Transportation Research Part A 164 (2022) 242–256

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Policy and industry implications of the potential market penetration of electric vehicles with eco-cooperative adaptive cruise control

Javier Bas [a,d,*], José L. Zofío [b,c], Cinzia Cirillo [d], Hao Chen [e], Hesham A. Rakha [f]

[a] Department of Economics, Universidad de Alcalá de Henares, Madrid, Spain
[b] Department of Economics, Universidad Autónoma de Madrid, Madrid, Spain
[c] Erasmus Research Institute of Management, Erasmus University, Rotterdam, the Netherlands
[d] Department of Civil and Environmental Engineering, University of Maryland, Maryland, USA
[e] Center for Sustainable Mobility, Virginia Tech Transportation Institute, VA, USA
[f] Charles E. Via, Jr. Department of Civil and Environmental Engineering, Virginia Tech, VA, USA

ARTICLE INFO

Keywords:
Eco-CACC
Electric vehicle
Fuel savings
Market share

ABSTRACT

The Eco-Cooperative Adaptive Cruise Control (Eco-CACC) makes use of an algorithm to compute energy-optimized speed profiles within the vicinity of signalized intersections. We conduct a stated choice experiment to unveil the inclination of drivers towards the Eco-CACC and to calculate its potential market share. To do so, we consider the performance of the system in field and simulated tests, as well as different types of drivers. Models of discrete choice are used to identify key elements in the adoption of this technology and its market penetration. The study has been performed for gasoline and electric vehicles, as well as for different categories of roads (arterial, highways and both), separately, exploring the effect of the advantages that the Eco-CACC features bring to both. Our results demonstrate, for the gasoline-powered, that potential purchasers perceive a clear trade-off between the cost of the system and the fuel savings that it provides. This is not the case for potential electric vehicles purchasers, for whom the cost-benefit analysis is adverse, mainly due to the low cost of electricity compared to gasoline. Nevertheless, the market shares resulting from the estimated models give a significant quota to the alternatives that include the Eco-CACC, resulting from favorable attitudes towards environmentally friendly technological innovations.

1. Introduction

This work aims to unveil the inclination of drivers towards the Eco-Cooperative Adaptive Cruise Control (Eco-CACC), a system that recommends in real-time a fuel-efficient speed profile when the vehicle drives through signalized corridors, passing through intersections. We do this with the purpose of calculating its potential market share for different types of drivers and of determining if the characteristics of the Eco-CACC are sufficient to stimulate the adoption of vehicles equipped with this system. We offer public officials insights on market adoption trends that will help to devise efficient regulations, and we inform industry stakeholders about the relevance of the Eco-CACC from a consumer choice perspective, providing evidence on their willingness to adopt it.

* Corresponding author.
E-mail address: javier.bas@uah.es (J. Bas).

https://doi.org/10.1016/j.tra.2022.08.007
Received 21 April 2021; Received in revised form 10 May 2022; Accepted 9 August 2022
Available online 24 August 2022
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The manufacture and purchase of efficient vehicles is probably-one of the measures that may have the greatest impact on fuel economy. However, the complete renewal of the fleet is a process that will take place in the long term. The growing presence of electric vehicles (EVs) on the roads is another source of environmental progress but, likewise, their introduction is a gradual process that will not explode until certain technological improvements are made and a critical mass is reached. An easy option to implement, but probably not given enough importance, is the modification of driving style. Moving from an aggressive driving style to a calmer one is one of the most direct actions for achieving significant reductions in greenhouse gas emissions. More genteel driving habits are known as eco-driving, which consists, among other aspects, of moderating acceleration and braking, avoiding starts and stops, and anticipating signals (Ando et al., 2010).

Although adopting this behavior can clearly be done by oneself, technology has a major role to play in this regard. For instance, McAuliffe et al. (2018) highlights the importance of Cooperative Adaptive Cruise Control (CACC) systems in vehicle-to-vehicle (V2V) communications, specifically in the context of truck platooning. Their results show energy savings that increase nonlinearly depending on the position of the vehicle in the platoon. Liu et al. (2020) also quantify the effect of CACC on fuel consumption in mixed traffic. Their analysis yielded up to 20 % reduction in energy consumption compared to human driving. Another kind of technology, the vehicle-to-infrastructure (V2I) connectivity, allows the driver/vehicle to have real-time information on the road conditions and traffic. With the help of this type of communication, De Vlieger et al. (2000) developed an algorithm to allocate in real-time signal phases, to optimize vehicle delay and queue lengths. Ando et al. (2010) went a step further, modeling a signal control algorithm for intersections used by conventional, connected, and automated vehicles, that finds both optimal departure sequence and trajectory. Another algorithm applied to signal phasing and timing is the Eco-CACC, developed by Kamalanathsharma (2014). Thanks to V2I communication within the vicinity of traffic signalized intersections, the system recommends in real-time a fuel-efficient speed profile with the purpose of minimizing fuel consumption when the vehicle is passing through the intersection. A proof-of-concept of the Eco-CACC system was tested in real environment trials (Chen et al., 2016), demonstrating its applicability and showing promising results in fuel and travel time savings. Those experiments led to further controlled-field evaluation of its effectiveness (Almannaa et al., 2019), evidencing the superiority of the automatic control (up to 31 % fuel savings when driving downhill) over human control (19 %). The system was also evaluated in more complex traffic conditions through software simulations. Specifically, queue effects, multiple intersections, and interaction of Eco-CACC and non-Eco-CACC vehicles has been studied in Almutairi (2017), and Yang et al. (2017).

