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Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area

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ABSTRACT

Emerging technologies and services stand poised to transform the transportation system, with large implications for energy use and mobility. The degree and speed of these impacts depend largely on who adopts these innovations and how quickly. Leveraging data from a novel survey of San Francisco Bay Area residents, we analyze adoption patterns for shared mobility, electrified vehicle technologies, and vehicle automation. We find that ride-hailing and adaptive cruise control have penetrated the market more extensively than have electrified vehicles or car-sharing services. Over half of respondents have adopted or expressed interest in adopting all levels of vehicle automation. Overall, there is substantial potential for market growth for the technologies and services we analyzed. Using county fixed effects regressions, we investigate which individual and location-level factors correlate to adoption and interest. We find that, although higher-income people are disproportionately represented among current adopters of most new technologies and services, low- to middle-income people are just as likely to have adopted *pooled* ride-hailing. Younger generations have high interest in automated and electrified vehicles relative to their current adoption of these technologies, suggesting that young people could contribute substantially to future market growth—as they are doing for ride-hailing. We find no evidence that longer commutes present a barrier to plug-in electric vehicle adoption. Finally, women are less likely than men to adopt and/or be interested in adopting most new transportation technologies, with the exception of ride-hailing; designing or marketing technologies with women's preferences in mind could contribute to future market expansion.

1. Introduction

The transportation system is quickly evolving as new technologies and services emerge. Ride-hailing and car-sharing, electrification technologies, and technologies that increasingly automate the task of driving are a growing reality. Such emerging transportation innovations may have a large impact on future energy use and sustainable mobility patterns—depending on how they are adopted. Our goal is to understand what drives the adoption of and interest in such technologies and services to gain insight into

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who the current users are, who they are likely to be in the future, and how the transportation system might optimally evolve with increased sustainability and equitable access to these technologies and services.

The need for this understanding is evident in a growing area of research that relies on transportation system simulation models to probe the potential impact of emerging technologies on energy demand and transportation patterns. Although these studies can inform public and private energy and transportation planning, recent analyses using some of these models depict vastly uncertain futures and thus do little to guide practical planning efforts. Stephens et al. (2016), for example, characterize the uncertainty surrounding potential energy impacts of automated vehicles (AVs) alone as ranging from a 60% reduction in energy demand to a 200% increase. Much of this uncertainty stems from the need to understand the potential adoption and use decisions of millions of people across the U.S. and around the world—not just for a single transportation technology, but for the portfolio of transportation modes that meet their travel needs. To reduce this uncertainty, transportation system models need consumer data and analyses that enable a more refined understanding of how human behavior drives demand for new transportation technologies and services.

In this paper, we present results that can help clarify relevant behaviors to better underpin these simulation models, inform system planners, and generate insights that can suggest pathways for increasing access to emerging transportation technologies and innovations. We focus on the following emerging technologies and services: shared-mobility services including ride-hailing (single-rider and pooled) and car-sharing, electrified vehicles including hybrid electric vehicles and plug-in electric vehicles (PEVs), and three different levels of AV technologies. Our analysis focuses on four types of factors that we hypothesize, based on our literature review, can explain adoption of and interest in these emerging developments: demographics (e.g., age, income, gender), location-specific factors (e.g., walkability, population density, commute distances), preferences for mode attributes (e.g., social interactions, convenience), and human characteristics (e.g., risk preferences, personality). Some factors have been found to be important for several but not all emerging transportation technologies and services. Other factors are understudied in the context of transportation, especially those found to be important for other emerging technologies and services in general, such as risk preferences. We help fill the knowledge gap by more fully exploring select factors that may influence the adoption of emerging transportation technologies and services. In addition, we distinguish current adoption and interest in future adoption, and we conduct the analysis across multiple technologies and services for the same pool of respondents.

We leverage a novel dataset generated by the WholeTraveler Transportation Behavior Study survey. We developed this survey with the support of the U.S. Department of Energy's (DOE's) Energy Efficient Mobility Systems (EEMS) program as part of the SMART Mobility Consortium, which strives to clarify energy implications and opportunities related to advanced mobility solutions.[1] We used the survey to elicit the mobility decisions and characteristics of 1045 households in the San Francisco Bay Area, which is a leading region for the introduction of advanced transportation solutions.

In Section 2 of the paper, we define our target technologies and services, and we review relevant behavioral studies. In Section 3, we provide detail on the WholeTraveler Transportation Behavior Study survey, our empirical approach, and our data. Section 4 presents our results, while Section 5 discusses the main takeaways and characterizes the contribution of the study. Section 6 concludes.

2. Background and literature review

In this section, we more carefully define each of the categories of transportation technologies we analyze (shared mobility, electrified vehicles, and AVs), and we summarize existing literature that addresses the relationship between adoption of these technologies and the four explanatory-factor groups that thematically emerge from this literature: demographics, location-specific factors, preferences over mode attributes, and personality and risk characteristics.

2.1. Shared mobility

Shared mobility—via ride-hailing, car-sharing, and other shared services—helps travelers meet mobility needs without reliance on personally owned vehicles. Ride-hailing allows users to request a driver and car for a trip from any given origin to their destination via a smartphone app. Traditionally, shared, on-demand transportation service has been provided by taxi fleets, but newer options such as transportation network companies (e.g., Uber and Lyft) have attempted to offer their services at a lower price-point and with more convenience via their apps, which has increased the impact and use of shared mobility. In contrast, car-sharing allows users to drive, for short periods, vehicles that are shared across other users of a car-share service. All shared-mobility services are more common in urban areas and may be used with other transportation options to enable greater adoption.

Our survey targeted three forms of shared mobility. We included two forms of ride-hailing: single-rider services (e.g., UberX or standard Lyft) and pooled services (those serving multiple riders with similar origins and destinations via a single driver/vehicle at a reduced cost, such as Uber Pool or Lyft Shared). The pooled option for ride-hailing is often referred to in the literature as "ride-splitting" (e.g., Shaheen, Cohen and Zohdy, 2016, Department of Energy, 2017). We also included car-sharing, which is less broadly adopted relative to ride-hailing, but reflects an alternative model of shared mobility currently available.

Most studies have found that users of ride-hailing and car-sharing services tend to be disproportionately younger, higher income/wealthier, and college educated with fewer or no children at home (Alemi et al., 2018; Clewlow and Mishra, 2017; Dias et al., 2017; Kooti et al., 2017; Smith, 2016; Cervero et al., 2007; Namazu and Dowlatabadi, 2018), although car-sharing adopters can tend to be

[1] More information about the SMART Mobility Consortium can be found in Appendix A in the supplementary materials.

older (Cervero et al., 2007). In studies of ride-hailing, gender has either not been considered (Clewlow and Mishra, 2017; Dias et al., 2017), or no effect has been found (Smith, 2016), although some studies have found that women tend to be more likely to use ride-hailing (Alemi et al., 2018; Kooti et al., 2017). A general trend of younger generations away from car ownership and toward use of shared or on-demand mobility may point to larger societal changes shaping mobility preferences. The phrase, "You are what you can access," illustrates this perspective, in contrast to an older paradigm that may more closely link identity with ownership (Belk, 2014).

Lee et al. (2018) found that perceived risks, benefits, and trust related to a ride-hailing platform mediate preference for the mode. The ability to quickly summon a ride from an app—which provides transparent travel routing, driver ratings, and communication channels—may improve perceptions of safety. Moreover, most ride-hailing is conducted via traditional automobiles, a strongly established transportation mode in the U.S. (Clewlow and Mishra, 2017).

The use of ride-hailing and car-sharing services is higher in urban areas than in rural areas (Becker et al., 2017; Smith, 2016). Therefore, studies of location-specific factors have concentrated on exploration of trip origins and destinations within an urban setting, and on location-specific pricing, which may rise or fall in conjunction with time of day and other events (Rayle et al., 2016). Ride-hailing service can be in high demand at peak times and in certain locations, such as airports, areas of concentrated entertainment, or sporting venues. Similarly, limited parking, availability of good public transit, high density, and mixed-use neighborhoods are associated with more car-sharing (Klintman, 1998; Muheim and Reinhardt, 1999; Clewlow and Mishra, 2017).

Personality[2] plays a key role in technology adoption (Amichai-Hamburger and Vinitzky, 2010; Ehrenberg et al., 2008), and it has been found to have a mixed influence on behaviors related to shared mobility. Greater extraversion is related to more willingness to engage in the sharing economy, whereas no relationship has been found with engagement and openness (Roy, 2016). Those who rate high on agreeableness worry less about unpleasant interpersonal incidents occurring across a wide range of transportation modes (e.g., bus, metro, taxi, tram) and hence may be more willing to use shared transportation (Backer-Grøndahl et al., 2009). However, those rating high in neuroticism worry more about these types of incidents and are more likely to change their mode or route to avoid them (Backer-Grøndahl et al., 2009). Somewhat related to several of these personality factors, some studies have suggested that shared transportation can deepen human connectedness, and thus individuals may be motivated (or not) to use shared transportation depending on their desire for connectedness (Crewe and Forsyth, 2011; McFarland, 2015; Pangborn-Dolde et al., 2015).

Levels of risk acceptance also affect adoption of shared-mobility services. For instance, older people who are making decisions about adopting new technologies and services are often impacted by their perception of risk (Beaud et al., 2016; Dixit et al., 2015; Czaja et al., 2009; Jackson and Jucker, 1982; Mitzner et al., 2010; Pan and Jordan-Marsh, 2010; Selwyn, 2004; Wolf and Seebauer, 2014). Watanabe et al. (2016) and Saelens et al. (2003) found that risk-averse people make less use of multiple modes during a single trip, suggesting that new mobility options may not serve well as a first-mile/last-mile complement for public transit to those who are risk averse.

