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Are californians willing to use shared automated vehicles (SAV) & renounce existing vehicles? An empirical analysis of factors determining SAV use & household vehicle ownership

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ABSTRACT

Future smart transportation systems are anticipated to integrate automation and sharing of vehicles. Responding to the expected changes in shared mobility services, this study used representative data from over 4100 households in California to examine consumers' affinity to use shared automated vehicles (SAV) and their willingness to renounce existing vehicle(s) in the presence of SAVs - two interlinked factors determining the long-term success of SAVs. Results of the study showed that around 50 % of the households reported willingness to use SAVs but unwillingness to renounce their current vehicle(s). As innovators, another 9.1 % stated their affinity to use SAVs and renounce existing vehicle(s) but with heterogeneity across vehicle ownership levels. Random parameter logit models revealed that households using existing vehicles to work for ride hailing companies were significantly less likely to use SAVs and renounce their current vehicle(s). Households who had high awareness about self-driving cars, possessed full electric vehicles, used sustainable work travel modes (bike, e-bike, bike-share), had greater number of leased vehicles and ridesharing trips were more likely to use SAVs and renounce current vehicle(s). Significant unobserved preference heterogeneity was recorded in the effects of behavioral and sociodemographic correlates. The study contributes by shedding new light on the behavioral determinants of the vehicle ownership impacts of SAVs. We discuss policy implications of the key findings.

1. Introduction

The future transportation system is anticipated to integrate automation and sharing of vehicles with the potential to majorly disrupt urban mobility systems and pave the way towards smart and sustainable cities (Wang et al., 2018; Marletto, 2019; Golbabaei et al., 2020; Gurumurthy and Kockelman, 2020; Khattak et al., 2020; Shaheen et al., 2020). On the one hand, the rapid advancements in technology have paved the way to achieve the vision of smart cities and automated driving systems (Marletto, 2019; Nastjuk et al., 2020). Defined as systems to assist or replace humans, eventually rendering human driver input unnecessary, Automated Vehicles (AVs) have the potential to greatly revolutionize transportation systems with tremendous foreseen impacts related to sustainability, road safety, travel behavior, transport supply, economy, and the environment (Fagnant and Kockelman, 2015; Narayanan et al., 2020). On the other hand, the emergence of shared mobility services, including car sharing (e.g., Zipcar) and on-demand ride services (e.g., Uber), has led to more flexible, sustainable, accessible, and convenient mobility services (Shaheen et al., 2015; Shaheen et al., 2021).

Recent simulation-based and empirical evidence highlights the huge economic, social, and environmental benefits of shared mobility services through enabling travel cost savings, mitigating congestion, reducing vehicle usage, ownership, and vehicle miles traveled (VMT), and ultimately lowering greenhouse gas emissions (Santi et al., 2014; Li et al., 2016; Yu et al., 2017; Shaheen, 2018; Vazifeh et al., 2018; Shaheen and Cohen, 2019; Yan et al., 2020; Khan and Shaheen, 2021). Importantly, the two emerging technologies of shared mobility and automated vehicles are complementary. Automated vehicle/driving systems can accelerate the deployment of and remove the inherent barriers in the existing non-automated shared mobility services including higher costs, congestion, and individuals' need to travel to (carsharing) stations to

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avail vehicles. Shared mobility systems, in turn, can enhance the financial viability of deploying AV systems considering the high initial costs of owning automated vehicles.

This natural synergy is realized and reflected not only by the huge investments made by transportation network companies (e.g., Uber, Lyft) in developing SAV systems but also through the change of business models for traditional vehicle manufacturers. Several major manufacturers including Ford and Volkswagen envision a fully automated vehicle system for on-demand mobility in the next couple of years (The Ford Company, 2016; O'Kane, 2018). This synergistic interaction between shared mobility and automated vehicle technologies has led to otherwise unusual partnerships between transportation network companies and traditional vehicle manufacturers. Both Toyota and Daimler have partnered with Uber for running fully-automated Mercedes-Benz and Toyota's Guardian vehicles on Uber's network (Daimler, 2017; Toyota, 2018). In summary, when combined, shared mobility services and AVs can interact synergistically to transform transportation systems and tackle existing and future challenges more sustainably and equitably.[1]

As the technological development of SAVs is progressing, it is important to understand the user adoption of SAVs and the potential impacts of SAVs on household vehicle ownership. The objective of this study is to examine the determinants of two key components critical to the long-term success of SAVs: users' affinity to use SAVs and their willingness to renounce existing vehicle(s) in the presence of SAVs. To realize the safety, mobility, and environmental impacts of SAVs more fully, users must not only be willing to use the disruptive technology but also relinquish their existing vehicle(s). As discussed in the next section, existing literature has largely focused on examining consumers' affinity towards SAVs (Nazari et al., 2018; Stoiber et al., 2019; Long and Axsen, 2022). Literature on the potential SAV impacts is largely based on simulation methods to quantify the "vehicle replacement" potential of SAVs under hypothetical SAV fleet operations (Narayanan et al., 2020). Empirical evidence on the impacts of SAVs on household vehicle ownership is scarce – with existing evidence limited by the use of focus groups (e.g., university population), focus on analyzing the vehicle ownership component in isolation, and examining only sociodemographic determinants of SAV impacts on future vehicle ownership with limited evidence on the behavioral and/or policy related factors (Menon et al., 2019). To our knowledge, no study has simultaneously examined consumers' interlinked affinity towards using SAVs and renouncing their existing vehicle(s) in the presence of SAVs. To better understand the mechanisms influencing households' affinity to use SAVs and renounce/relinquish their existing vehicles, a broad spectrum of policy-sensitive factors (beyond sociodemographic factors) is analyzed, including awareness of self-driving technology, attitudes, and opinions about AVs, sustainability-oriented attitudinal predispositions, experiences with existing ridesharing and car-sharing services, vehicle use patterns, travel behavior, and work-related travel. We account for the important methodological concern of unobserved heterogeneity in discrete outcome predictive framework. The analysis is conducted at the household level to better capture the multiple levels of interlinked behavioral and demographic factors that can influence the households' affinity towards using SAVs and renouncing existing conventional vehicles. Throughout the rest of the paper, the term "sharing" refers to the use of shared automated vehicles in a sequential manner (e.g., similar to Uber, Lyft) as opposed to the simultaneous use of the automated vehicle by different users at the same time (e.g., Uber Pool).

The paper is organized as follows. We present a synthesis of the existing literature in Section 2 along with identifying key research gaps. Section 3 presents the overall conceptual model with a focus on examining both users' affinity towards SAVs and their willingness to renounce existing vehicle(s). Data and modeling framework are also presented in Section 3. Section 4 presents the empirical results followed by a discussion/synthesis of the new results in Section 5 along with highlighting the policy implications and study limitations. We conclude the study in Section 6 by summarizing the key conclusions.

2. Literature review

Compared to individual AVs, the growing interest in SAVs has recently led to numerous research studies examining the impacts of SAVs on transport systems related to traffic safety (Shaheen and Bouzaghrane, 2019; Taeihagh and Lim, 2019), travel behavior (Eluru and Choudhury, 2019; Soteropoulos et al., 2019; Wali and Khattak, 2022), built environment (Wali and Khattak, 2022), transport supply (Narayanan et al., 2020), land use (Soteropoulos et al., 2019), economy, and governance (Narayanan et al., 2020). Related to the travel behavior impacts, SAVs have the potential to alter mode choice, vehicle occupancy, trip length, induced demand, and vehicle ownership (Eluru and Choudhury, 2019; Soteropoulos et al., 2019; Narayanan et al., 2020; Wali and Khattak, 2022) – with most previous studies focused on quantifying the mode choice and vehicle occupancy/trip duration related impacts of SAVs (Liu et al., 2017; Bansal and Kockelman, 2018; Bösch et al., 2018; Moreno et al., 2018). Likewise, consumers' affinity for using SAVs is relatively more examined (Krueger et al., 2016; Haboucha et al., 2017; Nazari et al., 2018; Stoiber et al., 2019). The empirical evidence on the simultaneous impacts of SAVs on vehicle ownership and use patterns is scarce. Little is known about households' affinity to renounce/relinquish traditional/conventional vehicles in the era of shared automated vehicles.

Related to SAV use, the issue of the minimum fleet problem or the potential of on-demand urban mobility in 'replacing' conventional vehicles on the road has received more attention. It was found that circulating taxis can be reduced by 40 % by developing and implementing a 'vehicle-sharing network' on 150 Million taxi trips in NYC (Vazifeh et al., 2018). Likewise, a broad spectrum of studies has simulated SAV fleet operations to quantify the vehicle replacement/displacement potential of SAVs under hypothetical scenarios (Narayanan et al., 2020) – with substantial variations ranging from as low as 1.18 to as high as 10 times the number of cars needed for self-owned personal-vehicle travel (Fagnant and Kockelman, 2014; Lang et al., 2018). Such estimates are useful from a policy and planning standpoint. However, a key premise upon which these simulation-based estimates are based relates to the assumptions about individuals' acceptance of SAV adoption and their affinity to renounce their existing personal vehicles. This is a major gap in the literature since the success of transportation systems driven by SAVs depends on the penetration as well as households' affinity to renounce their existing vehicles in the presence of shared automated vehicles. Only one study to our knowledge has empirically examined the impacts of SAVs on household vehicle

[1] The COVID-19 pandemic has disrupted the world with impacts on transportation systems. Studies have shown that the use of transit, ride hailing, and ridesharing decreased as the severity of the pandemic increased (Shamshiripour et al., 2020; Mashrur et al., 2022; Zhang et al., 2022). Likely, COVID-19 experiences may further stimulate the development and adoption of AVs but the shift from shared mobility that was observed during the pandemic may continue to hinder SAV promotion for a foreseeable future (Shamshiripour et al., 2020; Wali and Khattak, 2022). However, the impacts of COVID-19 on travel patterns and behaviors will likely not sustain as individuals' travel and preferences find an equilibrium over the long term (Bhat, 2020).

ownership[2] (Menon et al., 2019). The study provided unique exploratory insights by analyzing survey responses of 1214 individuals containing students, faculty, and staff at the University of South Florida and members of the American Automobile Association (AAA) South. Only 7.3 % of the respondents indicated that they consider their likelihood of relinquishing a household vehicle in the presence of SAVs as extremely likely. The study found that millennials, graduate degree holders, and males were more likely to relinquish their vehicles in the presence of SAVs (Menon et al., 2019). Contrarily, respondents who traveled >90 min per day and belonged to households with only one licensed driver were less likely to relinquish their existing vehicles (Menon et al., 2019).