The Eco-CACC system has recently been expanded to battery electric vehicles, and the results of the simulation test demonstrate that the energy-optimum solution for these vehicles is different from that for gasoline-powered vehicles. Chen and Rakha (2020) tested the performance of the system for battery electric vehicles in a simulated arterial corridor with three signalized intersections. Results show that the controller produced average savings of 9.3 % in energy consumption and 3.9 % in vehicle delay. Also, a similar control framework was used to develop a cruise control system for hybrid electric vehicles. This system implements a new energy model considering energies from fuel and battery electric power. The case study indicated that the developed system can effectively reduce stop-and-go traffic in the vicinity of signalized intersections by producing the average savings of 7.4 % energy consumption, 5.8 % traffic delay and 23 % vehicle stops, respectively (Chen and Rakha 2021). Another recent study developed a novel adaptive cruise control strategy for electric vehicles using a hierarchical framework, and the simulation test results showed great improvements in reducing vehicle acceleration and speed fluctuations, thereby reducing energy consumption (Xu et al. 2021).

Despite the advantages of Eco-CACC, there are potential drawbacks of adopting the new technology related to safety concerns. First, there may exist wireless communication issues among infrastructure and vehicles. Wireless V2I communications inevitably introduce network imperfections, resulting from communication range limit and/or delay, packet loss, and sampling intervals. Second, the Eco-CACC needs to be coupled with V2V technology to take full advantage of the system on signalized corridors. Vehicles that are not in sync with the intersection may adopt driving patters incompatible with Eco-CACC vehicles (i.e., altering the optimum speeding profile and disrupting the flow of traffic). Third, as vehicles equipped with Eco-CACC may pass through intersections with higher speed, this may cause driving hazards in the form of longer reaction times in case other road users fail to stop properly at the intersections, e.g., when running red lights. Although these issues rarely happen in experimental tests, it is worth to consider these situations to enhance the safety of the Eco-CACC in the future, as they might limit the confidence of drivers in the system.

The net benefits of Eco-CACC system arise a great interest in knowing the determinants of adopting this new cruise-control feature and its potential market penetration. However, modeling the adoption of disruptive goods is difficult as there is no reference market; oftentimes, not even similar markets with which to compare or extrapolate sales behavior. In the same way, there is literally no information about consumer preferences for a new technology that has not been implemented yet. It is in this context that Stated Choice Experiments (SCEs) and Discrete Choice Models (DCMs) provide a joint methodological framework to shed light on the matter (see the seminal works by Louviere and Hensher, 1983; Louviere and Woodworth, 1983 for the former; and Cook and Nachtrheim, 1980; Hensher et al., 2005; Louviere et al., 2000; Train, 2009, for the latter). SCEs are designed to present individuals with a series of choice tasks in which several alternatives, along with their respective attributes, are displayed. Users evaluate the information and then make a choice among the alternatives. These choice situations are hypothetical (overcoming the lack of real-life information) and therefore make it possible to assess unobserved scenarios of interest (for instance, an extraordinary rise in energy prices) or present an alternative option that does not yet exist (for instance, a proof of concept for a new product or service, a new transport mode not yet available in a given location, etc.). In our case, we present the Eco-CACC and its characteristics, a system that has not yet been

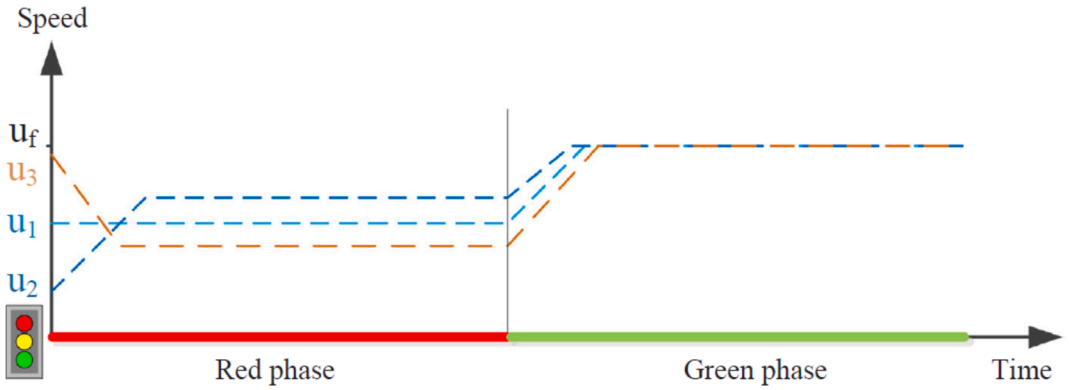

Fig. 1. Optimum speed profile when vehicle is approaching a signal in red phase. . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Source: Almannaa et al. (2019)

commercially developed. Subsequently, DCMs are the appropriate statistical tool to understand the behavioral process that leads to the users' choice. They yield the probability of an individual choosing each alternative of the choice set, as well as the contribution of each predictor to that outcome. Therefore, it can be said that SCE helps in collecting the information needed for the estimation of the DCMs that ultimately shed light on the inclinations of individuals towards a set of alternatives, which may include some that are not available at present. In our case the purchase of the Eco-CACC system.