2.2. Electrified vehicles

We consider vehicle technologies that use electricity in place of petroleum-based fuels. These vehicles can significantly reduce carbon emissions and overall energy use, especially when relatively efficient means are used to generate the power they use. Specifically, our survey used two terms for the electrified vehicle technologies of interest. "Hybrid vehicles (gasoline-electric)" were meant to represent vehicles propelled by both an internal combustion engine and an electric motor powered by batteries that are charged by the engine and regenerative braking. "Plug-in electric vehicles" could include battery electric vehicles (BEVs), which have only electric motors powered by batteries and require external charging to run, and plug-in hybrid electric vehicles (PHEVs), which combine an external combustion engine with a motor powered by batteries that can also be charged externally. We recognize that, based on the survey wording, respondents could have classified PHEVs as either "hybrid vehicles (gasoline-electric)" and/or "plug-in electric vehicles." In the interest of simplicity, for the remainder of the paper, we refer to the electrified vehicle technology categories as "hybrids" and "plug-in electric vehicles" (PEVs) to match the analysis and discussion with the wording of the survey. We separate our hybrid and PEV analyses to reflect the distinction made in the survey. However, interpretation of the results distinguishing these two categories should be done cautiously, because the existence of PHEVs means we may not be able to precisely distinguish the technology types depending on how respondents interpreted the questions.

Much of the recent literature regarding preference for electrified vehicles has concentrated on stated-preference studies for PEVs, attempting to identify how information can strengthen interest among potential car buyers (Liao et al., 2016; Cherchi, 2017). Preferences for PEVs may be shaped by forces beyond purchase economics, including a sense of societal value in ownership (Haugneland and Hauge, 2015) and—because of the smaller number of moving parts in PEV motors as compared to internal combustion engines—the sense that they are less expensive to fuel and maintain (Mi and Masrur, 2018).

[2] According to the American Psychological Association, personality refers to "individual differences in characteristic patterns of thinking, feeling and behaving" (Khatibi and Khormaei, 2016). The *Big Five* dimensions of personality are extraversion (vs. introversion), agreeableness (vs. antagonism), conscientiousness (vs. lack of direction), neuroticism (vs. emotional stability), and openness (vs. closedness to experience) (Pervin and John, 1999). Extraversion is associated with gregariousness, assertiveness, activity, excitement seeking, positive emotions, and warmth. Agreeableness is marked by trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness. Conscientiousness is marked by competence, order, dutifulness, achievement, self-discipline, and deliberation. Neuroticism is associated with anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability. Openness is marked by appreciation of unusual ideas, fantasy, aesthetics, emotions, and a variety of experiences. People possess all five dimensions, and they vary in terms of what proportion of each that they have.

Convenient availability of charging stations may also be important for PEV adoption and use. Electricity supply is nearly ubiquitous in the U.S., even if relatively fast-charging Level 2 or Level 3 PEV-charging stations are not. Much of the research in this area specific to location has used simulation models to identify strategies for siting fueling stations, to optimize the balance between demand, current PEV range, charging time requirements, and grid impacts (Sadeghi-Barzani et al., 2014; Luo et al., 2017). Some of this work has identified the difference in vehicle charging needs by location, such as residence location (urban, multi-unit dwellings vs. suburban homes), and by trip type (long-distance highway trips vs. short urban trips) (Wood et al., 2017). The simulation models usually include assumptions about charging demand. However, because PEV ownership has not yet reached a large segment of the population, there are many gaps in understanding behaviors associated with charging.

Many recent studies have found that users of electrified vehicles tend to be disproportionately male, younger, higher income/wealthier, and college educated with fewer or no children at home (Caperello and Kurani, 2011; Langbroek et al., 2017; Nayum et al., 2016; Plötz et al., 2014), although some exceptions to these general patterns emerge; for example, Ziefle et al. (2014) found women and older generations to be more interested in electrified vehicles. Much of the research on these vehicles with respect to risk focuses on "range anxiety" related to the constrained range of BEVs and the relative sparseness of vehicle-charging infrastructure as compared to the gasoline refueling infrastructure used by internal combustion engine vehicles. The findings suggest that people who are more concerned about range are less likely to be interested in buying a BEV. However, those who adopt a BEV seem to experience much less anxiety about range over time (Franke et al., 2012; Neubauer and Wood, 2014). Skippon and Garwood (2011) found that people tend to see the typical PEV driver as rating high on agreeableness, conscientiousness, and openness, because high-agreeableness individuals tend to care more about others, high-conscientiousness individuals like planning ahead, and high-openness individuals are interested in new things.

2.3. Automated vehicles

SAE International defines six levels of automation from no automation (0) to full automation (5).[3] Each level of automation provides increased assistance to drivers and reduced levels of driver input.

Our survey defines three categories of automation. With "adaptive cruise control (ACC)," a vehicle "brakes and accelerates to match the speed of the vehicle in front (only on highways), but requires driver to steer," corresponding to SAE automation level 1. A "partially automated" vehicle "automatically brakes and accelerates, and additionally steers itself sufficiently to stay in a lane (only on highways), but requires the driver to be paying attention, to change lanes and be available to override," corresponding to SAE automation levels 2–3. When it is "fully automated," a "vehicle drives itself and does not require driver to pay attention (i.e., rider could sleep, read, work, or otherwise not pay attention to the road)," corresponding to SAE automation levels 4–5.

Because the degree of automation changes how the vehicle is controlled, it affects the energy use and safety of vehicles, and it may affect how people purchase and use vehicles. In particular, fully automated vehicles are being considered by ride-hailing services as a way to lower the costs of shared mobility.

Studies have found that early and potential adopters of partially and fully automated vehicles tend to be male, technology savvy, and higher income/wealthier; have greater car-crash experience and greater willingness to pay for new technologies; and be less influenced by whether friends adopt the technology (Bansal et al., 2016; Fortune.com, 2018; Investopedia.com, 2018; Payre et al., 2014). Research on age is mixed. Some studies have found that older adults may be interested in fully automated vehicles for increased mobility (Abraham et al., 2016; Haboucha et al., 2017), whereas others have found that older individuals express less interest, perhaps due to concerns about learning to use the new technology and losing the pleasure of driving (Bansal and Kockelman, 2018).

From a user standpoint, AVs may enable improved access to mobility, convenience, safety, and reduced stress while traveling, reducing the drudgery and human error associated with driving. However, at the present state of development, concern over the safety of AVs exists, and the ethics issues surrounding machines making life-and-death decisions are considerable (Bonnefon et al., 2016). User attitudes toward the technology may also impact how it is deployed. Applying AV technology to shared mobility could reduce overall vehicle ownership, with users soliciting rides on an as-needed basis and shared AVs serving a greater number of passengers as compared to private ownership. A study found that shared AVs could be an inexpensive mobility on-demand service, potentially improving mobility access, if the balance between cost, waiting time, and travel time can be optimized for user experience (Krueger et al., 2016). Regardless of the mix of private and shared AVs, a recent survey found that people identify advantages in AV technologies for which they are willing to pay a premium, anticipating that AVs will constitute a substantial portion of the vehicle fleet by 2045 (Bansal and Kockelman, 2017).

The earliest existing fully automated vehicles are low-speed shuttles with a capacity of about eight passengers, operating on defined routes in campus or similar settings where they are likely to encounter only minimal traffic. Such AV shuttles may be a viable option for serving first/last-mile roles in conjunction with public transit (Winter et al., 2016; Scheltes and de Almeida Correia, 2017). From the standpoint of the potential impact of AVs by geography, there are both positive and negative potentials. AVs could enable densification in urban cores as the need to own, drive, and park private vehicles declines because of access to shared AVs. On the other hand, primarily private AVs may encourage urban sprawl (Fagnant and Kockelman, 2015; Milakis et al., 2018). By replacing the burden of driving with time that may be spent for productivity, entertainment, or even for sleeping, AVs may enable people to live farther from work, increasing commute distances and energy expended.

[3] The formal definitions for these levels are included in Appendix B in the supplementary materials.

Several psychosocial factors have been found to influence the use of AV technologies. “High sensation seekers”—those who drive faster, leave less space between vehicles, and brake more abruptly—may be less likely to use ACC and might adapt their behavior in a partially or fully automated vehicle by driving less carefully (Payre et al., 2014). People with greater openness to new technologies and stronger environmental views are more likely to intend to adopt AVs, whereas those with a stronger locus of control and greater enjoyment derived from driving are less likely (Haboucha et al., 2017; Sun et al., 2017; Zmud and Sener, 2017). Moreover, these factors influence people’s willingness to pay for the technology, with research suggesting that people are not willing to pay much more ($0–$3000) for an AV than for a conventional vehicle (Zmud and Sener, 2017). Hohenberger et al. (2017) found that increased feelings of self-enhancement from the use of AVs reduced AV-related anxiety and ameliorated the effect of anxiety on reducing positive feelings toward the technology.

An emerging factor that may prove important for adoption of AVs is the extent to which an individual is a “risk-lover” or “risk-taker.” A recent study by Hulse et al. (2018) found no difference with respect to risk perceptions about various automation technologies (e.g., automated trains versus cars) among risk-takers, perhaps because the technology is touted as being “safe” compared to other modes of transportation. However, more research is needed to better understand the extent to which risk matters for the adoption of the technology, particularly in light of recent publicity about fatal car accidents involving partially automated technologies.

3. Approach for analyzing adoption and interest patterns

3.1. WholeTraveler transportation behavior study survey

The data presented in this paper are derived from a web-based survey with questions related to a variety of demographic, preference, life history, and personality and psychological factors as well as technology adoption and interest.[4] The online instrument is part of a larger WholeTraveler Transportation Behavior Study that aims to understand travel choice patterns, preferences, and decision-making processes in the context of new mobility technologies, with a focus on the San Francisco Bay Area.

A sample of randomly selected addresses in the nine Bay Area California counties[5] was recruited to respond to an online survey via a mailed invitation letter followed by a reminder postcard. The invitation asked the household member who most recently had a birthday and is above the age of 18 to respond to the survey. To complete the survey, the respondent went online through a web browser on a desktop or laptop computer. The survey was only administered in English. Respondents received a $10 Amazon gift card for completing the survey.

Recruitment letters were sent to 60,000 households. Of these, 997 residents (1.7%)[6] completed the entire survey, and 48 completed the first portion of the survey instrument (the part used for this analysis) for a total of 1045 responses. All responses were completed during the period between March and June 2018, with a median completion time for those that finished the full survey of 28 min.