Key gaps remain in our understanding of the potential impacts of SAVs on vehicle ownership. First, only the vehicle ownership component of SAV impacts was empirically analyzed in the literature (Menon et al., 2019). However, the willingness of individuals to renounce/relinquish existing vehicles could be related to their affinity for using SAVs. In other words, a sizeable portion of the population may be willing to use SAVs but not yet ready to renounce their existing vehicles. To this end, an integrated empirical analysis considering both users' affinity towards using SAVs and their willingness to renounce conventional vehicles can provide richer behavioral insights. Second, the focus has been more on sociodemographic determinants of the potential impacts of SAVs on future vehicle ownership. However, household vehicle relinquishment decisions in the presence of SAVs represent a highly complex decision-making process and can be significantly influenced by a host of interlinked policy-sensitive factors both at the individual and household levels. Third, existing literature on this topic is limited to specific focus groups (e.g., university population/institutional members) with smaller sample sizes. Empirical evidence on the determinants of SAV use and existing vehicle renouncement components based on diverse samples does not exist.

3. Methodology

3.1. Conceptual framework

To achieve the study objectives outlined above, the present paper harnesses unique data from the 2019 California Vehicle Survey (CVS) (TSDC, 2019; Fowler et al., 2020). CVS evaluates consumer preferences for vehicles (including different vehicle technologies and fuel types) for residential and commercial light-duty fleet owners in California. Conducted periodically over the past two decades, CVS is a unique source of detailed information on shifting transport trends and consumer preferences collected using consistent and standardized procedures (Fowler et al., 2020). These data are used by the California Energy Commission to predict transportation needs in California and inform policy (TSDC, 2019; Fowler et al., 2020; Wali et al., 2021).

Building upon the key gaps in the literature, Fig. 1 presents a simplified conceptual model of households' affinity towards using on-demand SAVs and their willingness to renounce/relinquish existing conventional vehicles. Both SAV use and user willingness to renounce existing vehicles are imperative to realize the full potential of SAVs and at the same time represent a complex behavioral decision-making process. On the one hand, with SAVs in the mainstream in the future, a (admittedly small) segment of the population may not be only willing to use on-demand SAV services but also renounce their existing vehicles. From a vehicle ownership standpoint, this segment can include individuals/households who, instead of preference, own vehicles at present out of compulsion. Thus, they could be willing to use safer and more reliable on-demand SAV services and relinquish their existing vehicles. As one example, in the context of existing mobility-on-demand services (including, ride-sourcing and ridesharing), evidence suggests that the increase in the popularity of car- and ride-sourcing/ride-sharing services are contributing to a decrease in personal vehicle ownership (Martin and Shaheen, 2011; Namazu and Dowlatabadi, 2018). On the other hand, a segment of the population may be willing to use on-demand SAVs whenever needed but not willing to relinquish their current vehicles. This segment, likely containing a significant portion of the population, could include early adopters of the SAV technology, but who otherwise own vehicles at present out of their preference, rather than necessity. If only future vehicle ownership decisions were to be analyzed, a significant portion of the population who are willing to use SAVs but unwilling to renounce existing vehicle(s) would be overlooked. An integrated analysis that considers both components can provide new behavioral and policy-relevant insights given the interdependence between SAV use and user willingness to renounce existing conventional vehicles.

We also postulate that the households' affinity towards using SAVs and willingness to renounce their existing vehicle(s) can be a function of existing vehicle ownership. Single-vehicle households may be willing to use SAVs but relatively less willing to renounce their only current vehicle. Keeping in view this conceptual model, we explore and model the factors that can help understand the characteristics of the distinct population segments concerning their affinity to use SAVs and their willingness to renounce existing vehicles in the presence of SAVs (Fig. 1). These exogenous factors include awareness of and attitudes towards self-driving vehicles, experience with existing sustainable travel modes, vehicle ownership and use patterns, and sociodemographic characteristics. We account for the important methodological concern of unobserved heterogeneity. That is, unobserved latent variables, the effects of which can manifest through observed exogenous variables, are controlled for in analyzing the relationships between key correlates and households' affinity to use SAVs and relinquish their existing vehicles (Fig. 1).

3.2. Data source

The most recent 2019 California Vehicle Survey (CVS) includes several questions about consumer preferences for vehicle automation and other emerging technologies (Fowler et al., 2020). The 2019 CVS survey consists of multiple modules including a residential survey questionnaire, a commercial vehicle survey, and residential and commercial zero-emission vehicle (ZEV) surveys. The present study uses the survey module for the residential light-duty vehicle sector. We analyzed data streams including the main residential survey, residential current vehicles survey, and residential person survey - providing detailed information at the household, person, and vehicle level.

The 2019 CVS survey included stated and revealed preference survey components eliciting responses from residential light-duty vehicle sector consumers in California. A multi-method sampling approach was used for collecting survey data with a combination of address-based and online address-based sampling implemented through a market research panel (TSDC, 2019; Fowler et al., 2020). Sample stratification was done by the six regions across California (TSDC, 2019), including San Francisco, Sacramento, Central Valley, Los Angeles, San Diego, and the Rest of California (TSDC, 2019). A rigorous three-phase process was used to design the survey questionnaires. Initially, a draft survey questionnaire was designed by the research team based on a review of previous CVS surveys. This draft survey design was followed by a series of nine focus group sessions for residential fleet vehicle owners in four cities across different regions in California. Survey pretests were conducted in

[2] Potential vehicle ownership impacts of other mobility configurations including private automated vehicles or traditional shared mobility services are not the focus of this study. A separate stream of literature has empirically analyzed the personal vehicle ownership impacts of private automated vehicles (as opposed to shared automated vehicles) (Zhang et al., 2018) and traditional (non-automated) ridesharing (Yu et al., 2017; Gong et al., 2023) and carsharing services (Martin and Shaheen, 2011; Ter Schure et al., 2012; Stasko et al., 2013; Zhou et al., 2020). As discussed, the present study is positioned to empirically examine consumers' interlinked affinity towards using SAVs and renouncing their existing vehicle(s) in the presence of SAVs.

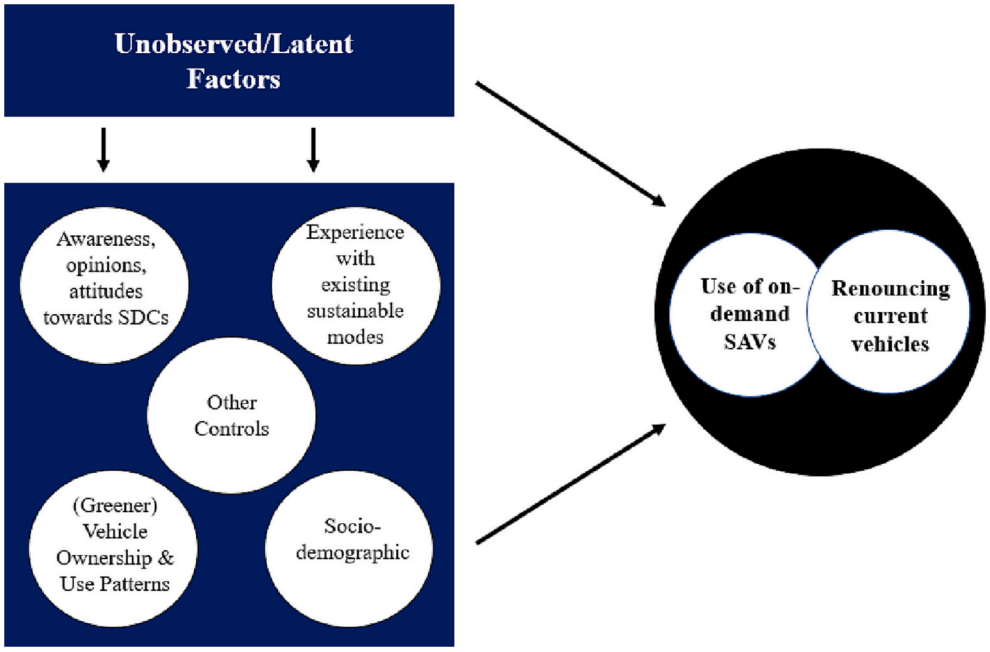

Fig. 1. Heterogeneity-based modeling framework.

residential market segments following the focus groups. Finally, the research team revised the survey questionnaire and instrument after each phase before arriving at the final design. For more details about the survey methodology, please see (TSDC, 2019, Fowler et al., 2020). The survey data were collected through a public-facing HTML-based web instrument. The webpage provided information about the CVS including contact information and frequently asked questions.

Relevant to the conceptual model shown in Fig. 1, the main residential survey asks respondents about the use of on-demand SAVs and their willingness to renounce existing vehicles. The key question asks, "*If on-demand driverless ride-hailing services were widely available today, which of the following best describes how your household would use these services and how it would impact the vehicle(s) you currently own*?" - with three possible options (TSDC, 2019):

(1) Keep current vehicles and do not use any driverless services (*referred to as baseline in the rest of the paper*)
(2) Keep current vehicles, but also use these driverless services whenever needed or convenient (*referred to as alternative 1*)
(3) Get rid of one (or more) household vehicles and use driverless ride-hailing services instead (*referred to as alternative 2*)

The discrete mutually exclusive responses to this question are used as the dependent variable in this study. A household serves as the unit of analysis in the present study since the households' affinity towards using SAVs and renouncing conventional vehicles in the presence of SAVs was reported by the head of the household. To assemble detailed information on policy-sensitive factors, we merged the main residential survey file with the current vehicle survey and residential person survey files. In doing so, new vehicle- and person-related independent variables conveyed below were created at the household level. Fig. 2 summarizes the household-level independent variables considered in this study, including awareness about self-driving technology, opinions and attitudes towards self-driving technology, experiences with existing ride- and car-sharing services, sustainable travel behavior, work travel, vehicle (fuel) types, vehicle ownership and use patterns, and detailed sociodemographic data (Fig. 2). The final merged and cleaned data contain 4136 households representing 9552 individuals and 8049

