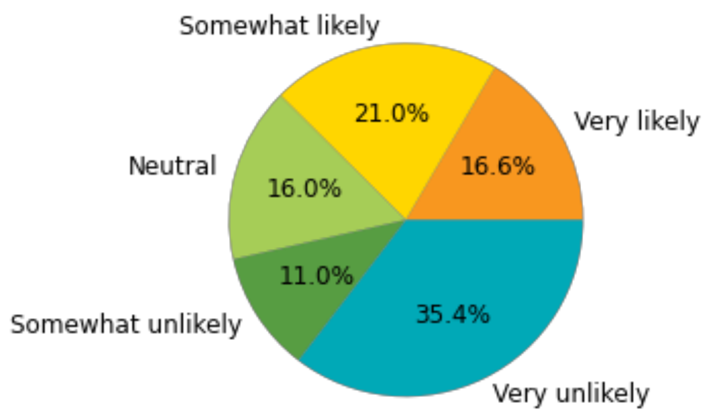

Figure 6. Willingness-To-Pay for Air-Based Drone Delivery of Goods

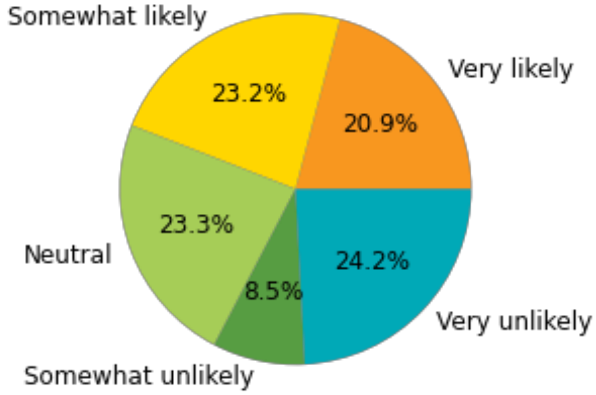

Figure 7. Willingness-To-Accept Neighbor's Use of Air-Based Drone Delivery

Finally, among the attitudinal questions, the ongoing COVID-19 pandemic has significantly increased the prevalence of remote work and led to questions about its continuation in the coming years (Holgersen et al., 2020; Mehdi & Morissette, 2021). While not a central focus of the research, a question about remote work preference was included in the survey. The majority of respondents express an interest in continuing to work remotely. Similar patterns are found for both employees and employers (see Figure 8).

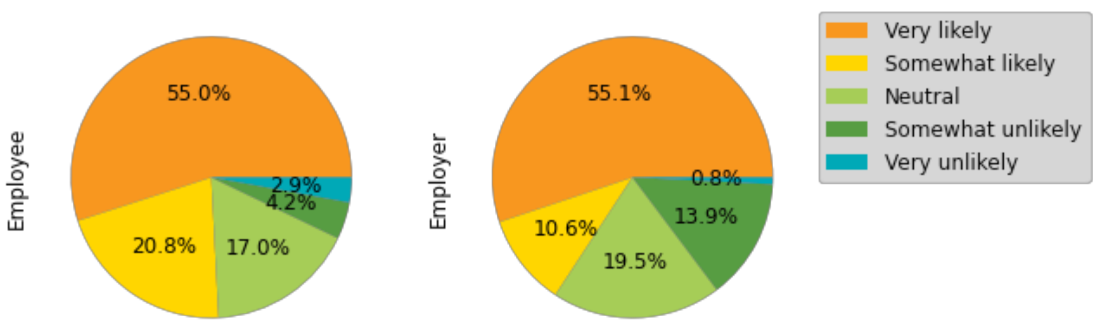

Figure 8. Interested in Working Remotely After the COVID-19 Pandemic

Comparison with Results from 2017

Several questions were included in the survey that parallel questions asked in the 2017 survey, allowing for analysis of how preferences have changed over the intervening five-year period. Table 4 suggests that Americans are becoming more confident about their preferences for AVs as the technology becomes more widely known. In 2017, only 12.4% of respondents expressed a strong WTP five dollars to have their vehicle drive them home for a 30-minute trip, whereas in 2021 this share had more than doubled. At the opposite end of the scale, those “definitely not willing to pay” increased by about ten percentage points. For a longer trip of 60-minutes, fewer respondents are willing to pay twice the price (i.e., the same price per minute of trip time), suggesting a diminishing marginal WTP for travel automation.