A key limitation of this research is that our sample was constrained to the San Francisco Bay Area, and those who answered the survey were disproportionately highly educated and high income even within the Bay Area. However, female response to the survey was high and more representative of the local population, suggesting that our findings reflect well the adoption of and interest in our target transportation modes among female residents in the surveyed area. An advantage of focusing on this geographic area is that it has been the subject of previous studies using other data-collection approaches (e.g., Clewlow, 2016; Cervero and Tsai, 2004; Alemi et al., 2018). Thus, it is relatively well characterized with respect to its strengths and weaknesses as a leading indicator for wider geographic demand.

The full WholeTraveler survey instrument can be found in Appendix C in the supplementary materials. The survey included questions around each user’s travel behaviors, mode choices, preferences over mode attributes, commute locations, car ownership, e-commerce behavior, and interest in new mobility technologies and services. It also included questions associated with demographic and household characteristics, personality traits, risk attributes, and a life-history calendar that looked at life events and travel behaviors undertaken while the respondent was between the ages of 20 and 50. Those taking the survey were then offered the chance to complete a second phase of the survey that recorded their movements and travel for one week using the Global Positioning System (GPS).

Table 1 summarizes the subset of questions from the survey relevant to our present study. The choice of the explanatory variables used in the analysis was primarily motivated by the existing literature reviewed in Section 2. A detailed description of the derivation and use of the outcome and explanatory variables is presented in Section 3.3.

Fig. 1 shows an example set of questions from the emerging technologies category. The respondents were given a technology or service and asked to indicate all statements that applied to their experience with the technology. They could choose whether they knew of someone who had used it, whether they themselves had used it, whether they regularly use it or owned it, and/or whether they were interested in using the service or purchasing it in the future. They could also indicate whether they had never heard of it or that it was not applicable. We focus our primary analysis on those who reported that they are regular users/owners of a service or technology, and those who selected that they are interested in using/purchasing it in the future.

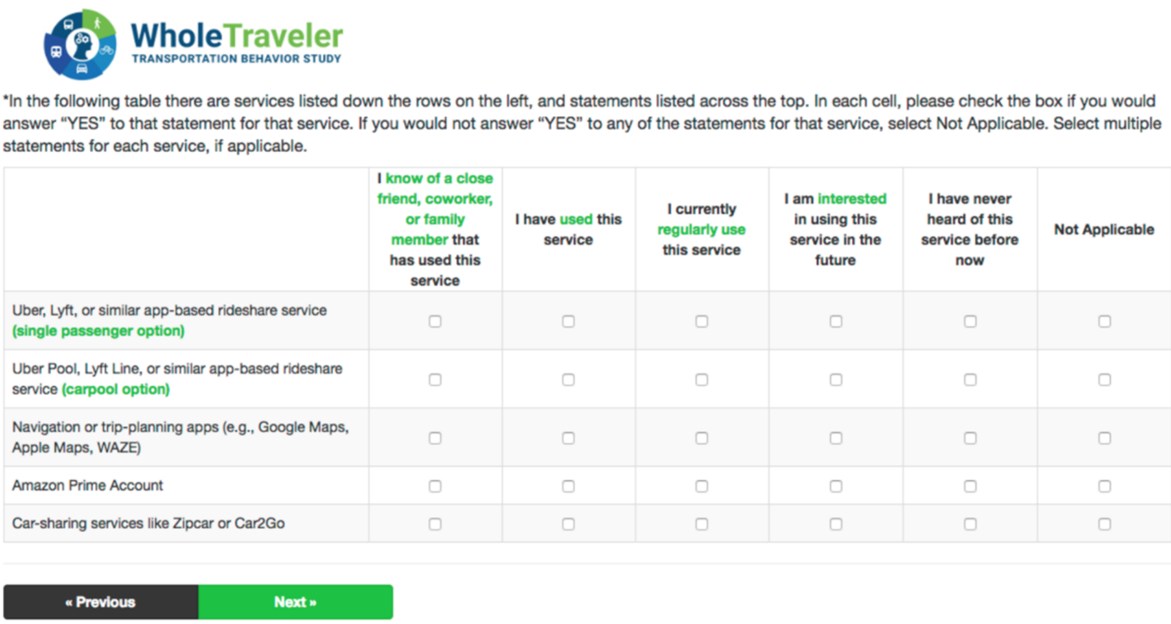
[4] More detail on this study and the DOE program it is funded by can be found in Appendix A in the supplementary materials.

[5] Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties.

[6] The response rate is consistent with other implementations using similar unsolicited mailings to recruit, and with similar incentive payment levels. For example, the 2015–2017 California Vehicles Survey has a 1.5% response rate overall (California Energy Commission, 2018).

Table 1
High-level summary of survey questions used in this analysis.

Survey instrument category	Question summary	Analysis relevance
Emerging technologies	Familiarity/adoption/interest in hybrid vehicles, PEVs, ACC, partial automation, full automation, ride-hailing services (single-rider or pooled), car-sharing, and some other technologies and services	Stated interest in and adoption of emerging technologies
Demographics	Year of birth, gender, level of education, annual household income, number of children under 8 years of age, and a number of other demographic and household characteristics	Observable demographic characteristics of the participants
Preference over mode attributes	Importance of mode characteristics to user's transportation choices: short travel time, low cost, predictable cost, predictable arrival time, ability to make multiple stops, low hassle, safety, environmental impact, social interactions	Stated determinants of current adoption choices and mode use
Personality	Questions to determine personality factors: extraversion, agreeableness, conscientiousness, neuroticism, openness to experience	Personality factors
Location-specific factors	Specific addresses for residence location and primary destination	Location characteristics of residence and destination (population density and walk score) and distances from residence to primary destination
Risk attitude	Repeated hypothetical choices between a certain prize amount for sure or taking a 50–50 chance at getting a higher prize amount with varying value trade-offs	Risk attitude


WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In the following table there are services listed down the rows on the left, and statements listed across the top. In each cell, please check the box if you would answer "YES" to that statement for that service. If you would not answer "YES" to any of the statements for that service, select Not Applicable. Select multiple statements for each service, if applicable.

	I know of a close friend, coworker, or family member that has used this service	I have used this service	I currently regularly use this service	I am interested in using this service in the future	I have never heard of this service before now	Not Applicable
Uber, Lyft, or similar app-based rideshare service (single passenger option)						
Uber Pool, Lyft Line, or similar app-based rideshare service (carpool option)						
Navigation or trip-planning apps (e.g., Google Maps, Apple Maps, WAZE)						
Amazon Prime Account						
Car-sharing services like Zipcar or Car2Go						

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Fig. 1. Sample question eliciting degree of adoption and interest in adopting.

3.2. Data preprocessing

To screen out any respondents who completed the survey only to receive the Amazon gift card incentive, and therefore clicked through responses without reading questions or answering meaningfully, we dropped all respondents with a response time less than 12 min. This removed 19 survey responses (1.82% of the data).

Next, we addressed a limited number of omitted responses to questions from which preference-over-mode-attribute variables are obtained. Cases in which respondents chose "not applicable" for variables in the preference-over-mode-attribute category were recoded with a score of zero, giving zero value to characteristics that a respondent deemed as factors that are not relevant to their commute mode choice.[7] Appendix D in the supplementary materials reports results where these values are instead assigned a score of three or omitted entirely, which shows that the main conclusions drawn from the models are unaffected. For a limited number of

[7] Six of eight questions in the preference-over-mode-attribute category have < 20 missing values. Only predictable cost and multiple stops have more, at 27 and 43, respectively. This results in 56 observations that would otherwise be omitted from analysis (7.3% of the reduced sample).

cases, population density of a primary destination was zero (because the relevant census block group is completely non-residential); for the analysis, all zero values of primary destination population density are replaced with the sample average value. This is a very limited change that allows the cases to be included in mathematical comparisons. These steps result in a final set of 1,026 observations that are used in the analysis.

3.3. Data analytical approach

To capture the distinction between current adoption and interest in future adoption, we define two sets of dependent variables and estimate linear probability model ordinary least squares (OLS) regressions for each analyzed technology or service.[8] The dependent variables are (1) Adopted: defined as an indicator variable equal to one if the respondent reported owning a given emerging technology or regularly using an emerging service, zero otherwise; and (2) Interested in Adopting: defined only for the subsample that has not already adopted the service or technology, this indicator variable is equal to one if the respondent reported interest in using the service or owning the technology in the future. The first set represents the segment that has already adopted, while the second represents the adoption potential of these technologies and services among those who have not already adopted.

The summary statistics for dependent variables used in this study are provided in Table 2. Both sets of variables are defined from responses to survey questions 1.11–13, which can be viewed in Appendix C in the supplementary materials; Fig. 1 shows question 1.13.