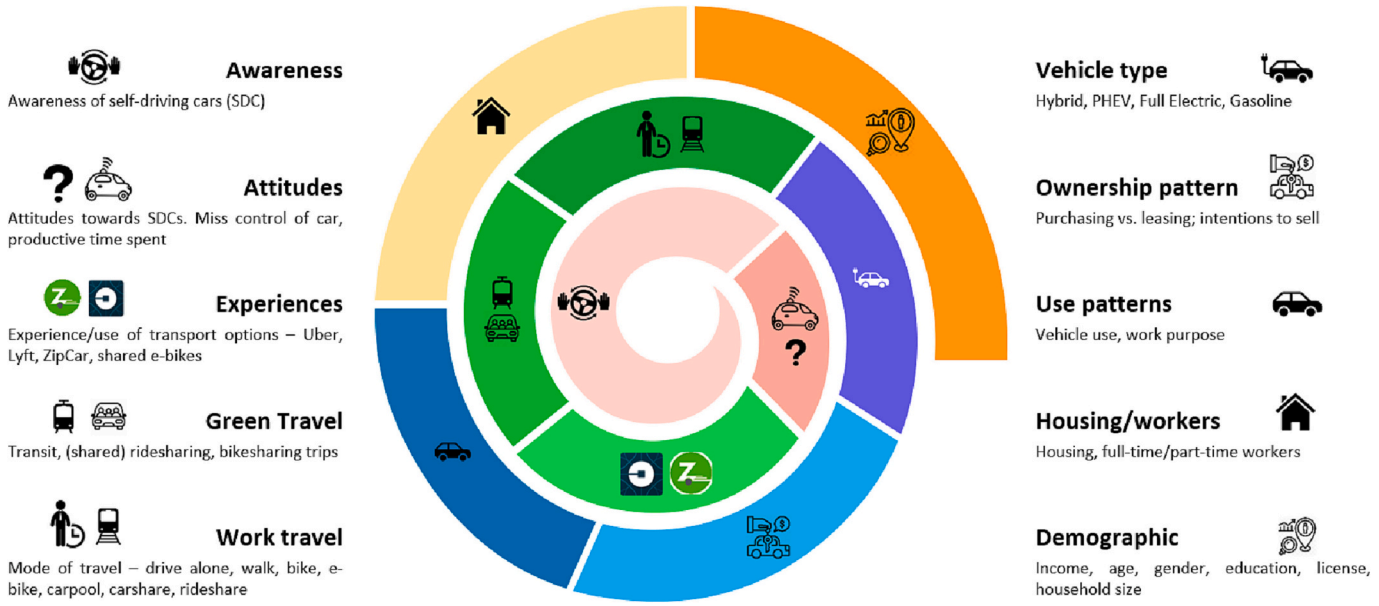

Fig. 2. Data elements considered in the current study.

vehicles.[3]

3.3. Heterogeneity-based discrete outcome modeling

To model a household's affinity to use SAVs and their willingness to renounce existing vehicles, a utility maximization-based conditional logit framework is used, given the discrete multinomial nature of the response outcome (see earlier section and Fig. 1). From here onwards, the three alternatives: "not using SAVs and keeping existing vehicles", "using SAVs and keeping existing vehicles", and "using SAVs and renouncing their existing vehicles", are referred to as *baseline*, *alternative 1*, and *alternative 2*, respectively.

A utility function is postulated to measure the extent to which a household's goals are achieved due to their preferences related to using SAVs and their willingness to renounce their existing vehicles (choosing one of the three alternatives defined earlier). In our case, a household is assumed to have preferences realized over a set of alternatives (for a detailed exposition of the modeling framework presented here, see Train (2009)):

$$\begin{aligned} U_{ALTERNATIVE\ 1} &= \beta_1' X_{i1} + \gamma_1' Z_i + \varepsilon_{i1} \\ &\cdots \\ U_{ALTERNATIVE\ j} &= \beta_J' X_{iJ} + \gamma_J' Z_i + \varepsilon_{ij} \\ U_{ALTERNATIVE\ j} &= \beta_J' X_{iJ} + \gamma_J' Z_i + \varepsilon_{ij} \end{aligned} \tag{1}$$

In the expanded exposition shown in Eq. (1), X_{iJ} denotes the attributes of alternative j faced by household i, where attributes/explanatory variables typically differ across alternatives and individuals/households. Z_i is used to denote the alternative invariant characteristics, i.e., household-specific characteristics. The individual heterogeneity terms (disturbances) in Eq. (1) are assumed to be independently and identically distributed (IID) with extreme value distribution, $F_{\varepsilon_J} = exp(-exp(-\varepsilon_J))$. Using this cumulative distribution function, the closed-form expression for choice probabilities is (Train, 2009):

$$\text{Prob}[\text{Choice/Alternative } j] = Prob[U_j > U_k], \forall k \neq j$$
$$\frac{exp\left(\beta' X_{ij} + \gamma_j' Z_i\right)}{\sum_{m=1}^{J} exp\left(\beta' X_{im} + \gamma_m' Z_i\right)}, m = 1, \ldots, j \tag{2}$$

where, i denotes the households, and j and m index the alternatives/choices. Once the utility functions of the three alternatives are estimated, the probability that a household selects a particular alternative conditional on X and Z can be calculated. However, the very stringent IID assumption on the individual heterogeneity terms leads to the Independence of Irrelevant Alternatives (IIA) feature that characterizes the modeling framework (Train, 2009), and typically does not represent the reality of real-world decision-making processes. Also, from a behavioral standpoint, the conditional logit model shown above assumes homogeneity in the effects of exogeneous variables on the probability of households choosing different alternatives (Train, 2009). That is, the estimates of β and γ associated with choice-varying and choice-invariant independent variables are a priori assumed to be fixed/constant – leading to a constrained behavioral model for SAV use and household willingness to renounce existing vehicles.

To this end, we expand the formulation to include random parameters that capture unobserved preference heterogeneity across the households. Precisely, the exposition in Eq. (2) is expanded to include individual household-specific random parameters (for intercept as well as independent variables) as (Train, 2009):

[3] We examined the general trends in demographic, housing, digital access, and transportation related factors for the reference area (CA) to determine how it compared with nationwide trends (https://www.census.gov/quickfacts/fact/table/CA,US#). Regarding general demographic factors, the percent change in population between 2010 and 2019 in California was 6.1 % (vs. 6.3 % nationwide) and percent population under 18 and over 65 years was 22.5 % and 14.8 %, respectively (22.3 % and 16.5 % nationwide). California is racially more diverse – percent white alone and percent foreign born individuals is 71.9 % and 26.8 %, respectively (76.3 % and 13.6 % nationwide). In terms of education, 33.9 % of individuals in CA aged 25+ have a bachelor's degree which is slightly higher than the percentage (32.1 %) nationwide. The average household size was 2.95 (compared to 2.62 nationwide). Related to housing and transportation, the mean owner-occupied housing unit rate was higher nationally (64 % vs. 54.8 % in CA), whereas the mean travel time to work was somewhat similar (29.8 min in CA vs. 26.9 min nationwide). Compared to the nation, the percent of households with a broadband internet subscription was slightly higher in California (93 % vs. 90.3 % nationwide). While California is unique in certain aspects, the general trends discussed above when combined with the great variation in demographics of survey participants can enable readers to infer broader similarity patterns between the survey region and other areas in United States.

$$\text{Prob[Choice/Alternative j]} = \frac{exp\left(\alpha_{ji} + \gamma_{ji}^{'} Z_i\right)}{\sum_{m=1}^{J} exp(\alpha_{mi} + \gamma_{mi}^{'} Z_i)}, m = 1, \ldots, j \quad (3)$$

Since a household serves as a unit of analysis in the present study, and there are no alternative-specific independent variables, we drop the exposition for alternative-varying attributes in Eq. (3). α_{Ji} represents the alternative- and household-specific random intercepts. The alternative-specific random parameters (and intercepts) are formulated as (Behnood et al., 2022):

$$\begin{aligned} \gamma_{ji} &= \gamma_j + \sigma_j \delta_{ij} \\ \alpha_{ji} &= \alpha_j + \sigma_j \delta_{ij} \end{aligned} \quad (4)$$

where, γ_j and α_j indicate the fixed estimated population means for the alternative-specific coefficients and constant terms; δ_{ij} is the individual household-specific heterogeneity, characterized by a mean zero and standard deviation one, and σ_j is the estimable standard deviation of the distributions of household- and alternative-specific coefficients and constant terms, γ_{ji} and α_{ji}, around alternative-specific γ_j and α_j. Following Eq. (4), a distribution must be specified for each (random parameter) element leading to the integration of the probability model in Eq. (3) over unobserved densities (parameters of which are estimated), $\text{Prob[Choice/Alternative } j] = \int_{k=1}^{R} \frac{exp\left(\alpha_{jiR} + \gamma_{jiR}^{'} Z_i\right)}{\sum_{m=1}^{J} exp\left(\alpha_{miR} + \gamma_{miR}^{'} Z_i\right)} f(\beta|\varphi) d\beta$; where $f(\beta|\varphi)$ indicates the functional form of unobserved heterogeneity and R indicates the number of draws taken from $f(\beta|\varphi)$ to evaluate/integrate the probability model. The estimation proceeds with Maximum Simulated Likelihood procedures where Halton draws (instead of random draws) are used to approximate the probability integral (Train, 2009; Wali et al., 2020). To produce accurate parameter estimates, 200 Halton draws are used (Train, 2009). Regarding the functional form of unobserved heterogeneity, we test different distributions including normal, lognormal, triangular, uniform, and Weibull distributions.

Finally, marginal effects are computed to better interpret the results. To fully explore the variations in the distributions of marginal effects due to both the intrinsic nonlinearity in the logit curve as well as to random parameters, marginal effects are computed at the individual household level and then averaged across the entire sample (Train, 2009).

4. Results

4.1. Variations in households' intentions to use SAVs & renounce current vehicles

Fig. 3 shows the distribution of the response outcome. Out of 4136 households, 41.8 % of the households ($N = 1728$) stated that they would neither use SAVs nor renounce their current vehicle(s). Interestingly, another 49.2 % of the households ($N = 2033$) stated their willingness to use SAVs but unwillingness to renounce their current vehicle(s). Only 9.1 % of the households stated their affinity to use SAVs as well as renounce current vehicle(s). These statistics have important implications in that overall, households are significantly more willing to use SAVs but substantially less willing to renounce their existing vehicle(s) in the presence of SAVs. If one only focuses on future vehicle ownership decisions, the largest portion of the population (49.2 %) who could be willing to use SAVs but not yet ready to renounce their current vehicle(s) would be overlooked (Fig. 1). In addition, understanding the characteristics of those who are willing to both use SAVs and renounce existing vehicle(s) is critical from an SAV implementation and policy perspective. Focusing only on vehicle ownership implications of SAVs, around 7.3 % of the respondents in the survey data by Menon et al. (2019) indicated "their likelihood of relinquishing a household vehicle in the presence of SAVs as extremely likely" (Menon et al., 2019). This percentage is quite in line with the 9.1 % of "innovators" in our analysis.