Table 4. Willingness-To-Pay for a Self-Driving Trip a) 30-minute urban or suburban trip b) 1-hour urban or suburban trip

a) 30-minute trip			
2017	**$5**	**$7.5**	**$10**
Willing to pay	12.4%	11.3%	5.7%
Probably willing to pay	25.9%	16.4%	9.9%
Not sure	17.9%	20.7%	24.0%
Probably not willing to pay	16.6%	19.8%	27.5%
Not willing to pay	27.3%	31.9%	32.9%
2021	**$5**	**$7.5**	**$10**
Willing to pay	23.9%	18.9%	14.3%
Probably willing to pay	11.2%	20.3%	19.5%
Not sure	10.3%	13.9%	19.1%
Probably not willing to pay	8.3%	10.7%	14.3%
Not willing to pay	34.6%	38.3%	42.2%
b) 60-minute trip			
2017	**$10**	**$15**	**$20**
Definitely willing to pay	7.3%	6.8%	4.2%
Probably willing to pay	26.4%	15.9%	10.2%
Not sure	15.9%	22.6%	27.6%
Probably not willing to pay	16.3%	18.9%	22.0%
Not willing to pay	33.9%	35.8%	36.0%
2021	**$10**	**$15**	**$20**
Willing to pay	17.7%	12.6%	10.1%
Probably willing to pay	19.0%	14.7%	10.0%
Not sure	15.9%	19.4%	17.1%
Probably not willing to pay	8.4%	11.9%	15.1%
Not willing to pay	39.1%	41.3%	47.7%

In addition to trip-level questions, a purchase decision was asked to assess the WTP for the inclusion of automation technology in the next vehicle purchase (see Table 5). It is interesting to note that the changes, in this case, are reversed from those in the case of trips: respondents are now less willing to pay for automation. One of the drivers of this change appears to be a lower vehicle purchase expectation among respondents. When asked at an earlier point in the survey about the timing of their next vehicle purchase, 27.3% of 2021 respondents (with weighting) indicated they do not plan to purchase another vehicle whereas only 8.4% of respondents indicated such a preference in 2017. The reason for this change is unclear. It may be partially attributed to younger generations not planning to purchase vehicles. Another potential reason may be a response to the inclusion of ride-sharing services in the survey prompting respondents to consider shared mobility alternatives.

Table 5. Willingness-To-Pay/Lease A Premium for Self-Driving Technology

2017	**\$2,000/\$60 (Purchase/ Annual Lease)**	**\$5,000/\$140 (Purchase/ Annual Lease)**	**\$7,000/\$200 (Purchase/ Annual Lease)**
Willing to pay	49.5%	31.0%	23.2%
Not willing to pay	44.0%	62.7%	70.7%
No future purchase	6.5%	6.4%	6.1%
2021	**\$2,000/\$60**	**\$5,000/\$140**	**\$7,000/\$200**
Willing to pay	29.1%	16.7%	15.6%
Not willing to pay	40.1%	52.9%	52.6%
No future purchase	29.3%	30.4%	31.8%

Residential location choice has a strong connection with travel patterns (Ewing and Cervero, 2010). As such, residence preferences are important considerations for forecasting the future of transportation. Related is the expectation that AVs may encourage low-density development and single-family detached homes as lower values of travel time disincentivize density (Nodjomian & Kockelman, 2019; Wellik & Kockelman, 2020). Comparison is again made to 2017 results, with similar patterns summarized in Table 6. In both surveys, respondents were prompted to consider whether they would reconsider their choice in the presence of shared AVs. The 2021 respondents showed a much stronger shift towards single-family detached homes specifically, and away from their previous choice in general. This change suggests that residence choice is an area requiring careful attention as new transportation technologies are introduced to the market. Simulation studies find that shared AVs, without dynamic trip matching, will increase VMT in the absence of mitigating policy (e.g., road pricing) (Yan et al., 2020).