To analyze the impact of explanatory factors on adoption and interest in adoption of technologies and services, we estimate the following model:

$$Y_{igc} = \alpha + \mathbf{X}_{igc}^{'}\boldsymbol{\beta} + \mathbf{P}_i^{'}\boldsymbol{\theta} + \epsilon_i \tag{1}$$

Equation (1) describes the outcome for individual i in census block group g in county c as a function of individual and geographic factors, personal-level characteristics, and an idiosyncratic error.

$$\mathbf{X}_{igc}^{'}\boldsymbol{\beta} = \beta_1 Child_i + \beta_2(>4yrCollege)_i + \beta_3 Female_i + \beta_4 WalkScore_i + \mathbf{BirthDec}_i^{'}\boldsymbol{\eta} + \mathbf{PopDens}_{gc}^{'}\boldsymbol{\delta} + \mathbf{PrimaryDistance}_i^{'}\boldsymbol{\lambda} + \mathbf{HHInc}_i^{'}\boldsymbol{\gamma} + \mathbf{C}_c \tag{2}$$

The first explanatory variable vector in Equation (1) captures the demographic and location-specific factors and is given by Equation (2) wherein the first three terms are dummy variables, equal to one when there is a child under age 8 in the home, the respondent has more than a bachelor's degree education, or the respondent identifies as female. We include three types of location-based factors in our analysis. First, the walk score of the residence (*WalkScore*)[9] is included to account for access to nearby amenities (e.g., grocery stores and restaurants). Walk scores are computed using an algorithm that calculates distance to the nearest amenity in a set of categories, where "amenities within a 5 min walk (0.25 miles) are given maximum points. A decay function is used to give points to more distant amenities, with no points given after a 30 min walk."[10] All categories of amenities are given equal weighting, then normalized and summed to produce a number ranging from 0 to 100. This measure is included to directly reflect the feasibility of walking as a mode choice, because walk scores have been found to strongly correlate with nearby access to reported primary commute destination types including grocery stores, fitness facilities, restaurants, coffee shops, libraries, and retail (Carr et al., 2011) and access to public transportation in the form of train and bus stop counts (Koohsari et al., 2018). The second location-based factor is population densities in the census block group of both the residence and the primary destination (*PopDens* in 1000 people per square mile), reflecting accessibility and likelihood of public transit use or walking (Reilly and Landis, 2002) and acting as "proxies for variables that represent the quality of the transit service" (Chen et al., 2008).[11] The third location-based factor is commute distances (*PrimaryDistance)*, determined by the address of the home and the primary destination (P.D.) provided by each participant in the survey and calculated using the Google API to reflect the distance in miles via driving route. This distance encompasses the operating costs, travel time in which the respondent would use the technology or service, and the range for BEV use. *PrimaryDistance* is captured by three included dummy variables indicating whether the respondent's primary commute distance falls into the following partitioned categories: 10–20 miles, 20.01–50 miles, and above 50 miles, while less than 10 miles serves as the omitted category.

Among the remaining factors, *HH Inc* represents annual household income before taxes and also enters as dummy variables after being partitioned into three categories: \$75,000–\$150,000, \$150,001–\$200,000, and above \$200,000, with less than \$75,000 as the omitted category. These bins approximate the quartiles of household income within the sample, with some slight deviation given the coarseness of the income categories respondents could select in the survey. The age of the respondent is accounted for through the inclusion of dummy variables indicating the decade in which the respondent was born (*BirthDec*): 1930s, 1940s, 1950s, 1970s, 1980s,

[8] Analyses were conducted using a Logit regression as well, with consistent results between that and the OLS regressions. Estimates from the Logit regressions can be found in Appendix D in the supplementary materials.

[9] See https://www.walkscore.com/professional/.

[10] See https://www.walkscore.com/methodology.shtml.

[11] Residential and workplace population densities are also a significant factor in determining San Francisco Bay Area vehicle choice (Kockelman, 1997); the decision to walk, bike, or take public transit in Hong Kong and Boston (Zhang 2004); vehicle miles traveled in Portland, Oregon (Sun et al. 1998) and nationwide (Chatman 2003); and engagement in work and shopping trips by foot in Puget Sound (Frank and Pivo 1994) and general walking trips in Baltimore and Washington DC (Mahmoudi and Zhang 2018). Additionally, residential population density can impact availability of street parking, a factor found to dramatically affect car ownership in New York City (Guo 2013).

Table 2
Summary statistics of outcome variables.

	N	Mean	SD	Min	Max
Adopted: Ride-hail Single	1026	0.27	0.44	0	1
Adopted: Ride-hail Pooled	1026	0.18	0.38	0	1
Adopted: Car-Sharing	1026	0.03	0.16	0	1
Adopted: Hybrid	1026	0.16	0.37	0	1
Adopted: Plug-in Electric	1026	0.06	0.25	0	1
Adopted: Adaptive Cruise Control	1026	0.17	0.38	0	1
Adopted: Partially Automated	1026	0.04	0.20	0	1
Interested in Adopting: Ride-hail Single	752	0.27	0.44	0	1
Interested in Adopting: Ride-hail Pooled	846	0.20	0.40	0	1
Interested in Adopting: Car-Sharing	1000	0.19	0.39	0	1
Interested in Adopting: Hybrid (Gas-Electric)	864	0.426	0.49	0	1
Interested in Adopting: Plug-in Electric	960	0.53	0.50	0	1
Interested in Adopting: Adaptive Cruise Control	851	0.46	0.50	0	1
Interested in Adopting: Partially Automated	984	0.47	0.50	0	1
Interested in Adopting: Fully Automated	990	0.51	0.50	0	1
Max Observations	1026				

Table 3
Summary statistics of demographic and household variables.

	N	Mean	SD	Min	Max
Born 1930s	1026	0.01	0.12	0	1
Born 1940s	1026	0.08	0.26	0	1
Born 1950s	1026	0.14	0.35	0	1
Born 1960s	1026	0.18	0.38	0	1
Born 1970s	1026	0.20	0.40	0	1
Born 1980s	1026	0.28	0.45	0	1
Born 1990s	1026	0.11	0.31	0	1
Any Children < 8yrs	1026	0.16	0.36	0	1
HH Income < 75 K	875	0.27	0.44	0	1
HH Income [75 K, 150 K)	875	0.34	0.47	0	1
HH Income [150 K, 200 K)	875	0.15	0.36	0	1
HH Income ≥ 200 K	875	0.25	0.43	0	1
> 4 yr College Ed.	1026	0.45	0.50	0	1
Female	989	0.49	0.50	0	1
Max Observations	1026				

and 1990s, with 1960s being the omitted category. C_c is a vector of county fixed effects, included to absorb unobservable differences in transportation mode choices and accessibility across counties in the San Francisco Bay Area. Summary statistics of demographic and location-specific variables are presented in Tables 3 and 4, respectively.

The second vector of explanatory variables in Equation (1) is specified in Equation (3),

which first contains the vector of the preference-over-mode-attribute category variables (*ModeAttrib)* covering respondents' strength of preference for characteristics of transportation modes used on commutes to their primary destination. Respondents rated how important—on a scale of not at all important (1) to very important (5)—each of the following characteristics of transportation options are in their choice of modes: vehicle safety, low travel cost, low hassle, predictable travel time, short travel time, predictable cost, ability to make multiple stops during a trip, minimizing environmental impact, and the ability to interact with individuals outside of one's immediate social circle.[12]

$$\mathbf{P}'_i\theta = \mathbf{ModeAttrib}'_i\pi + \mathbf{BigFivePersonality}'_i\tau + \mathbf{RiskPreferences}'_i\omega \tag{3}$$

[12] The environmental impact and social interaction variables are derived from two questions in the WholeTraveler survey instrument. First, in question 1.5 respondents were asked whether they view minimizing environmental impact and social interaction each as positive or negative attributes. If a respondent chose that those attributes were positive, they were then presented with "minimize environmental impact" and "ability to interact with others (other than close friends or family members)" in question 1.6 for evaluation of importance when determining mode choice. If they indicated they were negative attributes, the respondent was instead presented with "maximize environmental impact" and "not having to interact with other people (other than close friends or family)." Each respondent was shown only one version of the questions. For our analysis, we combine answers to the positive and negative responses to 1.6, coding a response to the negative form as a negative value from 1 to 5, and an answer to the positive version as a positive 1 to 5. Like the other importance variables, a "not applicable" response is coded as a zero.

Table 4
Summary statistics of location-based variables.

	N	Mean	SD	Min	Max
Res. Pop. Density	1026	13.20	15.09	0.01	169.29
P.D. Pop. Density	1026	9.15	12.94	0.02	130.77
Walk Score	1026	54.43	28.49	0	99
Distance to Primary Dest. (mi)	1026	12.50	18.49	0	389.33
Dist. to P.D. ≤ 10mi	1026	0.58	0.50	0	1
Dist. to P.D. (10, 20] mi	1026	0.21	0.41	0	1
Dist. to P.D. (20, 50] mi	1026	0.18	0.39	0	1
Dist. to P.D. > 50mi	1026	0.03	0.16	0	1
Alameda County	1026	0.25	0.44	0	1
Contra Costa County	1026	0.14	0.35	0	1
Marin County	1026	0.03	0.17	0	1
Napa County	1026	0.001	0.10	0	1
San Francisco County	1026	0.16	0.37	0	1
San Mateo County	1026	0.08	0.27	0	1
Santa Clara County	1026	0.23	0.42	0	1
Solano County	1026	0.04	0.19	0	1
Sonoma County	1026	0.06	0.23	0	1
Max Observations	1026				

Table 5
Summary statistics for preference-over-mode-attribute variables.

	N	Mean	SD	Min	Max
Safety	1026	4.25	1.08	0	5
Low Cost	1026	3.80	1.23	0	5
Low Hassle	1026	4.34	0.98	0	5
Short Time	1026	4.32	0.97	0	5
Predict. Time	1026	4.41	0.92	0	5
Predict. Cost	1026	3.66	1.31	0	5
Multiple Stops	1026	3.07	1.51	0	5
Min. Env. Impact	1023	3.34	1.78	−5	5
Social Interaction	984	0.35	2.82	−5	5
Max Observations	1026				

Table 6
Summary statistics for personality and risk variables.

	N	Mean	SD	Min	Max
BFI-10: Extraversion	1026	3.10	0.99	1	5
BFI-10: Agreeableness	1026	3.74	0.70	1.7	5
BFI-10: Conscientiousness	1026	3.97	0.82	1.5	5
BFI-10: Neuroticism	1026	2.66	0.95	1	5
BFI-10: Openness	1026	3.61	0.87	1	5
Risk Averse ($1–20 Reservation)	1026	0.23	0.42	0	1
Risk Averse ($30–40 Reservation)	1026	0.30	0.46	0	1
Risk Neutral ($50 Reservation)	1026	0.29	0.45	0	1
Risk Loving ($60+ Reservation)	1026	0.18	0.39	0	1
Max Observations	1026				

The second and third vectors account for individual personality and risk preferences. The term *BigFive Personality* captures the Big Five personality dimensions (agreeableness, conscientiousness, extraversion, openness, and neuroticism), placing people on a scale of 1–5 for each characteristic. These Big Five personality scales were generated using the 10-question Big Five Personality survey measure (BFI-10). *Risk Preferences* accounts for respondents' preferences over a 50–50 lottery of winning $100 or receiving nothing (a certainty equivalent of $50), and a set amount of money for sure ranging from $1 to $90. We include an indicator bin for high risk aversion (corresponding to a price at which the respondent prefers the sure amount, or reservation price, of $1–$20), moderate risk aversion ($30–$40 reservation price), and risk loving ($60 or higher reservation price), with risk neutrality ($50) serving as the omitted group. Summary statistics for the preference-over-mode-attribute, personality, and risk variables are presented in Tables 5

Table 7
San Francisco Bay Area representation in WholeTraveler survey.