Fig. 4 shows the distribution of the response outcome as a function of households' existing level of vehicle ownership. Several interesting insights can be obtained regarding the potential interactive effects between user affinity towards SAVs and existing vehicle ownership. Only 5.8 % of single vehicle households are willing to use SAVs and renounce their existing vehicle. Compared to single vehicle households, the proportion of two-vehicle and more than two vehicle households willing to both use SAVs and renounce their current vehicle(s) is significantly greater, 10.3 % and 12.3 %, respectively. Likewise, the proportion of households neither willing to use SAVs nor willing to renounce their existing vehicle(s) decreases significantly with an increase in household

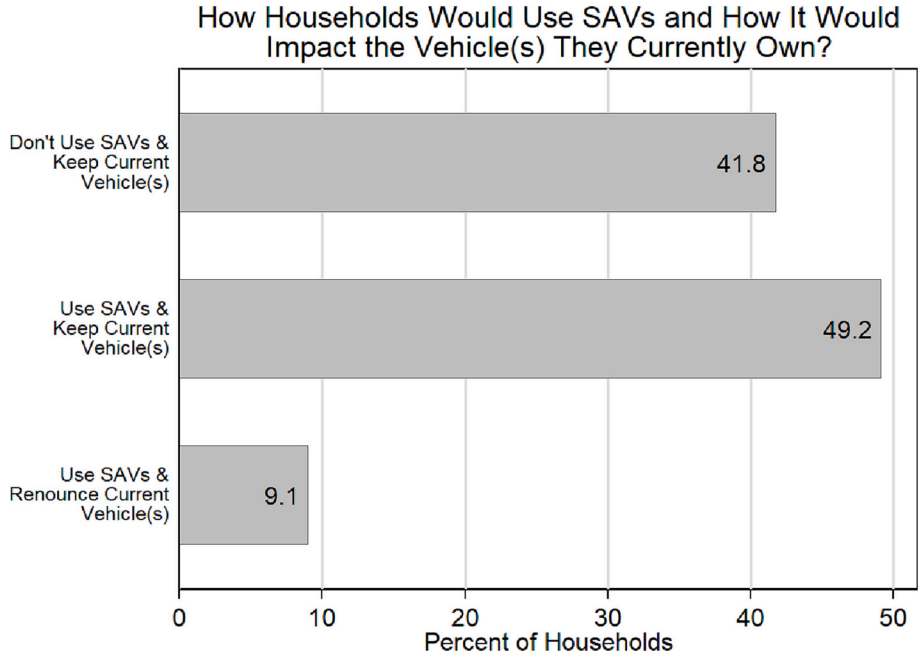

Fig. 3. Distribution of households affinity towards using SAVs & willingness to renounce current vehicles ($N = 4136$ households).

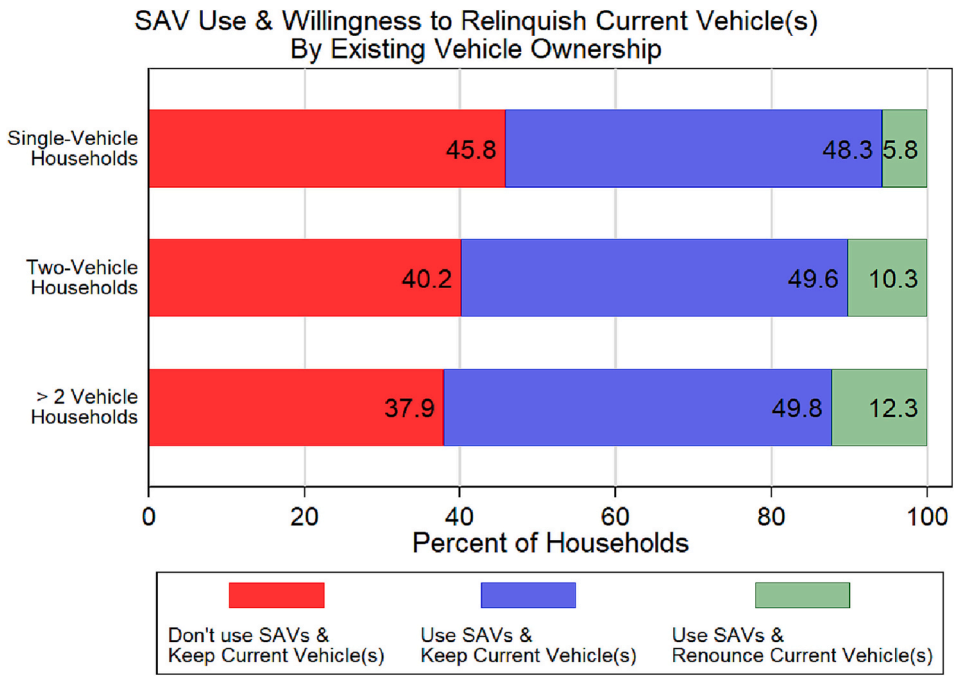

Fig. 4. Household existing vehicle ownership, affinity towards using SAVs & willingness to renounce current vehicles (N = 4136 households).

vehicle ownership (from 45.8 % for single-vehicle households to 37.9 % for more than two vehicle households) (Fig. 4).

4.2. Descriptive statistics

The descriptive statistics for the explanatory variables are shown in Table 1. Both variables obtained from the household survey file, as well as those derived/calculated from households' person and vehicle files, are shown. As reported by the head of the household, around 43 % and 14.3 % of the households are reported to have 'heard and somewhat familiar' and "heard and very familiar" with self-driving cars (SDCs). Over 31 % of the household heads strongly agreed with the statement that they would miss the joy of driving and being in control of the vehicle. Around 17 % strongly agreed that in the presence of SDCs, they would be able to travel more often even when tired, sleepy/fatigued, or under the influence of alcohol/medications. Reflecting safety and security concerns, over 60 % of the household heads strongly disagreed with the statement that they would send an empty self-driving car to pick up/drop off their children.

Regarding sustainable travel behavior, around 38 % and 19 % of the household heads stated the presence of ride hailing (Uber, Lyft) and shared ride hailing (UberPool, LyftLine) options around their home neighborhoods and stated their use of these services. Drive alone or motorcycle/moped remains to be the most used mode for work travel. On-average, 0.7 and 0.03 household members use drive-alone and active mobility (walk, bike, e-bike, bike share) to travel to work, respectively. On-average, the household members made 1.56 and 0.72 transit and ridesharing trips per week – with significant variability across the households, nonetheless.

Related to vehicle types, the sampled households own vehicles of different fuel types including gasoline, hybrid (gasoline), plug-in hybrid electric, and fully electric vehicles. Information on the number of vehicles used to work for ride hailing companies and food or product delivery companies is shown. Likewise, information on the total number of leased vs. purchased vehicles and households' short- and long-term intentions about selling/replacing vehicles is shown in Table 1.

Regarding vehicle ownership, around 37 %, 41 %, and 21 % of the sampled households are one-vehicle, two-vehicle, and more than two vehicle households, respectively. Concerning socioeconomic status, the sample represents a reasonably broad cross-section of Californians. Descriptive statistics for annual mileage and the average age of vehicles in the households, household structure, and detailed sociodemographic factors are shown in Table 1.

4.3. Modeling results

Initially, a fixed parameter conditional logit model was estimated considering statistical significance, policy-sensitive correlates, and intuition. The utility function for "Don't use SAVs and keep current vehicles" was treated as the baseline outcome. Next, a series of random parameter conditional logit models were estimated – allowing the alternative-specific intercept and parameter estimates to vary across the households. A variable was treated as a random parameter if the resulting distribution exhibited a statistically significant mean and standard deviation. Table 2 shows the goodness of fit results for the fixed and random parameter conditional logit models. Compared to the fixed parameter model, the Akaike Information Criterion of the random parameter counterpart reduced by over 16 points (Table 2) – showing substantial improvement in model goodness of fit. AIC considers both model complexity and predictive ability in comparing two competing models, and a difference of five points between the AICs of two competing models provides strong support in favor of the model with the lowest AIC (Bozdogan, 1987). The marked improvement in the goodness of fit of the random parameter logit model reveals preference heterogeneity in households' affinity to use SAVs and their willingness to renounce current vehicle(s). Precisely, the improvement can be attributed to the presence of systematically varying unobserved/latent factors leading to variations in the effects of observed independent variables.

Next, we test for potential differences in households' affinity towards using SAVs and renouncing their existing vehicle(s) as a function of their vehicle ownership levels. Segmented random parameter logit models were developed for single- and multi-vehicle households. Note that the pooled models shown in Table 2 already include vehicle ownership-related indicators as controls. Besides, the random parameter modeling framework also accounts for the potential heterogeneity in the households' affinity towards SAV use and vehicle relinquishment. The key motivation behind developing segmented random parameter logit models was to examine if the patterns in the data reveal distinct

Table 1
Descriptive statistics of key variables.