There is a number of recent works that use SCEs to gather data on consumer preferences in vehicle related emerging technologies, such as Krueger et al. (2019), who investigated changes in the valuation of travel time due to the presence of autonomous vehicles. Cherchi (2017) also used SCE to measure the effect of social conformity in the preferences for EV, including these social aspects in the choice tasks as additional attributes. Jensen et al. (2013) investigated how experience affects the preferences of individuals towards EVs, conducting a two/wave SCE where data was collected before and after the respondents experienced an EV for three months. Cirillo et al. (2017) analyzed household future preferences for gasoline, hybrid, and battery EVs in a dynamic marketplace. For a comprehensive review of studies that use SCEs, we refer to Gkartzonikas and Gkritza (2019). Studies that consider attitudinal aspects such as Bolduc et al. (2008), Daziano and Bolduc (2013), or Glerum et al. (2013) highlight the importance of indicators of environmental concern and technology inclination. In this line, Kim et al. (2018) found out that perceived operational monetary savings are the main motivator to EV diffusion, while charging risk is the main barrier. On the other hand, examples of the use of DCMs to simulate market shares are abundant, like Axsen and Wolinetz (2018) and Haaf et al. (2016). Tanaka et al. (2014) also offer an interesting summary of stated preference studies on electric vehicles, as well as Horne et al. (2005) and Hidrue et al. (2011).

In summary, while the works on V2I connectivity focus on traffic-related aspects, the literature on the Eco-CACC does on the technical aspects of the system and on the improvements that it provides in terms of fuel savings. Other studies emphasize the analysis of consumer preference for EVs carrying out market share simulations. However, there is no research that combines all these elements. This study fills this gap by designing a SCE specifically created for the case of the Eco-CACC to collect data on the inclination of consumers to purchase gasoline-powered and electric-powered vehicles equipped with this technology. These data serve to estimate models of discrete choice that allows knowing if the characteristics of the Eco-CACC are sufficient to stimulate the demand of vehicles equipped with this system; as well as to predict its market shares for different types of drivers. Our study develops this methodology to investigate the feasibility of the Eco-CACC systems in terms of private individual evaluations that weigh the cost-benefit of the system along with the positive social externalities associated to a reduction in polluting emissions. Our final goal is to provide guidance for policy making and commercial management, thereby contributing to its successful implementation.

Our results show that people willing to buy EVs are likely to pay the premium of adopting the Eco-CACC regardless its negative monetary cost-benefit outcome, based on the improvement it brings in terms of environmental efficiency. Consequently, these individuals are willing to internalize the externalities (i.e., damage or social cost) associated to polluting emissions. This remarkable result has critical implications from the perspective of infrastructure policy and industrial development. On the one hand it shows that investing in adaptive traffic control systems (ATCS) is worth it because individuals are willing to adopt the Eco-CACC. On the other hand, car manufactures should offer Eco-CACC as a standard feature in their self-driving packages, because it will be demanded by users.

Delving into infrastructure policy, and until environmental concerns took the center stage, the existing ATCS were mainly oriented towards reducing congestion times, saving energy costs, and increasing safety. An example is the Meadowlands Adaptive Signal System for Traffic Reduction (MASSTR) in New Jersey, based on the Sydney Coordinated Adaptive Traffic System (SCATS). SCATS is a traffic management strategy in which traffic signal timing changes, or adapts, based on actual traffic demand. Currently, the emphasis is placed on the reduction of emissions, and planners estimate savings in gasoline consumption by more than 1.2 million gallons per year and greenhouse gas emission by more than 11,000 tons per year, NJSAS (2016). The implementation of SCATS was estimated at

Table 1
Alternatives, attributes, and model.

	Gasoline Branch	Electric Branch
Alternatives	Gasoline	Electric
	Gasoline + Eco-CCA	Electric + Eco-CCA
	None	None
Attributes	Price	Price
	Energy savings	Energy savings
	Propulsion cost	Propulsion cost
	Annual propulsion costs	Annual propulsion costs
Design	Efficient with Bayesian priors	
Model	Multinomial Logit/Mixed Logit	

approximately $28,800 per mile per year by the U.S. DOT.[1] This sizable investment amount needs to be enhanced to include the necessary V2I technologies, such as that required by the Eco-CACC. However, only if individuals are willing to adopt the technology given their preferences, then these investments will have the expected returns in terms of emissions reductions.[2]

The rest of the paper is organized as follows; Section 2 describes in detail the SCE and the methodology adopted for this study. Regression models estimates and potential market shares are reported in Section 3. Finally, Sections 4 and 5 contain the discussion of our results and the conclusions, respectively.

2. Methodology for studying Eco-CACC adoption

2.1. The Eco-CACC system

Within signalized corridors, when a driver approaches an intersection there is uncertainty about when the traffic light will change phase. Consequently, some drivers tend to accelerate/decelerate sharply, which is a driving behavior that consumes too much fuel. The Eco-CACC connects to a controller located at signalized intersections, receiving data on the signal phasing and timing, and computing a fuel-optimized speed profile. Then, it automatically adjusts the speed to the pattern, upstream and downstream the intersection. Fig. 1 shows the optimum speed profile that the algorithm calculates when the vehicle approaches a signal in red phase. The blue lines exhibit the case in which the vehicle can pass the intersection without deceleration, whilst the brown the case in which it needs to decelerate to pass the intersection on green. u_f denotes the speed limit. As can be seen, if the vehicle can pass the intersection during the green phase without decelerating, the system maintains the speed; otherwise, the vehicle should accelerate. When the signal turns green, the vehicle dynamics model accelerates until reaching the speed limit. If, on the contrary, the vehicle is circulating at a speed that does not allow to pass the signal on green, it needs to slow down, to reach the intersection at the exact moment that it turns green. Then it accelerates until reaching the road speed limit. The controlling algorithm makes use of dynamic programming to discretize the solution space and solve the optimization problem to compute the optimum speed profile. More technical details on the algorithm, including the equations underlying the vehicle dynamics can be found in Chen et al. (2016) and Almannaa et al. (2019).