	Female	At Least HS Educ.	At Least Bachelor	HH Inc < $75 K	HH Inc $75–150 K	HH Inc $150–200 K	HH Inc > $200 K
United States	50.8%	87.0%	30.3%	63.2%	25.7%	5.4%	5.7%
Bay area counties							
Alameda	51.0%	87.3%	43.9%	47.4%	29.6%	10.1%	12.9%
Contra Costa	51.2%	89.1%	40.3%	45.7%	28.1%	10.1%	13.6%
Marin	51.1%	93.1%	57.1%	39.2%	27.7%	10.8%	22.4%
Napa	50.3%	83.9%	33%	50.2%	30.7%	8.6%	10.5%
San Francisco	49.0%	87.4%	54.8%	44.5%	26.7%	10.4%	18.4%
San Mateo	50.8%	88.6%	47.1%	38.5%	30.6%	11%	20%
Santa Clara	49.9%	87.1%	49.1%	38.3%	29.7%	12.1%	19.9%
Solano	50.3%	87.5%	25.1%	53.5%	32.5%	7.9%	6.1%
Sonoma	51.0%	87.2%	33.1%	55.0%	29.8%	7.7%	7.4%
Pop. Weighted Bay Area	50.5%	87.8%	44.7%	47.6%	28.5%	9.4%	14.1%
WholeTraveler	**49.1%**	96.8%	82.6%	26.5%	34.1%	14.7%	24.7%
Female WholeTraveler Respondents	100%	98.4%	80.9%	31.5%	35.9%	13.3%	19.4%

This table compares population and demographic characteristics of the WholeTraveler Transportation Behavior Survey to the populations of nine San Francisco Bay Area counties. Population and demographic information for the counties are from the 2016 ACS (see https://www.census.gov/programs-surveys/acs/). Bold statistics indicate t-tests in which we fail to reject the null hypotheses that the WholeTraveler sample has the same mean value as the population-weighted ACS values at the 95% level.

and 6, respectively.[13]

To confirm the robustness of our results and prevent spurious identification of predictors, we test combinations of predictor variable sets (demographics, preference over mode attributes, and personality/risk preferences) to ensure the identified significant predictors present consistently across model specifications.

3.4. How well WholeTraveler respondents represent the Bay Area

Examining how the respondents who constitute our sample represent the entire San Francisco Bay Area population is important for understanding both the context that generates the following results and the resulting implications for interest in and adoption of the emerging transportation technologies and services among the broader regional population. Table 7 compares gender, education levels, and household income population shares for survey respondents with those for the nine Bay Area counties, a population-weighted regional average, and the entire U.S.

Education and income vary across the different samples. While 87% of the nationwide American Community Survey (ACS) sample reported at least a high school education, the WholeTraveler sample reported almost 97% at this level of education. The disparity is even greater for higher education: 30% of the U.S. population reported a college education or higher, but the values were 45% averaged across the Bay Area and 83% for the WholeTraveler sample. Similar trends occur in the income distribution, where only 11% of the nationally sampled households earned greater than $150,000 per year, compared with 24% averaged across Bay Area counties and 39% for the WholeTraveler sample.

One area of parity is the proportion of female respondents. In our survey, we obtained approximately even numbers of responses from male and female participants, paralleling the Bay Area population. In fact, the proportion of men who responded was not statistically significantly different than the proportion of women: we fail to reject the null hypothesis that 50% of our sample are female with 99.9% confidence for both the full cleaned sample of 1026 respondents (confidence interval spans 43.8–54.2%) and the largest analyzed subsample of 826 (confidence interval from 43.5% to 55.0%). For female respondents only, education levels are comparable to the entire sample, and the income distribution exhibits less bias compared with the regional and national distributions. The percentage of respondents reporting household income above $200,000 annually falls from 25% to 19%, with the mass shifting almost entirely to incomes below $75,000.

The demographics observed in the WholeTraveler survey results are consistent with those of previous Bay Area transportation studies, which similarly obtained responses from a very highly educated and high-income group. The 2010–2012 California Household Travel Survey (CHTS) elicited responses from individuals with comparably high education levels (98% at least high school education, 73% at least a bachelor's degree, and 42% a graduate degree), albeit with a more representative income distribution (36% of respondents with household income below $75,000, 33% between $75,000 and $150,000, and 21% over $150,000) in a larger sample of 24,030 individuals from 9719 households (Clewlow, 2016). Surveys of City CarShare users and the 2015 California Millennials Dataset reveal similar patterns (Cervero and Tsai, 2004; Alemi et al., 2018). Therefore, our sample (and in particular the

[13] Appendix D in the supplementary materials presents regression results corresponding to running the model in Equation (1) including only the vector of variables defined in Equation (2). We provide these results to demonstrate the robustness of these factors to the inclusion and omission of Equation (3) regressors.

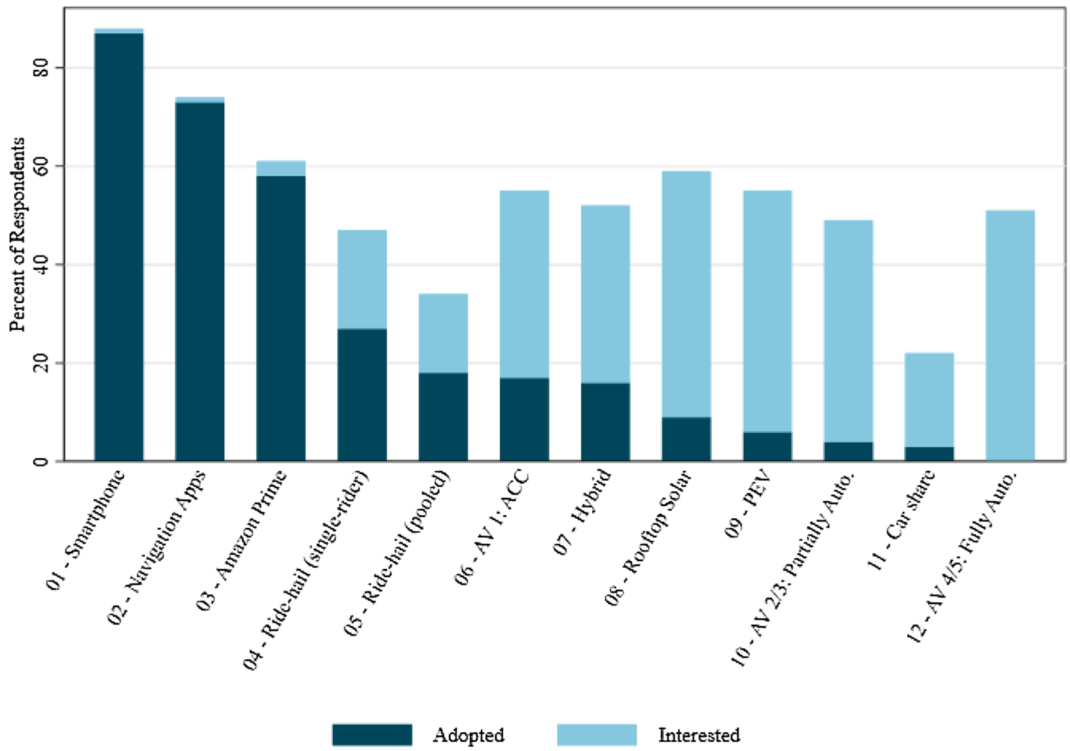

Fig. 2. Adoption and interest in adopting by technology/service.

sample of female respondents) reflects the samples from other regional studies.

4. Results: adoption, interest, and regression estimates

Here we first focus on the results of the WholeTraveler survey and discuss respondents' rates of adoption and interest in future adoption. Then, we present detailed results from our regression analysis.

4.1. Respondents' current adoption and interest in future adoption

Respondents' stated adoption and interest results allow us to understand both the current technology penetration within our sample and the receptiveness to future adoption. Fig. 2 reports the adoption and interest levels covering long-existing, accepted technologies through to more novel transportation modes and services. Interest in future adoption is stacked upon current adoption for each given technology, so each bar corresponds to the potential long-term market diffusion for that technology based on current engagement and perceptions.

Adoption and interest behavior for smartphones, navigation smartphone apps, and Amazon Prime memberships suggests these technologies and services have neared their saturation points within our sample. Respondents exhibit very high adoption rates, with roughly 90% of respondents in the sample owning a smartphone, 72% using navigation or trip-planning apps (e.g., Google Maps, Waze), and 58% having a membership to Amazon Prime. However, additional interest among those who have yet to adopt these technologies is limited. Only 1% of respondents are interested in purchasing a smartphone at a later point, while 3% are interested in starting to use navigation apps, and 6% are interested in adopting Amazon Prime.

Conversely, we observe generally low adoption but high interest for transportation technologies. Ride-hailing services (both single and pooled) exhibit the highest adoption rates (at 27% and 18%, respectively) among the transportation services. Both ride-hailing services receive similar levels of interest in future adoption: 27% express interest in adopting single-rider services, while 20% would consider using pooled ride-hailing. A mere 3% of respondents have adopted car-sharing services, while 19% of those sampled would be interested in eventually adopting car-sharing.

Among electrified vehicle technologies, hybrids (16% ownership rate) have been adopted at nearly three times the rate for PEVs (6%). However, interest in future adoption is higher for PEVs (53%) than for hybrids (42%).