Variables	Mean	SD	Min	Max
Awareness of self-driving cars				
Never heard	0.043	0.202	0	1
Heard but unfamiliar	0.384	0.486	0	1
Heard and somewhat familiar	0.430	0.495	0	1
Heard and very familiar	0.143	0.350	0	1
Opinions (attitudes) about (towards) self-driving cars (SDC) *(strongly agree)*				
SDC would enable me to enjoy traveling more (e.g., watch scenery, rest)	0.181	0.385	0	1
Miss the joy of driving and being in control	0.315	0.464	0	1
Reduce my time at the regular workplace and work more in SDC	0.054	0.227	0	1
I would send an empty SDC to pick up/drop off my child *(strongly disagree)*	0.611	0.487	0	1
Able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications	0.172	0.377	0	1
Experience with transportation options around home neighborhood (option: available where I live, and I use it)				
Ride hailing (Uber, Lyft)	0.382	0.486	0	1
Shared ride hailing (UberPool, LyftLine)	0.194	0.395	0	1
Car sharing (Car2Go, ZipCar)	0.021	0.144	0	1
Bike sharing (Bay Area Bike Share)	0.025	0.156	0	1
Shared electric bikes (e.g., Jump)	0.037	0.189	0	1
Work Mode (number of household members using a particular mode)				
Drive alone, motorcycle/moped*	0.777	0.830	0	5
Walk, bike, e-bike, bikeshare*	0.039	0.217	0	3
Transit (inc. bus, paratransit, subway, light rail, and intercity rail) *	0.052	0.239	0	2
Vanpool or employer shuttle*	0.005	0.069	0	1
Carpooling*	0.096	0.365	0	3
Carsharing*	0.001	0.027	0	1
Ridesharing*	0.004	0.060	0	1
Transit and ridesharing trips (all household members)				
One-way transit trips per week*	1.568	7.332	0	200
One-way ridesharing trips per week*	0.727	4.205	0	190
Vehicle ownership				
Single vehicle households	0.370	0.483	0	1
Two vehicle households	0.414	0.493	0	1
More than two vehicle households	0.216	0.412	0	1
Vehicle use patterns				
# of vehicles used to work for ride-hailing companies (Uber/Lyft) *	0.026	0.198	0	4
# of vehicles used to work for food or product delivery (inc. Doordash, Uber Eats, Instacart, Amazon Flex) *	0.022	0.180	0	3
Vehicle ownership patterns (in a household)				
Number of purchased vehicles*	1.662	1.009	0	8
Number of leased vehicles*	0.223	0.498	0	4
Intentions to Sell/Replace Vehicles (in household)				
# of vehicles to sell/replace within 2 years*	0.495	0.672	0	3
# of vehicles to never sell/replace*	0.355	0.750	0	6
Vehicle Fuel Type (in a household)				
# of gasoline vehicles*	1.532	0.991	0	8
# of hybrid (gasoline) vehicles*	0.142	0.383	0	3
# of plug-in hybrid electric vehicles (PHEV) *	0.053	0.236	0	3
# of full electric vehicles*	0.081	0.298	0	3
Vehicle Body Type (in a household)				
# of subcompact cars*	0.146	0.384	0	3
# of sedans (compact, midsize, large sedans) *	0.933	0.799	0	6
# of SUVs (compact-, midsize-, full size-SUVs) *	0.317	0.527	0	3
Mileage and Vehicle Age (household level)				
Average annual miles driven*	9651.250	8401.006	200	60000
Average age of vehicles*	9.736	6.103	1	40
Average number of years household owned the vehicle*	6.959	5.690	1	40
Household Structure				
Single-family (not attached)	0.676	0.468	0	1
Single-family (attached)	0.088	0.283	0	1
Apartment	0.206	0.405	0	1
Other	0.007	0.081	0	1
Sociodemographic				
Age of household head (respondent)				
18 to 34 years	0.123	0.329	0	1
35 to 64 years	0.529	0.499	0	1
65+ years	0.348	0.476	0	1
Annual household income				
Less than $35,000	0.109	0.312	0	1
$35,000–$49,999	0.082	0.275	0	1
$50,000–$74,999	0.144	0.351	0	1
$75,000–$99,999	0.147	0.354	0	1
$100,000–$149,999	0.187	0.390	0	1
> $150,000	0.330	0.470	0	1
# of males*	0.950	0.631	0	5
# of females*	1.012	0.623	0	5
# of full-time workers*	0.807	0.829	0	5
# of parttime workers*	0.226	0.492	0	3
# of unemployed/retired members*	0.812	0.838	0	6
# of self-employed*	0.127	0.380	0	3
# of postgraduate members*	0.555	0.734	0	4
# of members with some college education*	0.303	0.580	0	4
# of members with up to high school diplomas*	0.387	0.715	0	6
# of license holders*	1.868	0.758	0	6
# of total household members*	2.309	1.205	1	16

Notes: SD is standard deviation; N = 4136 households; (*) indicate variables derived/calculated in this study form the households' person or vehicle survey files.

statistical differences in the correlates of households' affinity towards SAV use and vehicle relinquishment across single- and multi-vehicle households – besides the differences captured by using vehicle ownership as a control in the pooled model and random parameter technique. The results are shown in Table 2. To test the need for segmentation, we compare the AICs of the segmented models with the AIC of the pooled model. Compared to the two segmented models, the AIC of the pooled random parameter logit model is lower by around 38 units (Table 2). Considering both model complexity and predictive capability, this provides substantial statistical evidence in favor of the pooled model. Additionally, considering the results of the Likelihood Ratio test comparing pooled and segmented random parameter models, we fail to reject the null hypothesis that the two segments based on vehicle ownership have the same choice-generating function at a 99 % level of confidence (Table 2).

Table 3 presents the results of the best-fit random parameter logit model. Results of the fixed parameter conditional logit model are also shown for comparison purposes. To interpret the heterogeneity-driven findings more fully, Table 4 shows the average marginal effects along with distributional statistics of the marginal effects across the sampled households.

5. Discussion

The forthcoming synthesis of the key and new findings is split into the following categories: (1) awareness and opinions about self-driving

Table 2
Model goodness of fit and segmented vs. pooled models.

Variable	Fixed parameter conditional logit model	Random parameter logit models		
		Pooled	One-vehicle households (s = 1)	Multi-vehicle households (s = 2)
N	4136	4136	1529	2607
Log-likelihood at constant	−3852.21	−3852.21	−1337.08	−2495.15
Log-likelihood at convergence, LL(β)	−3369.7	−3356.6	−1157.61	−2176.06
Number of parameters (K)	41	46	44	44
Chi-squared [DF]		2374.51 [46]		
(p-value)	965.02 [39] (0.00)	(0.00)	1044.32 [44] (0.00)	1376.03 [44] (0.00)
AIC	6821.4	6805.2	2403.2	4440.1
Comparison of Pooled and Segmented Random Parameter Logit Models				
$\Delta AIC\ [AIC_{SEGMENTED\ MODELS} - AIC_{POOLED\ MODEL}]$	—		$[(2403.2 + 4440.1) - 6805.2] = 38.1$	
Number of restrictions $(K_R) = \sum_{s=1}^{2} K_S - K_{POOLED}$	—		$[(44 + 44) - 46] = 42$	
LR Test Statistic: $-2 \times \left[LL_{\beta_{POOLED}} - \sum_{s=1}^{2} LL_{\beta_S}\right] \geq \chi^2_{K_R,p}$	—		$45.86 < 66.20_{0.99}$	

Notes: AIC is Akaike Information Criterion; LR is likelihood ratio; *p* indicates (99 %) level of confidence for the LR test; N is the sample size.

cars (SDCs); (2) shared mobility & sustainable travel behavior; (3) vehicle ownership and use for ride hailing; (4) vehicle ownership model, intentions, and fuel type; (5) sociodemographic factors. All the findings from the random parameter conditional logit model are interpreted with respect to the reference category: Neither using SAVs nor renouncing current vehicle(s).

5.1. Awareness and opinions about self-driving cars

Households who have heard and are very familiar (high awareness) of self-driving cars (SDCs) are more likely to use SAVs and renounce current vehicle(s) in the presence of SAVs (Table 3). Compared to the reference category, for households who are highly aware about SDCs, the likelihood of using SAVs as well as a renouncement of current vehicle (s) increased by around 1.15 percentage points (Tables 3 and 4). Substantial variation is found in the marginal effects with the increase in the likelihood of using SAVs and renouncing current vehicle(s) for some households as high as 24.31 percentage points (Table 4). Likewise, compared to households neither using SAVs nor renouncing current vehicle(s), the likelihood of households using SAVs but not renouncing current vehicle(s) also increased by 1.27 percentage points (standard deviation of 0.04 %) (Table 4). While this result is in line with relevant studies reporting a greater likelihood of AV adoption for those highly aware (or less concerned) of the technology (Nazari et al., 2018; Sharma and Mishra, 2020; Koppel et al., 2021; Wali et al., 2021), the findings bolster previous results by highlighting that technology awareness is also a predictor of users' willingness to renounce their existing vehicle(s) in the presence of SAVs.

As expected, those who think that they would miss the joy of driving and being in control of the vehicle are on-average less likely to use SAVs and renounce their existing vehicles. Contrarily, those who think SAVs would enable them to travel even when fatigued or intoxicated (discretionary travel) are more likely not only to use SAVs but to renounce their current vehicle(s) as well. Precisely, this opinion is correlated with a 1.83 % increase in the likelihood of using SAVs and renouncing current vehicle(s), compared to those neither using SAVs nor renouncing current vehicle(s). The indicator variable for missing the joy of driving and being in control in the utility function of alternative 2 was found to be a normally distributed random parameter. With a mean β of −4.64 and a standard deviation of 2.49, the associations are negative for 96.8 % of the population and negative for the rest. While the other variables discussed above are found fixed parameters, significant differences are observed in the magnitudes of parameter estimates between fixed and random parameter models (Table 3). This highlights the presence of preference heterogeneity in households' affinity and willingness towards using SAVs and renouncing current vehicle(s). These findings add to the existing body of knowledge on attitudinal determinants of SAV use as well as existing vehicle renouncement in the era of SAVs. These findings highlight the potential challenges in SAV adoption in line with few studies examining how driving control and sensation-seeking related factors could influence SAV adoption (Nordhoff et al., 2016; Musselwhite, 2019; Asmussen et al., 2020). An individual's desire to control the vehicle and his/her unwillingness to accept AVs taking over the driving task can discourage SAV use especially when such individuals could be more vulnerable to in-vehicle sickness as passengers (Asmussen et al., 2020). Besides the reluctance to use SAVs, the new finding that those desiring driving control and exhibiting sensation-seeking driving personalities are reluctant to give up their existing vehicle(s) could include individuals who currently own vehicles out of their preference, rather than necessity (Anable, 2005). Likewise, AVs are perceived more positively by fatigued drivers (Cunningham et al., 2019; Hardman et al., 2019). Our finding indicating a higher propensity to renounce existing vehicle(s) by those who think AVs can enable travel especially when fatigued, sleepy, and/or intoxicated adds to the existing body of knowledge and is intuitive since AVs can enable intoxicated (fatigued) individuals to undertake more utilitarian or discretionary travel that otherwise could not have been safely undertaken.

5.2. Shared mobility & sustainable travel behavior

Statistically significant correlations are found between indicators of sustainable travel behavior and households' affinity and willingness to use SAVs and renounce current vehicle(s). The presence of carsharing (Car2Go, ZipCar) around the home neighborhood and its use was correlated with an on-average 0.22 % [SD: 0.02 %, maximum: 28.43 %] increase in the likelihood of households using SAVs and renouncing their current vehicle(s) (Tables 3 and 4). Households with greater one-way ridesharing trips per week had a significantly higher likelihood of not only using SAVs but renouncing their current vehicle(s) as well (β: 0.37; t-stat: 2.50). *A* 1 % increase in one-way ridesharing trips per week for a household was associated with a 0.60 % increase in the likelihood of using SAVs and renouncing current vehicle(s) (Table 4). Sustainable work travel mode was also correlated with a higher likelihood of using

Table 3
Fixed & random parameter conditional logit models for households' willingness to use SAVs & their willingness to renounce existing vehicle(s).