The energy savings provided by following the optimal speed profile have been evaluated in several experiments already reviewed in the Introduction. Some of them were carried out in real facilities without traffic, whilst more complex traffic conditions were simulated through software (Chen and Rakha, 2020). For the field tests, a 2014 Cadillac SRX, gasoline-powered, was used. It was equipped with V2I communication, Differential Global Positioning system, a real-time data acquisition system, and a laptop with software to control the trips and road scenarios. Through the V2I communication unit, the vehicle received the data on the upcoming signal phases. This information, along with the distance and speed was used by the Eco-CACC algorithm to compute the fuel-efficient speed profile. Although this is the only vehicle that has been used in a real situation, many simulation tests with different types of gasoline vehicles were conducted, and their results were in accordance with the field tests: i.e., an overall average reduction of fuel between 8 % and 15 %. Other simulations were also carried out for battery EVs, which yielded savings around 10.5 % in arterial roads, on average (Chen and Rakha 2021). Therefore, real and simulated tests for both gasoline and EVs coincide in the range of 8–15 % energy savings.

2.2. Stated choice experiment

As mentioned above, SCEs and DCMs can be the right tool to predict market shares when no reliable information, or no information at all, exists on the demand of a certain good. The purpose of a SCE is to determine the influence of the characteristics of a set of

[1] Calculated as ((total cost/number of years) × number of signals within corridor/length of corridor in miles). Total costs are divided into initial investments plus maintenance. See the Cost Database on the website of the Intelligent Transportation Systems Joint Program Office: https://www.itskrs.its.dot.gov/costs.

[2] Eventually, regardless individuals' attitude and industry concerns, regulatory agencies could make the installation of the Eco-CACC compulsory, just as they force emissions standards for on-road vehicles and engines. For example, EPA regulations for the U.S. can be accessed at https://www.epa.gov/regulations-emissions-vehicles-and-engines/regulations-onroad-vehicles-and-engines.

Table 2
Levels of attributes and priors for both branches.

	Gasoline	Electric	Gasoline + Eco-CACC	Gasoline / Electric + Eco-CACC
Price ($)	22,500	30,000	Price + 1,000 1,500	Price + 1,000
Uniformly distributed	25,000	32,500	2,000	1,500
[-0.447, −0.26]	27,500	35,000		2,000
Energy Savings (%)[a]	0	0	8, 11, 15	8, 11, 15
Propulsion cost ($/per mile)	0.05, 0.055, 0.06	0.03, 0.035, 0.04	0.05, 0.055, 0.06	0.03, 0.035, 0.04
Annual Propulsion Cost ($)	Propulsion cost × Annual miles	Propulsion cost × Annual miles	(Propulsion cost × Annual miles) * (1 - Energy savings)	(Propulsion cost × Annual miles) * (1 - Energy savings)

[a] Figures adjusted by type of road mainly driven (-25% for arterial roads, −75% for highways, −50% for both).

alternatives on the probability of choosing them. A study of this type normally consists of an individual facing several hypothetical scenarios in which different levels of the attributes of the alternatives are shown. By evaluating the implicit trade-offs, the user makes a choice among the available alternatives. Therefore, in general terms, to carry out an experimental design it is necessary to define; i) the set of alternatives, their attributes and their levels; ii) the type of design; iii) and the underlying discrete choice model to be estimated once the data is collected. Table 1 summarizes these aspects considering the two branches of our survey. In this regard, although the main focus of this work was to explore the effect of the Eco-CACC in the adoption of EV, we conducted the same study also for internal combustion vehicles (gasoline). This way, we were able to assess whether the effect of the benefits associated to the Eco-CACC results in different evolutions of these two sub-markets, revealing specific preferences of potential EV purchasers.

Regarding the attribute levels, the price and propulsion cost to be displayed in the scenarios come from real information obtained from a medium-size vehicle of reference, as is usual in studies of this kind.[3] However, since one of the alternatives included the Eco-CACC system, it was particularly important to define its cost. Although unfortunately there is no such technology in existing cars that can be used as a reference, as previously shown the Eco-CACC is essentially an adaptive cruise control system (ACCS) that incorporates additional data from vehicle GPS (or smartphone) and traffic signals. According to the market price data in USDOT (2007), the cost of adding an ACCS to a vehicle already equipped with collision warning was estimated at around $300. A 5 % inflation index for the 2007 cost and the price differences between traditional cruise control and adaptive cruise control in the current vehicles on the market are considered to estimate the cost of the Eco-CACC system. In this way, we estimate the cost of additional hardware components such as GPS ($50 - $100), communication data receiver ($150 - $300), and software implementation ($800 - $1600). This brings the total cost of the Eco-CACC to the range of $1,000 - $2,000. Accordingly, we consider that the cost of existing vehicles is increased by $1,000, $1,500, or $2,000.