Among AV technologies, ACC displays relatively high levels of adoption (17%). Although this is a new technology, the results suggest that this level of automation is either increasingly ubiquitous in many newer automobiles and/or there is a preference among respondents for vehicles with this technology. In addition, 4% of respondents reported having adopted partially automated vehicles. The list of currently available vehicles with partially automated technology in the level 2–3 range is small. Interest in future adoption

Table 8
Adoption and interest for shared services.

	Adopted			Interested in Adopting		
	Ride-hail Single	Ride-hail Pooled	Car-Sharing	Ride-hail Single	Ride-hail Pooled	Car-Sharing
Demographic variables						
Born 1930s	0.1238	0.1106	0.0230	0.1478	−0.1638**	−0.1290
Born 1940s	−0.0730	−0.0580	0.0020	0.0920	−0.0925	−0.0563
Born 1950s	−0.0055	−0.0455	0.0122	−0.0218	−0.0552	−0.0098
Born 1970s	0.0622	−0.0023	−0.0009	−0.0048	0.0071	−0.1234***
Born 1980s	0.2001***	0.1615***	0.0172	0.1038*	0.0714	−0.1055**
Born 1990s	0.2515***	0.2305***	0.0390	0.1382*	0.0997	−0.0892
Any Child < 8yrs	−0.0526	−0.0605	0.0235	−0.0649	−0.0875*	0.0257
HH Income 75–150 K	0.0341	0.0556	0.0161	0.0311	0.0085	0.0787**
HH Income 150–200 K	0.0654	0.0562	0.0134	−0.0429	0.0086	0.0729
HH Income ≥ 200 K	0.1833***	0.0198	0.0352*	0.0312	0.0011	0.0323
> 4 yr College Ed.	0.0392	−0.0115	0.0163	0.0184	−0.0178	−0.0433
Female	0.0090	−0.0010	−0.0125	−0.0216	−0.0403	−0.0634**
Location-based variables						
Res. Pop. Density	0.0004	0.0024	0.0003	−0.0019	−0.0029*	0.0021
P.D. Pop. Density	−0.0007	0.0003	−0.0004	0.0000	0.0002	−0.0003
Res. Walk Score	0.0005	0.0007	0.0006**	0.0008	0.0016**	0.0008
Dist. to P.D. (10, 20]	−0.0032	0.0050	−0.0046	0.1506***	0.0020	0.0036
Dist. to P.D. (20, 50]	0.0252	−0.0314	0.0112	0.0503	−0.0675	−0.0467
Dist. to P.D. > 50mi	0.0574	0.0107	−0.0078	0.0363	0.0277	0.0108
Preference-over-mode-attribute variables						
Safety	0.0151	−0.0088	0.0049	−0.0033	−0.0077	0.0041
Low Cost	−0.0130	−0.0060	−0.0006	−0.0381*	0.0038	0.0041
Low Hassle	−0.0207	−0.0050	−0.0144*	0.0205	−0.0034	0.0013
Short Time	0.0102	−0.0073	0.0050	0.0445*	0.0103	0.0179
Predict. Time	0.0097	−0.0047	0.0077	−0.0089	−0.0028	−0.0460**
Predict. Cost	0.0076	0.0339***	−0.0000	−0.0007	−0.0029	0.0025
Multiple Stops	−0.0148	−0.0124	0.0035	0.0006	−0.0025	−0.0050
Min. Env. Impact	0.0260***	0.0124*	0.0011	−0.0018	0.0136*	0.0263***
Social Interaction	−0.0058	−0.0003	0.0010	−0.0086	−0.0080	0.0070
Personality and risk variables						
BFI Extraversion	0.0410**	0.0449***	0.0077	0.0252	0.0239	−0.0117
BFI Agreeableness	0.0210	0.0464**	−0.0029	−0.0062	0.0176	0.0356*
BFI Conscientiousness	−0.0143	0.0004	−0.0036	−0.0179	0.0090	−0.0355*
BFI Neuroticism	−0.0020	0.0024	−0.0061	−0.0138	0.0073	0.0033
BFI Openness	0.0151	−0.0028	0.0037	0.0116	−0.0185	0.0340**
Risk Averse ($1–20)	−0.0124	−0.0052	0.0006	−0.0752	−0.0480	−0.0013
Risk Averse ($30–40)	−0.0420	−0.0317	−0.0106	−0.0078	0.0365	0.0606
Risk Loving ($60 +)	−0.0346	−0.0526	−0.0302**	−0.0051	−0.0468	−0.0283
Observations	826	826	826	587	675	804
Observations Y = 1	239	151	22	170	145	167
Adjusted R^2	0.12	0.15	0.01	0.01	0.01	0.05

Results were generated using a linear probability model and include all $\mathbf{X}'_{igc}$ and $\mathbf{P}'_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent regularly uses the tech/service. 'Interested in Adopting' utilizes the subsample that does not regularly use the technology and = 1 when interested in future use of the service. Model results with t-stats, without $\mathbf{P}'_i$ variables, and using logistic regression are located in Appendix D in the supplementary materials.
* p < 0.10 reports statistical significance for robust standard errors.
** p < 0.05 reports statistical significance for robust standard errors.
*** p < 0.01 reports statistical significance for robust standard errors.

of these technologies is strong and similar across all levels of automation: 46% of respondents interested in adopting ACC, 47% interested in partial automation, and a striking 51% of respondents in the sample are interested in adopting fully automated vehicles.

Although these results provide valuable insight into current rates of adoption and interest in future adoption, the regression analysis in the following subsections clarifies the drivers of and barriers to adoption, allowing better interpretation of these patterns. We present results by technology group. In Table 8, we report coefficient estimates for all variables we considered. The significant predictors identified in large part do not vary across model specifications when included in different combinations of variable sets (demographics, preference over mode attributes, and personality/risk preferences). Therefore, for the sake of brevity, in Tables 9 and 10 we only report the variables that show significance in the full model specification.

Table 9
Adoption and interest for electrified vehicle technologies.

	Adopted		Interested in Adopting	
	Hybrid	PEV	Hybrid	PEV
Demographic variables				
Born 1940s	0.0576	0.0078	−0.0557	0.1440*
Born 1950s	0.1626***	−0.0259	0.0475	0.1028
Born 1980s	−0.0940**	−0.0835***	0.0400	0.0614
Born 1990s	−0.0803*	−0.0644**	0.1880***	0.0792
Any Children < 8yrs	−0.0037	0.0569*	−0.0103	−0.0164
HH Income [75 K, 150 K)	0.0545*	−0.0002	0.0213	0.0332
HH Income [150 K, 200 K)	0.0841**	0.0467*	−0.1216*	0.0820
HH Income ≥ 200 K	0.1316***	0.0740**	−0.1583***	0.0928
> 4 yr College Ed.	0.0933***	0.0298	0.0241	0.0974**
Female	0.0382	−0.0102	0.0334	−0.0985**
Location-based variables				
P.D. Pop. Density	−0.0015*	−0.0003	−0.0021	−0.0020
Dist. to P.D. (10, 20]	0.0081	0.0325	0.0099	0.0779*
Preference-over-mode-attribute variables				
Low Cost	0.0036	0.0261***	0.0130	0.0063
Low Hassle	0.0185	−0.0236**	0.0149	0.0137
Short Time	−0.0209	0.0047	0.0414*	0.0412*
Predict. Cost	0.0066	−0.0208**	−0.0423**	−0.0281
Multiple Stops	−0.0071	0.0032	−0.0198	−0.0352***
Min. Env. Impact	−0.0012	0.0055	0.0192*	0.0368***
Personality and risk variables				
BFI Extraversion	−0.0048	−0.0116	−0.0418**	0.0052
BFI Agreeableness	0.0220	0.0096	0.0240	0.0652**
BFI Conscientiousness	−0.0325**	−0.0408***	0.0390	−0.0453*
Risk Averse ($1–20)	0.0026	−0.0421*	−0.0899*	−0.0772
Risk Loving ($60+)	0.0394	−0.0467*	−0.1400**	−0.1561***
Observations	826	826	699	772
Observations Y = 1	127	54	306	426
Adjusted R^2	0.07	0.06	0.05	0.07

Results were generated using a linear probability model and have all $\mathbf{X}'_{igc}$ and $\mathbf{P}'_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent owns the technology. 'Interested in Adopting' utilizes the subsample that does not own the technology and = 1 when interested in future ownership. Constant and coefficients for variables that do not appear statistically significant in any of the models presented in this table (Born 1930s; Born 1970s; Res. Pop. Density; Res. Walk Score; Dist. to P.D. 20-50mi, Dist. to P.D. > 50mi; Risk Averse ($30–40); Safety; Predict. Time; Social Interaction; BFI Neuroticism; BFI Openness) are not reported in this table, but are reported in Appendix D in the supplementary material. Model results with t-stats, without $\mathbf{P}'_i$ variables, and using logistic regression are located in Appendix D in the supplementary material.

* $p < 0.10$ report statistical significance for robust standard errors.
** $p < 0.05$ report statistical significance for robust standard errors.
*** $p < 0.01$ report statistical significance for robust standard errors.

4.2. Predictors of adoption and interest, shared services

Table 8 shows our results for shared services including ride-hailing and car-sharing. The coefficient estimates represent percentage point differences relative to the omitted category. For example, a point estimate of 0.2 for those born in the 1980s regarding adoption of single passenger ride-hailing indicates that this age cohort is associated with a 20 percentage point marginal effect, or in other words is 20 percentage points more likely to have adopted this service relative to the omitted category (in this case, those born in the 1960s). In the following, we highlight what we consider to be the most important results of those presented in the table.