Category	Variables	Fixed parameter logit				Random parameter logit			
		Alternative 1		Alternative 2		Alternative 1		Alternative 2	
		β	t-stat	β	t-stat	β	t-stat	β	t-stat
Awareness & Opinions About SDCs	Constant	0.251	1.42	−1.956	−8.04	0.222	0.89	−2.069	−5.94
	Awareness of self-driving cars								
	Heard and very familiar	0.428	3.69	0.812	4.88	0.602	3.52	1.038	4.19
	Opinions (attitudes) about (towards) self-driving cars (SDC) *(strongly agree)*								
	Miss the joy of driving and being in control[a]	−1.339	−17.27	−2.219	−11.86	−1.807	−7.54	−4.640	−2.83
	standard deviation of normally distributed random parameter	—	—	—	—	—	—	*2.496*	*2.21*
	Able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications	—	—	0.680	5.33	—	—	1.179	5.08
Sustainable Travel	**Experience with transportation options around home neighborhood (option: available where I live, and I use it)**								
	Carsharing (Car2Go, ZipCar)	—	—	0.761	2.54	—	—	1.223	2.56
	Work Mode (number of household members using a particular mode)								
	Drive alone, motorcycle/moped	0.132	2.66	—	—	0.158	1.99	—	—
	Walk, bike, e-bike, bikeshare	0.437	2.64	—	—	0.670	2.48	—	—
	Transit and ridesharing trips (all household members)								
	One-way ridesharing trips per week (log-form)	—	—	0.212	2.33	—	—	0.375	2.50
Vehicle Ownership & Use	**Vehicle ownership**								
	One vehicle household (base)	—	—	—	—	—	—	—	—
	Two vehicle households	—	—	0.559	3.77	—	—	0.757	3.72
	More than two vehicle households	—	—	0.678	3.81	—	—	0.887	3.51
	Vehicle Usage for Ride Hailing Service								
	# of vehicles used for ride hailing [1 if >0, 0 otherwise]	−0.614	−2.45	−0.594	−1.38	−1.020	−2.55	−0.894	−1.46
	Mileage and Vehicle Age (household level)								
	Average annual miles driven (in 1000 miles)[a]	0.013	2.84	0.016	2.18	0.037	2.86	−0.023	−0.83
	standard deviation of normally distributed random parameter	—	—	—	—	*0.140*	*2.59*	*0.090*	*2.68*
Ownership Model & Intentions, Fuel Type	**Leased vs. Purchased Vehicles (in a household)**								
	Number of leased vehicles	0.313	3.72	0.359	2.91	0.427	3.30	0.492	2.89
	Intentions to Sell/Replace Vehicles (in household)								
	# of vehicles to sell/replace within 2 years	0.165	2.78	0.220	2.36	0.216	2.55	0.249	1.98
	Vehicle Fuel Type (in a household)								
	# of gasoline vehicles	−0.098	−2.47	—	—	−0.104	−1.80	—	—
	# of full electric vehicles	0.715	4.35	0.559	2.60	0.952	3.86	0.571	1.97
Sociodemographic Factors	***Age of household head (respondent)***								
	18 to 34 years (base)	—	—	—	—	—	—	—	—
	35 to 64 years	−0.522	−4.33	−0.328	−1.63	−0.698	−3.66	−0.416	−1.43
	65+ years	−0.764	−5.73	−0.616	−2.66	−0.989	−4.59	−0.784	−2.45
	Household Structure								
	Apartment	0.149	1.70	—	—	0.205	1.64	—	—
	Annual household income								
	Less than $35,000 (base)	—	—	—	—	—	—	—	—
	$35,000–$49,999	0.351	2.25	—	—	0.337	1.58	—	—
	$50,000–$74,999	0.258	1.88	—	—	0.260	1.39	—	—
	$75,000–$99,999	0.340	2.45	—	—	0.359	1.88	—	—
	$100,000–$149,999	0.648	4.62	0.408	2.34	0.710	3.66	0.498	2.18
	> $150,000	0.545	4.02	0.432	2.75	0.603	3.25	0.546	2.65
	# of full-time workers[a]	—	—	−0.144	−1.71	—	—	−0.851	−1.80
	standard deviation of normally distributed random parameter	—	—	—	—	—	—	*1.263*	*2.21*
	# of postgraduate members	0.187	3.32	0.302	3.53	0.217	2.72	0.402	3.27
	# of members with up to high school diplomas	−0.161	−2.89	—	—	−0.291	−2.77	—	—
	# of household members[a]	0.054	1.52	—	—	0.099	1.59	—	—
	standard deviation of normally distributed random parameter	—	—	—	—	*0.412*	*2.34*	—	—

Notes: (—) indicates Not Applicable; (a) indicates normally distributed random parameters; Outcome categories: (1) Baseline: Don't use SAVs and keep current vehicle (s); (2) Alternative 1: Use SAVs and keep current vehicle(s); (3) Alternative 2: Use SAVs and renounce current vehicle(s); Utility function for Baseline treated as reference category.

SAVs compared to neither using SAVs nor renouncing current vehicle(s). Each additional household member using a sustainable travel mode (walking, biking, e-bike, bike share) for work was associated with a 0.34 % increase in likelihood of the household using SAVs (Table 4). To get a fuller picture, Fig. 5 visualizes the simulated effects of household-level sustainable work travel mode on the likelihood of using SAVs. The increase in the likelihood of using SAVs varied between around 50 % and 80 %. This indicates the strong correlation between household-level sustainable work travel mode and the affinity to use SAVs (see the trajectory for the simulated direct effect of this variable in Fig. 5). Shared

Table 4
Direct marginal effects of best-fit random parameter conditional logit model of households' affinity to use SAVs and their willingness to renounce current vehicle(s).

Category	Variables	Direct marginal effects of variables in utility function of alternative 1 (*100)			Direct marginal effects of variables in utility function of alternative 2 (*100)		
		Mean	SD	Max	Mean	SD	Max
Awareness & Opinions About SDCs	**Awareness of self-driving cars**						
	Heard and very familiar	1.270	0.049	14.310	1.153	0.052	24.310
	Opinions (attitudes) about (towards) self-driving cars (SDC) ***(strongly agree)***						
	Miss the joy of driving and being in control	−7.712	0.180	−42.514	−0.703	0.028	−29.350
	Able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications	—	—	—	1.830	0.070	27.400
Sustainable Travel	**Experience with transportation options around home neighborhood (option: available where I live, and I use it)**						
	Carsharing (Car2Go, ZipCar)	—	—	—	0.220	0.020	28.430
	Work Mode (number of household members using a particular mode)						
	Drive alone, motorcycle/moped	1.690	0.028	9.807	—	—	—
	Walk, bike, e-bike, bikeshare	0.345	0.030	21.070	—	—	—
	Transit and ridesharing trips (all household members)						
	One-way ridesharing trips per week (log-form)	—	—	—	0.607	0.028	21.143
Vehicle Ownership & Use	**Vehicle ownership**						
	One vehicle household (base)	—	—	—	—	—	—
	Two vehicle households	—	—	—	1.920	0.047	16.575
	More than two vehicle households	—	—	—	1.230	0.040	20.780
	Vehicle Usage for Ride Hailing Service						
	# of vehicles used for ride hailing [1 if >0, 0 otherwise]	−0.290	0.030	−22.080	−0.090	0.014	−20.930
	Mileage and Vehicle Age (household level)						
	Average annual miles driven (in 1000 miles)	3.930	0.066	23.050	0.780	0.020	12.980
Ownership Model & Intentions, Fuel Type	**Leased vs. Purchased Vehicles (in a household)**						
	Number of leased vehicles	1.350	0.048	27.330	0.739	0.030	33.327
	Intentions to Sell/Replace Vehicles (in household)						
	# of vehicles to sell/replace within 2 years	1.550	0.034	13.680	0.777	0.022	14.780
	Vehicle Fuel Type (in a household)						
	# of gasoline vehicles	−2.370	0.025	−13.100	—	—	—
	# of full electric vehicles	0.975	0.057	43.650	0.337	0.022	19.630
Sociodemographic Factors	***Age of household head (respondent)***						
	18 to 34 years (base)	—	—	—	—	—	—
	35 to 64 years	−5.340	0.080	−16.610	−1.212	0.020	−9.670
	65+ years	−5.580	0.120	−23.590	−1.470	0.040	−17.340
	Household Structure						
	Apartment	0.640	0.020	4.870	—	—	—
	Annual household income						
	Less than $35,000 (base)	—	—	—	—	—	—
	$35,000–$49,999	0.410	0.023	8.010	—	—	—
	$50,000–$74,999	0.560	0.020	6.100	—	—	—
	$75,000–$99,999	0.800	0.031	8.550	—	—	—
	$100,000–$149,999	1.996	0.060	16.890	0.542	0.022	9.990
	> $150,000	2.900	0.060	14.210	1.206	0.034	12.322
	# of full-time workers	—	—	—	0.098	0.030	−15.883
	# of postgraduate members	1.781	0.037	13.817	1.502	0.040	26.604
	# of members with up to high school diplomas	−1.525	0.040	−18.350	—	—	—
	# of household members	3.170	0.040	22.700	—	—	—

Notes: Alternative 1: Use SAVs and keep current vehicle(s); (3) Alternative 2: Use SAVs and renounce current vehicle(s); Utility function for Baseline (Don't use SAV and keep current vehicle(s)) treated as reference category; (—) indicates Not Applicable. For brevity, only direct marginal effects (along with distribution – standard deviations and maximum +ve/-ve effects) are shown, i.e., marginal effects shown relate to the effect of the attribute for the utility function in which the attribute appears.

mobility is one of the key pillars of future smart cities driven by connected, automated, shared, and electric vehicle systems (Mahdavian et al., 2021; Huang et al., 2022). Sharing of vehicles (especially with its manifestation through smart phone based services such as Uber and Lyft) has been viewed as the single most significant innovation to revolutionize urban transport systems (Sperling, 2018). As discussed earlier, the relationships between the use of existing shared mobility services and SAV adoption (especially vehicle relinquishment in the era of SAVs) are not empirically well-established in the literature (Menon et al., 2019). Collectively, our findings add to the literature by exemplifying the links between existing sustainable (shared) mobility servicecs (including carsharing and ride-sharing) and individuals' willingness to use SAVs and renounce existing vehicle(s) in the presence of SAVs.