On the other hand, the calculation of fuel savings also presented a challenge, as the Eco-CACC system is only activated in the vicinity of signalized intersections. Driving time in signalized corridors may be a small part of the total driving time and may also depend on the type of roads traveled. Therefore, it would not be accurate to inform individuals of 8 % − 15 % general savings obtained in the aforementioned field and simulation tests. To limit this problem, the type of road that the respondent usually drives (*Arterial*, *Highway* or *Equally both*) is asked at the beginning of the survey, and the savings adjusted accordingly. Namely, if the driving takes place mainly in in arterial roads, where there are more traffic lights, the total savings are reduced by 25 %, for a range of 6 % − 11.25 %. On the contrary, if it occurs mainly in highways, where there are less traffic lights, they are reduced by 75 %, which means a range of savings of 2 % − 3.75 %. For the third option they are reduced by 50 %. These assumptions provide the respondents with a more realistic perception of the savings they can obtain.[4] In addition to this information, the annual propulsion cost is also displayed to provide a better understanding of how much this savings would be. It is computed based on the propulsion cost per mile and the savings of the scenario, and on the annual mileage declared by the interviewee in a previous section of the survey.

Finally, we opted for an *efficient* design with Bayesian priors, uniformly distributed, with preliminary values obtained form (Cherchi, 2017).[5] This specification, in general terms, aims to produce scenarios that generate parameters estimates with as small as possible standard errors. Table 2 summarizes the levels for all attributes that are combined in the mathematical design in order to create a number of unique choice tasks.

Since we considered two types of vehicles and three type of roads, the survey was organized in 2 main logic branches (gas/electric) which were further subdivided into 3 subsections (by type of road), comprising 12 utility functions. With respect to the choice

[3] We choose our reference vehicles among the best-selling models in the US market, whose fuel economy characteristics can be consulted in the joint official website of the US Department of Energy and the Environmental Protection Agency. The cars are the 2018 Honda Civic 2.0 L, 4 cyl., Automatic (https://www.fueleconomy.gov/feg/Find.do?action=sbs&id=39566) for the gas scenario, and the 2018 Nissan Leaf Automatic (A1) (https://www.fueleconomy.gov/feg/Find.do?action=sbs&id=39860) for the EV scenario.

[4] Notice that including fuel saving is technically equivalent to the enhanced driving range provided by Eco-CACC. Therefore, by explicitly presenting information on less fuel consumption, which directly associates the system with an environmentally friendly technology, individuals are also implicitly weighing the advantage of driving more on the same battery charge or fuel tank.

[5] Performed with the Ngene software for experiment design (ChoiceMetrics, 2014).

situations, we defined 36, divided into 4 blocks. Therefore, each respondent faced 9 different scenarios to respond to. That allowed for attribute level balance, which ensured that the parameters could be estimated on the whole range of levels.

2.3. Questionnaire

The questionnaire consisted of 4 sections and was designed and distributed using Qualtrics (Qualtrics Research Core, 2021) via web. It develops sequentially as described in what follows. Subject are presented with several choices that follow a logical pattern of successive choices. For example, they decide on their preferred propulsion system and then identify the type of roads they drive. This way respondents are led to the appropriate branch of the SCE questionnaire depending on the answers given in the first section. Target population consisted of Maryland residents older than 18 with a drivers license. After several pilots in which we made sure that the values of the choice tasks were coherent, the final survey was taken by 317 users between October 2019 and December 2019, which provided 2,853 pseudo-observations. They took the survey via web with a response rate of 85.7 % and an average duration of about 11 min.

2.3.1. Preliminary questions

The two questions of this section, shown in Fig. A.1 of the Appendix, allow to particularize the choice tasks. The first refers to the type of engine of the next vehicle that the interviewee would be willing to purchase (*Gasoline, Electric, Hybrid, Other)*. The second question asks about the roads driven by the respondent on a typical day (*Arterial, Highways, or Equally both*). As described above, this information is used to lead the user to the branch of the survey that shows the specific scenarios corresponding to these choices.

2.3.2. Car ownership

In this section information about the vehicle choice is collected since the propulsion cost displayed later in the choice tasks are calculated using the mileage introduced here. Some other questions are also asked on the number and type of vehicles owned in the household.

2.3.3. Stated choice experiment

Before accessing this part of the questionnaire implementing the SCE, the respondent reads relevant information about the Eco-CACC system and its attributes, so that s/he can make informed decisions. Fig. A.2 in Appendix 1 shows this information as well as the link to the explanatory video on the Eco-CACC system. Moreover, before moving on to the choice situations, they must indicate whether this information was sufficient to understand the system and its associated advantages (no one in our sample answered this question negatively).

After this opening explanation presenting the Eco-CACC system, a choice task corresponding to the vehicle and road type is displayed, see Fig. 2. The user evaluates the information an makes a choice. This process is repeated 9 times, facing a different choice task each.