Table 6. Next Residence Type and Effect of Access to a Shared Autonomous Vehicle on Choice

Reference	**2017**	**2021**
Single-family detached	60.6%	60.5%
Duplex	1.9%	8.7%
Townhome	8.8%	11.1%
Multi-family ≤6 floors	17.3%	10.2%
Mixed use ≤6 floors	0.7%	6.0%
Multi-family ≥7 floors	5.2%	1.6%
Other	5.4%	1.9%
With SAVs	**2017**	**2021**
Single-family detached	15.5%	28.0%
Duplex	1.0%	8.3%
Townhome	3.2%	7.9%
Multi-family ≤6 floors	2.2%	8.2%
Mixed-use ≤6 floors	1.8%	4.5%
Multi-family ≥7 floors	0.2%	3.5%
Will change but not sure which type	4.7%	5.9%
Will not change	70.7%	33.2%
Other	0.6%	0.4%

MODEL ANALYSIS

The final component of the analysis is a series of econometric models, which help to draw out demographic attributes contributing to preferences. Results are first presented from a series of ordered probit models for WTP for various technologies. Then, detailed results are presented from two models. The first detailed analysis examines the vehicle purchase decision using a simple multinomial logit choice model. The WTP for vehicle automation is then examined using a hurdle regression model. All models incorporate population weights in the estimation.

WTP for Transportation Technologies

Many models were estimated for WTP. In the interest of brevity, only the highlights are provided here. For many technologies, single individuals are likely to be early adopters: personal rapid transit (PRT), drone delivery, and vehicle-to-pedestrian alert systems. Women show a higher WTP than men for shared parking, automated parking in parkades, remote vehicle control, and VTOL. Those with children are less willing to pay for remote vehicle control, perhaps because they have concerns about its safety for their children.

Interestingly, those with children are not willing to pay for vehicle-to-pedestrian alert systems. There may be concerns about children becoming less cautious in the presence of such systems, but it is difficult to draw a definitive conclusion without further questioning of respondents. Intermittent bus lanes, which dynamically allow personal vehicles to use the lane, are favored among those closer to CBDs but also among those further from public transit and with more household vehicles. Such households likely perceive a benefit as they are drivers, lack good access to public transit from their home, but likely interact with transit vehicles due to their proximity to the CBD. Finally, model results indicate that those with multiple vehicles and children are more willing to pay for vehicle platooning. These households may see a benefit from using the technology when traveling as a family in multiple vehicles.

Next Vehicle Purchase

The next vehicle purchase model distinguishes between 16 alternatives formed from the combination of vehicle class (coupe, sedan, SUV, & truck) and powertrain (ICE, BEV, HEV, & PHEV). Results are summarized in Table 7. The coupe ICE alternative is taken as the reference when interacting sociodemographic variables. Higher-income households are more likely to choose EVs (i.e., BEV & PHEV). It was also found that males tend to purchase trucks and PEVs. Larger households appear to prefer PHEVs over BEVs. An inertia term is included in the model to test whether owners of SUVs and trucks are more likely to prefer ICE and HEV powertrains for their next vehicle. No significant effect was found for current SUV owners, but it appears that truck owners are less willing to make the switch to PEVs than other respondents. Both education and race variables were tested but no significant effects were found for either vehicle class or powertrain preference.

Several more advanced models (nested logit, cross nested logit, and latent class with feedback) were explored but none provided a significant statistical improvement over the reference MNL specification.

Table 7. Next Vehicle Purchase Choice (MNL specification)

Variable	Coeff.	t-stat
ASC coupe ICE	0	ref
ASC coupe BEV	-4.67	-1.9
ASC coupe HEV	-1.14	-2.8
ASC coupe PHEV	-5.44	-4.6
ASC sedan BEV	-4.03	-1.7
ASC sedan HEV	-4.42	-4.1
ASC sedan ICE	-0.48	-3.6
ASC sedan PHEV	-20.78	-2.6
ASC SUV BEV	-6.21	-3.0
ASC SUV HEV	-1.55	-3.1
ASC SUV ICE	0.68	5.0
ASC SUV PHEV	-6.84	-6.0
ASC truck BEV	-9.95	-5.7
ASC truck HEV	-5.38	-2.4
ASC truck ICE	0.59	1.8
ASC truck PHEV	-11.78	-13.3
Age (6 categories) – SE	-0.51	-9.3
Age (6 categories) – SUV	-0.10	-2.6
Age (6 categories) – TR	0.13	1.6
Household size – BEV	-0.16	-2.8
Household size – PHEV	0.26	3.3
HH income (12 categories) - CO & BEV	0.21	3.5
HH income (12 categories) - SE & PHEV	1.14	1.9
HH income (12 categories) - SUV & BEV	0.30	2.8
HH income (12 categories) - SUV & HEV/PHEV	0.18	3.6
HH income (12 categories) - TR & BEV	-0.31	-1.6
HH income (12 categories) - TR & HEV	0.18	1.5
HH income (12 categories) - TR & ICE	-0.11	-2.9
HH income (12 categories) - TR & PHEV	-0.17	-6.3