Younger generations are both more likely to have already adopted and to be interested in adopting ride-hailing services: those born in the 1980s and 1990s are 16–25 percentage points more likely to have adopted single-rider and pooled options for services like Uber or Lyft and are 10–14 percentage points more likely to express interest in future adoption of single-rider options than those born in the 1960s. On the other hand, relative youth is associated with somewhat less interest in car-sharing; those born in the 1970s and 1980s are 11–12 percentage points less likely to be interested in adopting car-sharing relative to those born in the 1960s.[14] Having a child under 8 years of age has a sizable and weakly significant negative impact on interest in adopting pooled ride-hailing services (9

[14] Although covariates such as age carry statistically significant coefficients in many cases, model adjusted R-squared values are generally low, suggesting many unobserved factors play key roles in determining technology and service choices. All models in Tables 8–10 have adjusted within R-squared values negligibly different than the overall adjusted R-squared value, suggesting they explain a similar amount of within-county variation as they do overall variation.

Table 10
Adoption and interest for AV technologies.

	Adopted		Interested in Adopting		
	ACC	Partially Autom-ated	ACC	Partially Autom-ated	Fully Autom-ated
Demographic variables					
Born 1940s	0.0271	0.0269	0.0698	0.2159***	0.0491
Born 1950s	−0.0960**	−0.0300	0.0647	0.0615	0.0076
Born 1990s	−0.0706	−0.0115	0.1043	0.2218***	0.2297***
HH Income [75 K, 150 K)	0.0427	0.0089	0.0487	0.0686	0.1083**
HH Income [150 K, 200 K)	0.0513	0.0024	0.1128*	0.0567	0.1186**
HH Income ≥ 200 K	0.1131***	0.0434**	0.1115*	0.1502***	0.1934***
Female	−0.0070	−0.0273*	−0.1576***	−0.1579***	−0.2600***
Preference-over-mode-attribute variables					
Min. Env. Impact	−0.0242***	−0.0122**	0.0188	0.0203*	0.0072
Social Interaction	0.0019	0.0012	−0.0168**	−0.0038	−0.0024
Personality and risk variables					
BFI Agreeableness	0.0448**	0.0048	−0.0017	0.0057	0.0095
Risk Averse ($1–20)	−0.0471	−0.0232	−0.0628	−0.1470***	−0.1218**
Risk Averse ($30–40)	−0.0093	−0.0295	−0.1060**	−0.1003**	−0.0538
Risk Loving ($60 +)	0.1254***	0.0065	−0.1198*	−0.1002*	−0.1405***
Observations	826	826	688	793	823
Observations Y = 1	138	33	329	384	438
Adjusted R^2	0.04	0.01	0.03	0.06	0.11

Results were generated using a linear probability model and have all $\mathbf{X}'_{igc}$ and $\mathbf{P}'_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent owns the technology. 'Interested in Adopting' utilizes the subsample that does not own the technology and = 1 when interested in future ownership. Constant and coefficients for variables that do not appear statistically significant in any of the models presented in this table (Born 1930s; Born 1970s; Born 1980s; Any Children < 8 yrs; > 4 yr College Ed.; Res. Pop. Density; P.D. Pop. Density; Res. Walk Score; Dist. to P.D. 10–20mi; Dist. to P.D. 20–50mi; Dist. to P.D. > 50mi; Safety; Low Cost; Low Hassle; Short Time; Predict. Time; Predict. Cost; Multiple Stops; BFI Extraversion; BFI Conscientiousness; BFI Neuroticism; BFI Openness) are not reported in this table, but are reported in Appendix D in the supplementary material. Model results with t-stats, without $\mathbf{P}'_i$ variables, and using logistic regression are located in Appendix D in the supplementary material.

* $p < 0.10$ report statistical significance for robust standard errors.
** $p < 0.05$ report statistical significance for robust standard errors.
*** $p < 0.01$ report statistical significance for robust standard errors.

percentage points less likely to be interested in adoption relative to those without young children); having a young child has no significant impact on current adoption.

High household income (being in the highest income quartile, above $200,000) is a strong predictor of single-rider ride-hailing adoption (18 percentage point marginal effect) and a weak predictor for car-sharing adoption (4 percentage point marginal effect) as compared to those with household incomes below $75,000. While adoption and interest do not significantly vary across income groups for pooled ride-hailing, a higher importance placed on predictable travel cost is associated with higher adoption rates for pooled ride-hailing (3 percentage point marginal effect).

Individuals who value minimizing environmental impact are slightly more likely to have already adopted ride-hailing services (2–5 percentage point increase for a one standard deviation increase in this score) and similarly more likely to be interested in adopting car-sharing services.[15] Other than age, and income in the case of single-rider ride-hailing, the strongest predictor of ride-hailing adoption is an extravert personality: a one standard deviation increase in Big Five extraversion (roughly 1 point) is associated with a 4 percentage point higher adoption rate for both single-rider and pooled ride-hailing options. Big Five agreeableness has a positive impact with a similar magnitude for pooled ride-hailing services as well.[16] While Big Five dimensions of personality play little role in informing current car-sharing adoption, future interest in car-sharing adoption is positively associated with agreeableness and openness and negatively associated with conscientiousness. In our sample, risk preferences broadly do not predict adoption of or interest in ride-hailing or car-sharing, although risk-loving people have a 3 percentage point lower car-sharing adoption rate.

[15] The variable Min. Env. Impact takes on values between −5 and 5. This variable has a standard deviation of 1.78. Therefore, an increase of one standard deviation in this variable is associated with a 2.2 percentage point increase in the adoption of pooled ride-hailing, and a 4.6 percentage point increase in the adoption of single-rider ride-hailing.

[16] BFI variables take values from 1 to 5 with a standard deviation close to 1. Therefore, the marginal effect (in percentage point) of a one standard deviation change is approximately equivalent to the coefficient estimate itself. However, the difference between someone scoring 1 versus 5 on a given BFI scale means a sizeable difference in adoption probability (i.e., 4 * 4 = 16 percentage point increase in likelihood of adoption for someone rating 1 on the extraversion or agreeableness scale versus someone rating 5).

4.3. Predictors of adoption and interest, electrified vehicle technologies

Table 9 shows results for our electrified vehicle analyses, and we highlight some of the more noteworthy results below. Age mediates adoption of hybrids and PEVs in a meaningful way. Those born in the 1980s and 1990s are 6–9 percentage points less likely to have adopted hybrid or PEV technologies relative to those born in the 1960s, while those born in the 1950s have a 16 percentage point higher likelihood of currently owning a hybrid vehicle relative to the same comparison group. However, when it comes to interest in future adoption, those born in the 1980s are just as likely to be interested in adopting these technologies, and those born in the 1990s are 19 percentage points more likely to be interested in adopting hybrid vehicles than the comparison group. When only demographic and location regressors are included, those born in the 1980s and 1990s are significantly more likely to be interested in adopting PEVs (11–12 percentage points) relative to the omitted category (see Appendix Table D5 in the supplementary materials). This suggests that younger generations are significantly more interested in future PEV adoption than the omitted category, but age is correlated with some of the mode attribute, personality, and risk preference measures included in the primary specification reported here. The only exception to this general trend is that those born in the 1940s appear to have a particularly high interest in adopting PEVs (14 percentage points more likely to be interested than those born in the 1960s).

Higher incomes are monotonically associated with adoption of electrified vehicle technologies, with a roughly 3–5 percentage point step-up increased adoption likelihood when moving between the second, third, and fourth income quartiles. In total, households earning above $200,000 are 13 and 7 percentage points more likely to adopt hybrids and PEVs, respectively, than are households earning under $75,000. There is no significant difference across income groups with respect to interest in adopting PEVs, and the two highest income quartiles are 12–16 percentage points less likely to be interested in adopting hybrids. This suggests that PEVs are roughly equally appealing across income groups, even if those with lower incomes are not yet able to adopt. On the other hand, hybrids appear less compelling to those with higher incomes when they consider future adoption.

Education beyond a bachelor's degree, a factor positively correlated with income, is positively associated with current adoption of hybrids (9 percentage points) and interest in adopting PEVs (10 percentage points). Identifying as female is associated with a 10 percentage point decreased likelihood of interest in future adoption of PEVs, an effect not seen for the more established hybrid vehicle technology. Population density in the census block group of the primary destination is negatively associated with adoption of hybrid vehicles, which conversely suggests that hybrids are relatively more popular in less densely populated areas.

High levels of both risk aversion and risk loving weakly predict a small decreased likelihood of current PEV adoption relative to risk-neutral respondents. In addition, risk-loving preferences are associated with decreased interest in future adoption of both electrified vehicle technologies (-14 percentage points for hybrids and -16 percentage points for PEVs), suggesting either that risk-loving individuals view these technologies as proven and ordinary, or they are drawn toward vehicle characteristics and appearances not typically found in hybrids or PEVs. Those placing high importance on low travel cost are 3 percentage points more likely to adopt PEVs, while high regard for low hassle and predictable costs decreases PEV adoption rates (approximately 2 percentage points). Those placing high value on minimizing environmental impact are more likely to be interested in both technologies. Finally, a higher Big Five conscientiousness score is negatively associated with current adoption of both electrified vehicle technologies and interest in future adoption of PEVs (-3 percentage points for a one standard deviation increase), and a one standard deviation increase in agreeableness is associated with a 7 percentage point increase in interest in PEV adoption.

Finally, commute distance does not appear to be an obstacle to adoption of PEVs for most survey respondents. Strong evidence of commute "range anxiety" would manifest itself as statistically significant, negative effects on all three bins of commute distance, growing in magnitude as the commute distance lengthened. We do not observe such a pattern; instead we find that living more than 50 miles away from one's primary commute destination yields no effect on current adoption statistically distinguishable from zero. The only statistically significant effect found for commute distance is an 8 percentage point increased likelihood of interest in adopting PEVs for those in the 10–20 mile bin relative to those less than 10 miles from their destination. However, this interpretation may need to be tempered by the recognition that the PEV technology category could include responses associated with PHEVs, because this category was not separately defined. It would be expected that PHEVs are associated with less range anxiety than BEVs.

4.4. Automated vehicle technologies

Table 10 shows results for our AV analysis, and selected results are discussed in the following.[17] Younger respondents are more likely to express interest in the relatively more advanced AV technologies: those born in the 1990s have a 22–23 percentage point increased interest in adoption for either partially or fully automated AVs relative to those born in the 1960s. Being born in the 1950s is negatively associated with current adoption of ACC (-10 percentage points relative to those born in the 1960s), although being born in the 1940s is positively associated with adoption interest for partially automated technologies (22 percentage points). Female identification is negatively associated with current adoption of partially automated technologies (-3 percentage points) and interest in future adoption of all automation levels (-16 percentage points for ACC and partial automation, -26 percentage points for full automation).