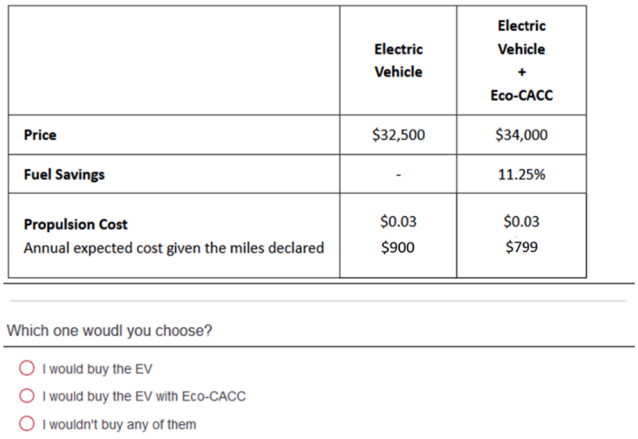

Fig. 2. Screenshot. Choice task for an individual who declared to drive mainly in arterial roads and her next purchase will be an EV.

Table 3
Percentage of choice by branch and type of road driven.

Choice	Gasoline			Electric Vehicle (EV)		
	Arterial	Highway	Both	Arterial	Highway	Both
No Eco-CACC	41.00	55.60	49.10	27.80	40.90	20.80
Eco-CACC	44.20	41.00	41.90	55.60	54.50	67.90
None	14.80	3.40	9.00	16.70	4.50	11.30

2.3.4. Socioeconomic information and attitude towards EV

This section has two parts. The first gathers general sociodemographic information. The second presents a question (see Fig. A.3 in Appendix 1) in which it is necessary to select a level of agreement to attitudinal statements. These statements pertain to three different categories (unknown to the respondent): *Environmental concern*, *Technology innovator*, and *Pro-EV*. In order to group in one only indicator user's attitude towards each aspect, we assigned a score from −2 (*strongly disagree*) to 2 (*strongly agree*) to each response. Then the scores of the same category were added up to create an overall representative score for that attitude.

2.4. Analytical approach

As for the analysis of the cruise control system choice, we start with a Multinomial Logit (MNL) model to set a baseline against which to compare more complex specifications, such as Multinomial Mixed Logit (MML). MML overcomes the limitations of MNL by allowing random taste variation, realistic substitution patterns, and the capture of the effect of multiple choices made by the same individual (panel structure). These capabilities are especially convenient for the case at hand, as users responded to 9 different scenarios in which two alternatives, substitutes to each other to some extent, were presented.

Based on the Random Utility Models paradigm (Marschak 1974) and following (Train 2009), the utility obtained by an individual n when choosing the alternative j pertaining to a set J is:

$$U_{nj} = \beta_n^{'} x_{nj} + \mu_n^{'} z_{nj} + \varepsilon_{nj} \tag{1}$$

where x_{nj} and z_{nj} are observed attributes of alternative j, $\beta_n^{'}$ is a vector of coefficients representing individuals' tastes, $\mu_n^{'}$ is vector of random terms with zero mean, and ε_{nj} is independent and identically Gumbel distributed. If $\beta_n^{'}$ are random and vary over decision makers representing taste variation, they do with density $f(\beta)$, which is a function of parameters β. The terms in z_{nj} are error components that define the stochastic portion of the utility along with ε_{nj}. This second part of the utility, $\mu_n^{'} z_{nj} + \varepsilon_{nj}$, can be correlated among alternatives depending on the specification of z_{nj}, to form specifications analogous to, for instance, nested logit (Hackbarth and Madlener 2013). In the logit model z_{nj} is zero, so that there is no correlation, resulting in the Irrelevance of Independent Alternatives (IIA) property.

Conditional on β, the probability that a person makes a sequence of choices $i = \{i_1, \cdots, i_T\}$ is:

$$L_{ni}(\beta) = \prod_{t=1}^{T} \left(\frac{e^{\beta_n^{'} x_{ni_t t}}}{\sum_j e^{\beta_n^{'} x_{njt}}} \right) \tag{2}$$

and the unconditional probability is the integral of this product over all values of β:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \tag{3}$$

This probability needs to be simulated taken draws from the β distribution. Then the logit formula in equation (2) is calculated for each choice i, and its product is taken. This process is repeated a certain number of times and the results are averaged.

In our models we made use of both random coefficients and error components. For the former, we considered lognormal distributions for *System cost* and *Energy savings*. For the latter, we did not try to identify a specific pattern of substitution; we incorporated an error component normally distributed with zero mean in each alternative to seek to capture correlations across the alternatives or heteroskedasticity. This approach dramatically improved the goodness of fit of the models with respect to the Logit baseline and helped finding coherent estimates.

3. Results: Estimating effects and market shares

3.1. Data

The main statistics of the distribution of the 2,853 samples collected can be found in Appendix 2. The percentage of individuals working for the government is high, which in this case is consistent since this survey was taken in the State of Maryland, which "surrounds" Washington D.C, a center of public jobs. Also, some of the counties of this state are among the wealthiest ones in the US, which justifies the high maxima of individual and household incomes as well. On the other hand, 68.15 % of the interviewees stated that the type of engine of the next vehicle they would buy would be gasoline. Therefore, this percentage of users were directed to the

Table 4
Model estimations for the Gasoline branch.