Male - CO & BEV/PHEV	-0.60	-2.1
Male - CO & HEV	-1.59	-3.1
Male - SE & HEV	2.06	2.1
Male - SE & PHEV	4.36	2.0
Male - SUV & BEV	0.86	1.8
Male - SUV & ICE/HEV	-0.36	-2.2
Male - SUV & PHEV	1.54	2.9
Male - TR & BEV	6.12	3.7
Male - TR & HEV	2.56	1.8
Male - TR & PHEV	6.08	4.4
Fuel economy (MPGe for primary fuel)	0.061	2.8
Purchase price (ln($1000))	-0.16	-1.8
Previous vehicle TR - Next vehicle BEV/PHEV	-1.09	-3.3
ρ^2	0.27	
Adj-ρ^2	0.25	

Note: CO = coupe, SE = sedan, SUV = SUV & van, TR = pickup truck.

Practical significance values (i.e., the effect of a standard deviation change in the explanatory variable) were calculated for all variables and are presented in Table 8. BEV alternatives show the highest fuel economy sensitivity. A one standard deviation (9%) increase in the MPG equivalent for a battery-electric truck is associated with a 55% increase in the probability of choosing it as the next vehicle. Fuel economy is likely acting as a surrogate for range in this case. The lack of an explicit presentation of vehicle attributes to respondents likely contributes to the low price sensitivity. For each alternative, only two prices are included in the model (averages of new & used prices, respectively).

Table 8 Practical Significance of Variables in Next Vehicle Choice Model

Variable	CO-ICE	CO-BEV	CO-HEV	CO-PHEV	SE-ICE	SE-BEV	SE-HEV	SE-PHEV	SUV-ICE	SUV-BEV	SUV-HEV	SUV-PHEV	TR-ICE	TR-BEV	TR-HEV	TR-PHEV
Age	/	/	/	/	13%	**-64%**	-14%	**48%**	14%	**-83%**	-14%	**51%**	14%	**-48%**	-15%	**49%**
HH size	/	**-30%**	/	**68%**	/	-28%	/	**55%**	/	**-35%**	/	**65%**	/	-22%	/	**67%**
HH income	/	**46%**	/	/	/	/	/	**442%**	/	**76%**	**42%**	26%	**-48%**	**-65%**	28%	**-73%**
Male	/	**-39%**	-1.5%	**-43%**	/	/	**77%**	**97%**	-3%	**39%**	-21%	**61%**	/	**99%**	**85%**	**99%**
Previous vehicle truck	/	**-43%**	/	**-46%**		8.5%	/	**-73%**	/	**-42%**	/	-43%	/	**-44%**	/	**-61%**
Fuel economy	0.8%	14%	19%	16%	3.5%	5.1%	3.1%	12%	5.0%	**42%**	2.3%	1.0%	4.0%	**55%**	3.5%	6.1%
Purchase price ($1000)	-1.8%	-1.9%	-2.1%	-2.2%	-2.0%	-2.0%	-2.2%	-1.9%	-1.6%	-2.0%	-2.0%	-2.1%	-2.0%	-2.2%	-2.2%	-2.2%

Note: CO = coupe, SE = sedan, SUV = SUV and van, TR = pickup truck

Willingness to Pay for Self-driving Vehicles

The survey included two questions about willingness-to-pay for vehicle automation: an option that allows human intervention and a fully autonomous vehicle. A variety of model structures were explored to represent this process. A double hurdle model fits the use case. This model can represent the fact that many respondents (about 23%) were not willing to pay an additional cost beyond a traditional vehicle for automation. The double hurdle model represents two drivers of zero consumption: a selection process (whether to buy an AV or not) and a desired consumption process (the person may be willing to buy an AV but has a negative WTP) (Carlevaro et al., 2018). The model is essentially a joint Tobit/probit model. Results are given in Table **9**. More formally, the model is provided in Equations 1 and 2 below (Cragg, 1971).