5.3. Vehicle ownership and use for ride hailing

Following intuition, two-vehicle and more than two vehicle households had a significantly greater affinity and willingness to use SAVs and renounce current vehicle(s) as compared to one-vehicle households. In particular, the likelihood of households' using SAVs and renouncing current vehicle(s) increased by 1.92 and 1.23 percentage points for two- and more than two vehicle households, respectively (Tables 3 and 4). This finding is intuitive since, compared to single-vehicle households,

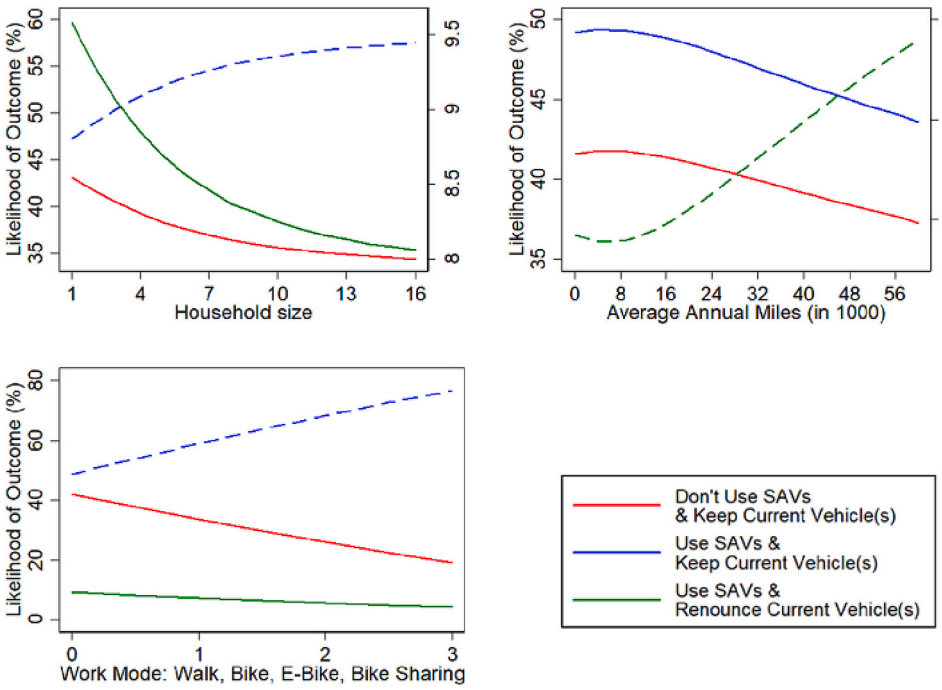

Fig. 5. Likelihood of households' affinity towards using SAVs and willingness to renounce current vehicle(s) (simulated effects of household work mode, average annual vehicle miles, and household size).
Notes: direct effect(s) on particular outcome(s) shown with dashed trajectories; secondary y-axis shows likelihood for alternative 2 (use SAVs & renounce current vehicle(s)).

multi-vehicle households may be more willing to renounce one of their existing vehicles where the additional vehicle(s) in the household could offset users' reliability concerns about SAVs. On the contrary, one-vehicle households may be unwilling to relinquish their only vehicle due to, for example, reliability concerns. The vehicle ownership indicator variables were statistically insignificant in the utility function of alternative 1. Past research has shown a greater vehicle ownership reduction potential for multi-vehicle households (compared to one-vehicle households) as a result of owning private automated vehicles (Zhang et al., 2018). Our findings extend the literature by demonstrating the links between SAV use and potential to renounce existing vehicles as a function of operating vehicles in a household.

Important insights regarding vehicle use and purpose are also observed. If a household used existing vehicles to work for ride hailing companies (Uber, Lyft), they were significantly less likely to use SAVs and renounce their current vehicle(s). Compared to those households who do not use existing vehicles for providing ridesharing services, those who did were more likely to be in the baseline category (Don't use SAVs and keep current vehicle(s)). The likelihood of using SAVs and renouncing current vehicle(s) for households who use their vehicles for ride sharing reduced by around 0.09 percentage points – with a reduction of as much as 20.93 percentage points for some households (Table 4). Note that while the parameter estimate for this variable was statistically significant at only 85 % level of confidence (Table 3), the marginal effect was nonetheless statistically significant at a 99 % level of confidence (significance levels of marginal effects not shown for brevity). None of the previous studies have examined the relationship between vehicle usage for ride-hailing services and user willingness to renounce existing vehicle(s) in the era of SAVs. The above finding has important implications because it suggests that the vehicle ownership-related benefits of SAVs may not be realized to a greater extent. Especially, recent estimates suggest that there are around 2 Million Uber and Lyft drivers in the US (Berry, 2020) – with around 30 % aged between 51–60 years and over 70 % of the drivers aged 50 years or more (Wong, 2020). Since a significant portion of the population works for ride-sharing companies to make a partial/full living, this segment of the population could be unwilling to renounce their existing vehicles and, with them, a source of income. In addition, the inertia to relinquish vehicles can be even greater since over 70 % of Uber drivers are aged over 50 (Wong, 2020) - a segment of the population who may not have that much flexibility to switch to other jobs to make a living.

An increase in the average annual mileage of household vehicles was associated with an increase in the propensity of the household to use SAVs. A 1000-mile increase in average annual vehicle mileage correlates with a 3.9 % increase in the likelihood of using SAVs – compared to neither using SAVs nor renouncing current vehicle(s). This seems intuitive since older vehicles typically have greater operating and maintenance costs (Baklouti et al., 2022) – and thus households with older vehicles may be more willing to use SAVs. Average annual vehicle mileage is also intuitively correlated with a higher likelihood of a household using SAVs as well as renouncing their existing vehicle(s) (alternative 2). Note that while the sign of this variable in the best-fit random parameter model is negative, substantial heterogeneity is observed in that the associations are negative for 60 % of the population and positive for the rest. This highlights the importance of accounting for unobserved preference heterogeneity. To gain a fuller insight into the effects of average mileage of household vehicles, Fig. 5 shows the simulated effects of average annual vehicle mileage in the utility function of alternative 2. As the vehicle mileage increases, the likelihood of a household using SAV and renouncing existing vehicle(s) increases sharply in a non-linear fashion (Fig. 5).

5.4. Vehicle ownership model, intentions and fuel type

Regarding the ownership model, the key finding is that households with a greater number of leased vehicles are more likely to use SAVs and more willing to renounce their current vehicle(s). A one unit increase in the number of leased vehicles correlates with a 0.73 % increase in the likelihood of households using SAVs and relinquishing existing vehicle (s). Likewise, a household's intention to sell/replace vehicles within 2 years was correlated with a 1.5 % and 0.7 % increase in the likelihood of using SAVs but keeping existing vehicle(s) and the likelihood of both using SAVs and renouncing existing vehicle(s), respectively (Table 4). The finding related to the impact of users' current vehicle ownership model on their willingness to renounce existing vehicle(s) in the era of SAVs is novel and captures the distinct characteristics of individuals following a lease-based ownership model compared to individuals who finance their vehicles (Dasgupta et al., 2003). A lease-based vehicle

ownership model provides greater flexibility to users and enables them to engage in vehicle-replacing behavior more easily relative to those who own their vehicles. Few previous studies have noted the higher affinity of individuals who own leased vehicles towards emerging technologies such as automated vehicles (Sheela and Mannering, 2020) or the introduction of a component-leasing model (such as battery-leasing) as a competitive alternative to an electric vehicle buying model (Huang et al., 2021). However, none of the existing studies have examined the potential impact of the vehicle ownership model on users' willingness to renounce existing vehicles in the era of SAVs. A greater number of gasoline vehicles in a household correlates with a lower likelihood of a household using SAVs. This finding is intuitive since households with greater number of conventional gasoline vehicles may be less interested in emerging technology (such as SAVs). In particular, ownership of greater conventional (gasoline) vehicles could be (to an extent) a proxy for non-technological attitudinal predispositions (Shin et al., 2015). Contrarily, a greater number of fully electric vehicles in a household correlates with a higher likelihood of using SAVs as well as renouncing existing vehicle(s) (alternative 2). Fig. 6 shows how the likelihood of alternative 2 non-linearly increases with an increase in the number of electric vehicles (Fig. 6). The finding related to electric vehicle ownership and vehicle relinquishment in the era of SAVs is intuitive since electric vehicle early adopters seem to have positive perceptions of automated vehicles (Hardman et al., 2019) and exhibit a positive affinity towards connected and automated vehicles (CAVs) and fully automated vehicles (Wali et al., 2021).

5.5. Sociodemographic factors

Compared to young respondents (18–34 years old), older household heads were less likely to use SAVs and relinquish their existing vehicle(s) (Table 3). This finding seems intuitive since younger individuals are usually less risk-averse, and thus more likely to embrace disruptive transportation technologies (Lavieri and Bhat, 2019; Spurlock et al., 2019; Asmussen et al., 2020; Wali et al., 2021). Even after controlling for a host of factors, statistically significant and strong income-based differences are also observed. Compared to low-income households (earning less than $35,000 annually), high-income households have a higher likelihood to use SAVs and relinquish existing vehicle(s). As expected, households with a greater number of postgraduate members are more likely to use SAVs and renounce existing vehicle(s) – possibly reflecting greater affinity of more educated individuals towards a more sustainable lifestyle (Wali and Khattak, 2022). This finding is in agreement with Menon et al. (2019) who found a higher propensity of vehicle relinquishment for graduate degree holders (Menon et al., 2019). Those living in apartment buildings are found to be more likely to use SAVs. This finding may be tracing the latent effects of built environment densification – since individuals living in denser and more compact areas are found to be more likely to use existing ride-hailing services (Conway et al., 2018; Dean and Kockelman, 2021; Wali et al., 2022) and automated ride-sourcing/carsharing services (Wali and Khattak, 2022). Overall, the role of demographic factors concerning vehicle renouncement in the era of SAVs is examined in past research and our findings are largely in agreement (Menon et al., 2019).