	Model 1		Model 2		Model 3		Model 4	
	Estimate	***t*-ratio**	**Estimate**	***t*-ratio**	**Estimate**	***t*-ratio**	**Estimate**	***t*-ratio**
ASC_GAS	1.544***	4.54	3.9336***	5.408	4.094***	7.02	4.28***	7.04
ASC_GASSYS	2.441***	4.75	2.91***	3.76	3.462***	4.36	3.658***	4.87
System cost	−0.244***	−3.14	−0.301***	−2.61				
System cost (mean)					−0.73**	−2.47	−0.78***	−2.74
System cost (sd)					1.902***	6.87	−1.529***	−8.13
Energy savings	−0.044	0.35	0.761***	3.74				
Energy savings (mean)					0.372***	3.39	0.372***	3.24
Energy savings (sd)					0.36***	6.69	0.467***	5.34
Technology inclination att.							0.361***	4.67
Male			2.53**	2.82				
EC GAS sd			−2.963***	−6.9	2.587***	6.17	2.359***	−7.64
EC GASSYS sd			−1.951***	−3.34	−0.459	−0.94	0.711***	4.29
EC NONE sd			−3.079***	−6.22	−3.064***	−8.65	−3.08***	−7.75
LL (final)	−1847.06		−1153.13		−1126.91		−1116.51	
Adj. rho-square (0)	0.15147		0.4697		0.4813		0.4856	
AIC	3702.13		2322.28		2271.81		2253.02	
BIC	3724.42		2366.86		2321.96		2308.75	

** significant at 5%, ***significant at 1%.

Table 5
Model estimations for the Electric branch.

	Model 1		Model 2		Model 3		Model 4	
	Estimate	***t*-ratio**	**Estimate**	***t*-ratio**	**Estimate**	***t*-ratio**	**Estimate**	***t*-ratio**
ASC_EV	1.078***	3.56	4.824***	2.57**	4.38**	2.65	4.112***	3.37
ASC_EVSYS	1.502***	2.18	5.447***	2.78	4.548**	2.55	4.754***	3.37
System cost	0.018	−0.19	−0.005	−0.04			−0.007	−0.05
System cost (mean)					0.007	0.05		
System cost (sd)					−0.091**	−1.80		
Energy savings	0.062	0.43	0.235	1.41			0.231	1.34
Energy savings (mean)					0.402**	2.23		
Energy savings (sd)					−0.526***	−4.43		
Technology inclined att. EV							0.462***	3.07
Technology inclined att. EV + Eco-CACC							0.441***	3.14
EC EV sd			1.868***	5.27	−0.987***	−2.73	1.952***	5.015
EC EVESYS sd			1.349***	3.25	1.651	5.55	−1.25***	−3.10
EC NONE sd			3.048***	2.79	3.604***	3.97	3.182***	5.50
LL (final)	−877.38		−647.70		−646.89		−644.22	
Adj. rho-square (0)	0.1663		0.3788		0.377		0.3802	
AIC	1762.77		1313.41		1315.78		1310.46	
BIC	1782.02		1356.72		1368.72		1363.39	

** significant at 5%, ***significant at 1%.

gasoline branch, whilst 31.85 % were directed to the electric one, where they faced scenarios with information on their preferred type of propulsion. Regarding the roads driven, 20.81 % mainly drove arterial roads, 19.23 % mainly drove highways, and 59.94 % equally drove both. Regarding the main socioeconomic variables concerning gender and age, the sample differs from the census characteristics of the target population in the state of Maryland. To prevent unreliable estimations due to selection bias we adjusted the sample weights following a post-stratification procedure (cell weighting, or dynamic interlock response), so the final sample reflects the characteristics of the population − for an early discussion of weighting methods see Sharot (1986).

With respect to the choices, Table 3 shows the percentage of each alternative by branch and type of road driven by the user. For the gasoline engine, the alternative with the Eco-CACC is the most selected by individuals who mainly drive arterial roads. For electric, the vehicle with this technology is the most chosen in all road categories.

Table 6
Actual and predicted choices; gasoline and EV.

	Gas	Gas + Eco-CACC	None	EV	EV + Eco-CACC	None
All						
Times chosen (actual)	822	942	180	240	571	98
Times chosen (prediction)	820	987	136	284	533	91
Diff (actual-predicted)	−2	45	−44	44	−38	−7
t-ratio	−0.06	2.11	−3.91	3.16	−2.54	−0.71
p-value	0.94	0.03[a]	0.00[b]	0.00[a]	0.01[b]	0.47
Arterial group						
Times chosen (actual)	191	177	64	45	90	27
Times chosen (prediction)	156	249	26	44	100	16
Diff (actual-predicted)	−35	72	−38	−1	10	−11
t-ratio	−3.44	7.12	−7.68	−0.04	1.69	−2.64
p-value	0.00[b]	0.00[a]	0.00[b]	0.96	0.09	0.00[b]
Highway group						
Times chosen (actual)	144	195	12	81	108	9
Times chosen (prediction)	174	147	29	69	110	18
Diff (actual-predicted)	30	−48	17	−12	2	9
t-ratio	3.35	−5.34	3.31	−1.76	0.32	2.38
p-value	0.00[a]	0.00[b]	0.00[a]	0.07	0.74	0.01[a]
Both group						
Times chosen (actual)	487	570	104	114	373	62
Times chosen (prediction)	488	591	80	170	322	56
Diff (actual-predicted)	1	21	−24	56	−51	−6
t-ratio	0.11	1.27	−2.65	5.19	−4.37	−0.83
p-value	0.91	0.20	0.00[b]	0.00[a]	0.00[b]	0.40

[a] Model significantly overestimates at 5%, [b] Model significantly underestimates at 5%.