$$f(y_t = 0|X_{1t}, X_{2t}) = C(-X_{2t}\gamma/\sigma) + C(X'_{2t}\gamma/\sigma)C(-X'_{1t}\beta) \tag{1}$$

$$f(y_t|X_{1t}, X_{2t}) = (2\pi)^{-1/2}\sigma^{-1} exp(-(y_t - X'_{2t}\gamma)^2/2\sigma^2)C(X'_{1t}\beta) \tag{2}$$

where X_{1t} and X_{2t} are vectors of independent variables at observation *t*, and β and γ are parameter vectors. The function C(z) is the cumulative normal distribution given by

$$C(z) = \int_{-inf}^{z} (2\pi)^{-1/2}\, exp(-t^2/2)dt \tag{3}$$

From an economic satiation perspective, one would assume that more automation should be preferable to less automation. However, results (see Table 8) suggest that human-driven vehicles are slightly preferred by respondents. Perhaps, respondents fear giving up full control and the option of human intervention is appealing to them. Women tend to be willing to pay less than men for automation, which fits typical associations between technology adoption and risk-taking by gender (Shaouf & Altaqqi, 2018; Tamás et al., 2019). Results also suggest generic technology adoption and income effects, with current BEV owners (often higher income) having higher WTP than ICE vehicle owners. WTP also tends to decrease with age, matching the expectation of younger individuals being more willing to adopt new technologies. A related effect in intermediate model specifications was a negative sign on income parameters. Theory suggests that WTP should increase with income. Given that income tends to correlate with increasing age, it seems that the age-technology adoption interaction was biasing this parameter sign.

Table 9. Double Hurdle Regression for WTP for Vehicle Automation

	Coeff.	**t-stat**	**ΔProb**
Probit Selection Model			
Intercept	-1.86	-1.6	
Fraction of population that is working age	4.56	2.9	7.5%
ICE vehicle owner (ref: no vehicles owned)	-0.74	-2.0	-25%
Human-driven	0.24	0.95	2.9%
#Jobs within 45-min drive	0.012	1.8	7.1%

Tobit WTP Model			
Intercept	1.49	-4.2	
Female	-0.16	-4.4	-14%
ICE vehicle owner (ref: no vehicles)	-0.20	3.2	-18%
EV vehicle owner (ref: no vehicles)	0.27	5.6	**30%**
Married (ref: single, divorced, widowed)	0.22	-13.1	25%
Age (ordinal variable)	-0.016	0.89	**-32%**
Human-driven setting	0.035	5.3	3.5%
Jobs within 45 minutes drive	0.0052	17.5	10%
Std. Dev.	0.073	7.7	
ρ^2	0.23		
Adj-ρ^2	0.22		

CONCLUSIONS

This survey provides a range of insights and opportunities for analysis of emerging and future transportation technologies. Results were compared with a 2017 survey containing many of the same questions, which provided useful insights into the changes in preferences as these technologies evolve and enter the market. There is an increased interest in PEV relative to 2017 (up by about 18% percentage points). However, current pickup truck owners remain reluctant to make the switch. The development of BEV pickup trucks by Ford, Rivian, and other OEMs (Ford Motor Company, 2021b; Rivian, 2021) should help alleviate concerns about the performance of BEV trucks (e.g., towing capacity). Across the population, there remains significant concern about vehicle charging and range. These concerns are increasingly founded on a lack of knowledge rather than technical limitations. Investment in charging infrastructure is expected at all levels of government and vehicle range continues to increase. Public information campaigns and opportunities to test drive PEVs would be beneficial.

The preference for vehicle autonomation depends on the use case. Automation of driving tasks tends to be preferred by residents of low-density, car-dependent areas where long commutes are common. These individuals see a benefit in reducing, or eliminating, the driving task so they can perform other activities while traveling. In contrast, automated parking technologies tend to be favored by those living in denser communities, who are more likely to use parkades. Such individuals would reduce their monthly expenses with automated parking because it reduces the required space per vehicle and therefore the cost of parking infrastructure in high land value areas.

Other technologies require additional analysis to draw strong conclusions. Intermittent bus lanes are favored by those living in high population density areas, but not those in areas with a high percent of zero-vehicle households. This result suggests the presence of factors not captured in the survey. The WTP for drone delivery shows a strong association with marital status. A targeted set of questions would help to identify preferences for this technology.

Remote work is a current topic of interest to the transportation community, among other stakeholders. Survey results indicate a stronger preference for remote work among younger workers. However, other recent studies have found the opposite preference. Confounding factors of occupation variability between age cohorts likely contribute to these unclear results.

This paper summarizes only a small subset of the questions included in the survey. The wide scope of the survey provides an opportunity to examine demographic variations across technologies. For example, comparing the market for AVs with VTOL or whether those who are willing to share parking share commonalities with those willing to share rides. The speculative nature of many of the technologies examined in the survey means that caution is required as to the interpretation of results. Tracking preferences as these technologies evolve and enter the market will be an important avenue for future research.

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