5.6. Study contribution

This study contributes by examining consumers' affinity to use shared automated vehicles (SAV) and their willingness to renounce existing vehicle(s) in the presence of SAVs – two interlinked factors determining the long-term success of SAVs. The study offers substantive and methodological contributions to literature. As discussed earlier, current knowledge on the potential impacts of SAVs is limited by the use of focus groups and the consideration of vehicle ownership components

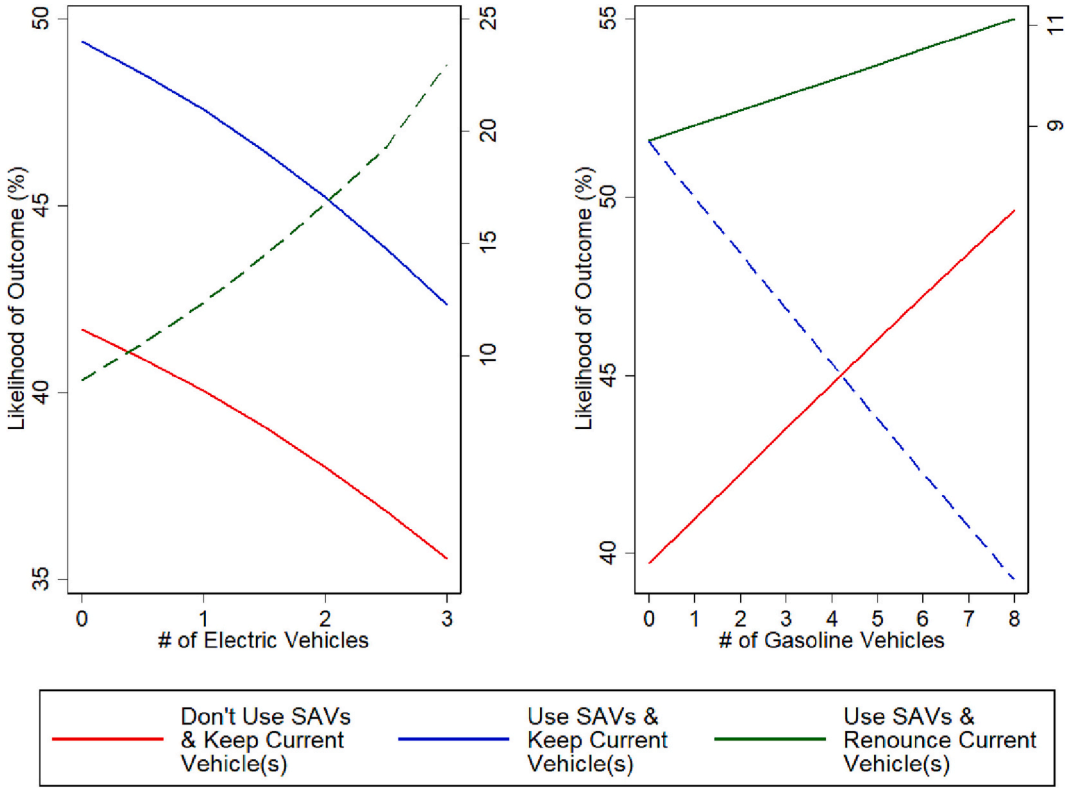

Fig. 6. Likelihood of households' affinity towards using SAVs and willingness to renounce current vehicle(s) (simulated effects of number of electric and gasoline vehicles in a household).
Notes: direct effect(s) on particular outcome(s) shown with dashed trajectories; secondary y-axis shows likelihood for alternative 2 (use SAVs & renounce current vehicle(s)).

in isolation (Menon et al., 2019). This study fills these gaps by simultaneously analyzing the use of SAVs in the future and its potential impact on vehicle ownership using comprehensive data from California comprised of households exhibiting considerable behavioral and sociodemographic diversity. Additionally, while the literature on the determinants of SAV use is relatively large (Krueger et al., 2016; Haboucha et al., 2017; Nazari et al., 2018; Stoiber et al., 2019), empirical examination of the potential impacts of SAVs on future vehicle ownership is largely limited to sociodemographic factors (Menon et al., 2019). The findings from the current study extend the literature by demonstrating how a broad spectrum of behavioral and attitudinal factors relate to SAV use and individuals' willingness to relinquish vehicle(s) in the era of SAVs. Methodologically, the study controlled for unobserved heterogeneity to better understand the role of multiple levels of interlinked behavioral and demographic factors associated with households' affinity towards using SAVs and renouncing existing conventional vehicles.

5.7. Policy implications

The empirical findings from this study have several implications. First, they can assist in targeting behavioral and demographic subgroups that are more likely to use SAVs and renounce existing vehicle(s). Among the demographic factors considered, age and low education-related variables seem to exhibit a relatively stronger negative effect on attitudes towards SAVs – with older respondents significantly less likely to use SAVs and renounce existing vehicles. To this end, policies that focus on providing incentives to the elder population group and/or addressing their concerns about technology can potentially increase their affinity towards using SAVs and subsequently relinquish their conventional vehicles. The policy interventions may also focus on enhancing the technological savviness of elder individuals by demonstrating the benefits of SAVs in relevance to their special needs, such as the enhanced ability to travel more as their driving capability diminishes over time or the potential for safer travel that does not require the physical/mental workload otherwise associated with driving. Serving as evidence-based tools, such interventions can also help with increasing their awareness about self-driving technology. We found that low-income individuals are less likely to use SAVs and relinquish their conventional vehicles. This finding may be an outgrowth of their impression that they could not afford self-driving capabilities (especially keeping in view the high premiums for owning automated vehicles currently available in the market, e.g., Tesla). To this end, interventions that can highlight and market the added benefits of SAVs (such as potentially lower costs of ownership compared to privately-owned automated vehicles) may increase the affinity of low-income individuals/households towards using SAVs.

Among the other variables considered, the level of household vehicle ownership seems to have a relatively greater association with attitudes towards SAVs. Given that single-vehicle households have the lowest affinity towards SAVs, incentives based on the number of vehicles in the household may help in increasing consumers' affinity towards using SAVs. Single-vehicle households may be unwilling to renounce their only current vehicle in the presence of SAVs. Strategies that can highlight the reliability of SAV systems and potentially lower premiums of using SAVs (compared to self-owned automated vehicles) can help increase affinity levels of households who rely on a single vehicle in their daily lives. A linked strategy could be to provide incentives to enhance the attractiveness of vehicle leasing programs (compared to purchasing vehicles). Compared to those who own vehicles, individuals possessing leased vehicles presumably have lower inertia to vehicle relinquishment, and incentives that can further lower the costs of leasing a vehicle can help in reducing concerns about breaking established habits (of owning vehicles). Likewise, by increasing incentives for ownership of 'greener' vehicles, policy interventions can discourage the use of gasoline vehicles since the ownership of gasoline vehicles is strongly and negatively related to attitudes towards SAVs.

Our findings also contribute by shedding new light on some contrasting challenges in SAV deployment due to the supply and demand differentials between the use of SAVs and the renouncement of existing vehicle(s). From the demand side, households with sustainability-oriented travel behavior and attitudinal predispositions are more likely to use SAVs and relinquish existing vehicle(s). This suggests that investments in increasing sustainable or green travel could also enhance users' affinity towards SAVs and their willingness to renounce existing vehicle(s). Contrarily, from the supply side, those who rely on existing vehicles to provide ride hailing services are unwilling to relinquish existing vehicle(s) - implying that the vehicle ownership-related benefits of SAVs may not be realized to a greater extent. Further adding to the complexity is the fact a significant portion of existing ride-hailing drivers is comprised of elder individuals – who could have even greater inertia to renounce their vehicles in the era of SAVs.

Overall, the interrelated behavioral findings emerging from this study suggest that a multi-pronged, and not single-pronged, strategy may achieve relatively better results in terms of enhancing consumers' interest in SAVs and increasing their willingness to renounce existing vehicles in the era of SAVs – two key elements that will determine the success of SAVs over time.

5.8. Limitations & future research

The present study has several known limitations. The study uses comprehensive statewide data on over 4000 households, but the findings should be interpreted with caution since California is unique in several aspects despite the broader similarities with the nation in terms of demographic and other factors discussed earlier. For example, California is among the first few states to enact legislation allowing automated vehicle licensing (Fagnant and Kockelman, 2015) and Californians are relatively more aware of automated vehicles compared to other US states (Howard and Dai, 2014). Future research should analyze the conceptual model presented in this study using data from other locations to examine the generalizability of the findings to other contexts. Second, this is a cross-sectional/static study. Consumers' perceptions and affinities towards emerging technology are changing rapidly. While the findings of this study are based on the most recent statewide CVS data, insights into the longitudinal evolution of consumers' affinity and preferences for SAVs could not be obtained. As newer waves of the CVS data become available, future studies should examine the affinity towards SAVs and the potential impacts of SAVs on household vehicle ownership in a repeated cross-sectional study design. Third, the study is based on self-reported data since SAV technology does not yet exist. The new findings presented intrinsically assume that households' self-reported responses may reflect reality in the future – an assumption that is not always true (an issue with all studies exploring possible effects of emerging technologies). Until such technology becomes widely available and real-world objectively assessed activity patterns associated with such disruptive technology are observed, the choice is between imperfect vs. no information. Also, while information on individuals' experiences with real SAV systems does not yet exist, the detailed data on existing travel patterns, preferences, and habits used in this study are widely known to predict acceptance of disruptive technologies including AVs (Lavieri et al., 2017; Nazari et al., 2018; Barbour et al., 2019; Nair and Bhat, 2021; Wali et al., 2021; Batur et al., 2022; Wali et al., 2022). Future studies can extend the results of this study by designing stated preference experiments to elicit and model individuals' preferences for SAVs and their potential impacts on household vehicle ownership.

6. Conclusions

This study presented an empirical analysis to examine households' affinity towards using on-demand SAVs and their willingness to renounce existing vehicles – two key factors that will determine the

long-term success of SAVs. Using comprehensive data on over 4100 households in California, around 50 % of the households reported willingness to use SAVs but unwillingness to renounce their current vehicle(s). Another 9.1 % stated their affinity to use SAVs as well as to renounce existing vehicle(s) – with significant variations across households' existing vehicle ownership. Only 5.8 % of single-vehicle households were both willing to use SAVs and renounce their existing vehicle – compared to 10.3 % and 12.3 % of two-vehicle and more than two-vehicle households, respectively.

Random parameter logit models revealed new meaningful empirical insights regarding the mechanisms influencing households' affinity to use SAVs and renouncing existing vehicle(s). If a household used existing vehicles to work for ride hailing companies (Uber, Lyft), they were significantly less likely to use SAVs or renounce their current vehicle(s). An increase in the average annual mileage of household vehicles was associated with an increase in the propensity of the household to use SAVs and renounce current vehicle(s). Households with greater ride-sharing trips and those who used carsharing had a higher likelihood of using SAVs and renouncing their current vehicle(s). A greater number of household members using a sustainable travel mode (walking, biking, e-bike, bike-share) for work were more likely to use SAVs - with the increase in the likelihood of using SAVs varying between around 50 % and 80 % revealing unobserved preference heterogeneity. Finally, households with a greater number of leased vehicles and fully electric vehicles were on-average more likely to use SAVs and renounce/relinquish their current vehicle(s). Those individuals who thought that SAVs would enable them to travel even when fatigued or when intoxicated were more likely not only to use SAVs but to renounce their current vehicle(s) as well. The reverse was true for those who think they would miss the joy of driving and being in control. Overall, the empirical links between key policy-sensitive factors and consumers' willingness to use SAVs and/or renounce current vehicle(s) were characterized by significant unobserved preference heterogeneity. The study contributes by shedding new light on the behavioral determinants of SAV adoption and user willingness to renounce existing vehicles in the presence of SAVs.

CRediT authorship contribution statement

Behram Wali: Conceptualization, Methodology, Formal analysis, Visualization, Software, Writing – original draft, Writing – review & editing, Project administration. **Paolo Santi:** Methodology, Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Carlo Ratti:** Methodology, Writing – review & editing, Supervision, Funding acquisition.

Data availability

Data will be made available on request.

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