As expected, these results also highlight the importance of income as a driver for adoption of technologies with a high upfront cost. Income above $200,000 is a strong positive predictor of ownership of a vehicle with either ACC (11 percentage points) or partially automated (4 percentage points) technology. Newer cars are more likely to have these technologies, so this finding may

[17] Fully automated vehicle technology is not included in models of adoption, because this technology is not currently available in the market.

reflect the ability to buy recent model vehicles. Additionally, high household incomes continue to serve as a signal of adoption interest: belonging to the second-highest income quartile confers a 12 percentage point higher interest in fully automated AVs relative to those in the lowest income quartile, while membership in the highest income quartile yields an 11–19 percentage point higher interest in any of the AV technologies.

Finally, individual personality and risk preferences play a role in adoption and interest in future adoption of AV technologies. A one standard deviation increase in the Big Five agreeableness personality dimension is associated with a roughly 3 percentage point higher adoption rate for ACC, while risk lovers exhibit a 13 percentage point greater likelihood of ACC adoption relative to risk-neutral respondents. Focusing on those who are not current adopters, adoption interest is significantly higher for those expressing risk-neutral preferences. Extreme risk aversion is correlated with 12–15 percentage point lower interest in partially and fully automated vehicles, whereas moderate risk aversion is correlated with 10–11 percentage point lower interest in partial automation and ACC. Similarly, risk-loving respondents exhibit interest in all levels of automation that is 10–14 percentage points lower than the interest of risk-neutral individuals who have not yet adopted.[18]

5. Takeaways for adoption and interest

Key finding 1: **Although higher-income people are disproportionately represented among current adopters of most new technologies, low- to middle-income people are just as likely to have adopted *pooled* ride-hailing.** Previous studies have found that electrified (Caperello and Kurani, 2011; Langbroek et al., 2017; Nayum et al., 2016) and automated (Fortune.com, 2018; Investopedia.com, 2018) vehicle technologies as well as ride-hailing use (Alemi et al., 2018; Dias et al., 2017; Smith, 2016) all tend to be associated with relatively higher incomes. In contrast, while our study confirms that those in the highest income group are significantly more likely to have adopted almost all of the analyzed technologies and services, we find one important exception: pooled ride-hailing. We find that all income groups are similarly likely to have adopted or be interested in adopting pooled ride-hailing. Ride-hailing does not include high upfront costs, as many other options do, and pooled ride-hailing costs less than single-rider ride-hailing. Shared pool service may therefore help lower- and middle-income people by giving them more flexibility and making it easier for them to engage in and access the benefits of these emerging transportation technologies and services.

Key finding 2: **The gap between current adoption and future adoption interest suggests younger generations have the potential to fuel automated and electrified vehicle market penetration, just as they are currently fueling ride-hailing uptake, if given the means to do so.** Those born in the 1980s and 1990s are 16–25 percentage points more likely to have already adopted either single-rider or pooled ride-hailing services in comparison to those born in the 1960s. Average adoption of single and pooled ride-hailing for those born in the 1960s is 21% and 12%, respectively. Therefore, those born in the 1980s and 1990s are about twice as likely or more to have adopted ride-hailing than the omitted category. This result is consistent with past research (Alemi et al., 2018; Clewlow and Mishra, 2017; Dias et al., 2017; Kooti et al., 2017; Smith, 2016). However, we find that, while these cohorts exhibit 6–9 percentage point lower current adoption rates for electrified vehicles, they are just as likely or more likely to be interested in future adoption of electrified vehicle technologies relative to older generations. This indicates that future interest in electrified technologies is not as highly concentrated in older generations as has been found with regard to current ownership (e.g., Langbroek et al., 2017). In addition, those born in the 1990s exhibit rates of interest in future adoption of higher levels of automation that are 22–23 percentage points higher than exhibited by those born in the 1960s. Consistent with the mixed findings on age shown in other studies of AV technologies (Abraham et al,. 2016; Haboucha et al., 2017; Bansal and Kockelman, 2018), we show this strong effect associated with interest in adoption by the youngest cohorts in the study, but also relatively higher interest in PEV and partially automated vehicle technologies associated with being born in the 1940s relative to the 1960s.

Key finding 3: **A longer commute does not appear to be a barrier for high interest in PEV adoption.** Those with daily commutes of greater than 10 miles are as likely to have adopted PEVs, and are 8 percentage points more likely (in the case of those with commutes between 10 and 20 miles) to be interested in future adoption of PEVs, compared with those who have commutes of less than 10 miles. This is perhaps because a longer commute could provide a faster return on investment via greater fuel-cost savings. At the same time, the fixed nature of commuting distances may mitigate what is traditionally thought of as “range anxiety” (Franke et al., 2012; Neubauer and Wood, 2014), even if the commute is relatively long, since PEV ranges may already be seen as sufficient to satisfy the needs of many Bay Area commuters. However, this interpretation may need to be tempered by the recognition that the PEV technology category could include responses associated with PHEVs, because this category was not separately defined within the survey. PHEVs would likely be associated with less range anxiety than BEVs, which might be contributing to this result.

Key finding 4: **Women are less likely to adopt and/or be interested in adopting most new transportation technologies, with the exception of ride-hailing.** In particular, women are 3 percentage points less likely to have adopted partially automated vehicles, 16–26 percentage points less likely to be interested in adopting vehicles with any level of automation, 10 percentage points less likely to be interested in adopting PEVs, and 6 percentage points less likely to be interested in adopting car-sharing. Similar patterns have been found in other studies as well (Langbroek et al., 2017; Plötz et al., 2014; Payre et al., 2014; Investopedia.com, 2018). On the other hand, we find that female identification is associated with no significant difference in current use of or future interest in ride-hailing. This finding is consistent with Smith (2016), whereas Alemi et al. (2018) and Kooti et al. (2017) both found

[18] The high relative interest among risk-neutral respondents may be due in part to strong correlations with high levels of both education and income within the subsample: 34% of risk-neutral respondents have household incomes above $200,000, while 85% have at least a bachelor’s degree and 46% additional education beyond a bachelor’s.

that women were actually more likely to use ride-hailing services. In any case, designing and/or promoting emerging transportation technologies to cater to women's needs and wants could increase market potential and substantially impact overall transportation energy use. Ride-hailing may provide an opportunity to better understand what types of transportation innovations are more appealing to women.

Key finding 5: Much about transportation technology adoption remains to be explained. Although we include many explanatory variables—particularly those associated with mode attribute preferences, personality, and risk characteristics in addition to the more traditional demographic and locational regressors—our variables only explain around 5–15% of adoption (based on adjusted R-squared values). Our results help identify important characteristics that inform our understanding of adoption, and the results are sometimes consistent with and sometimes contradict previous findings. For example, in contrast to what we might expect based on previous studies (Skippon and Garwood, 2011), we find that PEV ownership is not positively correlated with agreeableness and openness, and is significantly negatively associated with conscientiousness. Also in contrast to previous findings (Haboucha et al., 2017), we find that current adoption of AV technologies tends to be negatively correlated with wanting to minimize environmental damage, although the result for future adoption interest becomes less clear. On the other hand, we find results somewhat consistent with Hulse et al. (2018) in that risk-loving individuals seem relatively uniformly uninterested in all three levels of automation relative to risk-neutral individuals, but risk-loving preferences are positively associated with current ACC adoption. The fact that both risk-averse and risk-loving individuals tend to be less interested in future adoption of all AV technologies relative to risk-neutral individuals is a novel and interesting finding, but it poses more questions than it answers. All of this suggests that additional analysis is necessary. For example, because many characteristics are related (e.g., age and income), cluster analysis can combine these to identify similar types of people who may have similar adoption patterns. Conversely, such characteristics may need to be further separated through interactions. For example, openness to new technology may be moderated by age or risk preferences. We intend to explore these topics in future research.

6. Conclusions

The transportation technologies and services we examine have great potential to change future energy use and sustainable mobility patterns. The impact of these technologies will depend largely on their adoption by users in key geographies. The results of our analysis provide information about the characteristics of current users as well as the potential drivers of adoption. These insights contribute to ongoing efforts to plan the efficient transportation systems of the future.

The relative value of some new transportation technologies may be driving adoption already. For example, low- to middle-income people may benefit from pooled ride-hailing options just as much as higher-income people, and people with long commutes may benefit from the low per-mile cost of PEVs. Our results also suggest that market penetration may be increased by helping already-interested groups access the resources necessary for adoption; in particular, young people demonstrate great interest in AV technologies and are just as interested as most older generations in adopting PEVs but are much less likely to have already done so, which suggests they may need additional resources to enable them to move to adoption. In addition, women represent a large potential driver of market expansion for new transportation technologies. Although women are currently less likely to adopt or be interested in adopting PEV and AV technologies, designing or marketing these technologies with women's preferences in mind might help overcome this inequality. Insights might be gained from ride-hailing adoption patterns, as women appear to be just as open to ride-hailing services in our sample as men.

While our study is specific in its geographic scope (the San Francisco Bay Area) and has disproportionately high education and income of respondents even within the Bay Area, we feel it can provide valuable insights into transportation development in other regions as well. The analysis of associations reflected in this survey should reflect many urban environments where these technologies are well developed. The results should be carefully examined for applicability when used in new contexts.

In future research, we will analyze the survey results in more depth and address other themes related to new transportation technologies. Specific approaches will include factor analysis that defines groups of people with similar characteristics to attempt to eliminate the correlation between our variables, and factorial interaction analysis to separate characteristics into smaller groups of people. We will also delve deeper into the effects of having children on transportation choices, estimate how future price reductions may impact ride-hailing, and examine whether ride-hailing replaces public transit use or enables it by facilitating access to public transit hubs.

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Appendix A. Supplementary material

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