3.2. Estimation results

3.2.1. Gasoline branch

Table 4 presents the results for all models estimated using the case scenarios for which the respondent stated that s/he would buy a gasoline vehicle in her next purchase.[6] This includes all type of roads. We start with a standard MNL model (Model 1) including all the attributes of the alternatives. In this case, the effect of fuel saving is not significant and has the opposite sign. Therefore, following the approach described above, MML models with error component and panel effect are estimated (Models 2 to 4). Adding error components (Model 2) immediately improves the estimation significantly (adj. rho-square = 0.4697) and finds correct signs for the attributes. Nevertheless, exploring the existence of taste heterogeneity yields even better results. Model 3 considers random the coefficients of the system cost and the energy savings that it provides (lognormally distributed). Both the means and the standard deviations are highly significant, justifying this approach. Regarding socioeconomic variables, none of them contributed to a better adjustment of the data, except for gender in Model 2, and those related to the individual's attitude towards new technologies in Model 4, which ultimately presents the best fit. Likelihood ratio tests confirm these improvements. On the other hand, Models 3 and 4 yield a willingness-to-pay of \$509 (=0.372/0.73×\$1,000) and \$477 (=0.372/0.78×\$1,000) for 1 % of savings, respectively, which seems reasonable given that a vehicle is a durable good. It is worth to mention that other specifications have also been estimated, such as the combination of error component, random coefficients, and systematic heterogeneity among type of roads and for different levels of income. However, none of those provided significantly better results than Model 4.

3.2.2. EV branch

Table 5 presents the results for all models estimated using the case scenarios for which the user stated that she would buy an Electric Vehicle in her next purchase. This includes all type of roads. The procedure followed is similar to that for gasoline, estimating firstly an MNL model (Model 1). In this case, the effect of fuel saving is not significant and has the opposite sign. Model 2 adds error component, resulting in a dramatic improvement in the goodness-of-fit. Model 3 is an attempt to improve estimation by considering taste heterogeneity (lognormally distributed), which seems to be present in the fuel savings that the system provides. Finally, Model 4 adds the only socioeconomic variable that helps to improve the performance, which is the positive attitude towards new technologies, alternative specific, in this case. Likelihood ratios among models confirm the improvements. It is worth to mention that, as in the case of the gasoline vehicle, systematic heterogeneity was also explored, specifically among type of road and among different levels of income. However, neither the interaction of *Energy savings* and type of road, nor that of *System cost* and income were found significantly different from zero.

Although the consistent non-significance of the cost and energy savings coefficients among models may seem like a negative result, it is indeed illuminating. The main reason for that is probably the low cost of propulsion. That is, the price of electricity per mile traveled is actually very low. This makes the savings that the Eco-CACC provides very little, even in its more beneficial range. At the

[6] The package *Apollo* (Hess and Palma 2019a; Hess and Palma 2019b) available for the R programming language was used for model estimation.

Table 7
Market shares predicted by selected models, Gasoline and EV.

	Gas	Gas + Eco-CACC	None	EV	EV + Eco-CACC	None
All						
Market share (data)	42.28 %	48.46 %	9.26 %	26.40 %	62.82 %	10.78 %
Market share (prediction)	42.21 %	50.79 %	7.00 %	31.25 %	58.67 %	10.08 %
Arterial group						
Market share (data)	44.21 %	40.97 %	14.81 %	27.78 %	55.56 %	16.67 %
Market share (prediction)	36.33 %	57.64 %	6.03 %	27.61 %	61.98 %	10.41 %
Highway group						
Market share (data)	41.03 %	55.56 %	3.42 %	40.91 %	54.55 %	4.55 %
Market share (prediction)	49.79 %	41.93 %	8.28 %	34.95 %	55.68 %	9.38 %
Both group						
Market share (data)	41.95 %	49.10 %	8.96 %	20.77 %	67.94 %	11.29 %
Market share (prediction)	42.11 %	50.92 %	6.97 %	30.99 %	58.78 %	10.23 %

same time, since the cost of the cruise system is between $1,000 and $2,000, it is unlikely that the users perceive a trade-off between cost and benefits. In other words, the energy is inexpensive, with savings representing 11.5 % in a best-case scenario. For a hypothetical case of an individual driving 20,000 miles a year, and considering a propulsion cost of 4 cents per mile, that would translate into annual savings of $92 (or $920 in total for a vehicle service life of 10 years). For a technology that may cost up to $2,000, it is possible that the user simply does not see a benefit. Note that this is also the case even for models that do not control for the users' attitude towards the environment and new technologies, whose effect could have been captured by *Energy savings*, reflecting the adoption decision. Besides the undisputed lack of profitability of the Eco-CACC system in terms of energy savings, an additional underlying cause may be the unfamiliarity of sampled drivers with adaptive traffic control systems (ATCS), which have not been deployed in the State of Maryland.[7] Consequently, since the distance range of EVs is limited, drivers anticipate that they will not take advantage of the Eco-CACC in their area since signalized intersections are not capable of incorporating this technology. That is why state and federal agencies should make further efforts to deploy the system across metropolitan areas to encourage the adoption of smart cruise control systems based on V2I technology.

3.3. Market shares

Reliable predictions of the market share of a new product are strategic for the industry (Calfee, 1985). Also, as stated above, they can also be essential for public agencies since product adoption rates may impact regulation (Mabit and Fosgerau, 2011). With a full set of alternative specific constants, the Multinomial Logit regression allows recovering the market shares of the alternatives at sample level. However, this property does not hold in the case of the Multinomial Mixed Logit, nor in the case of data subsets (i.e., road categories). Therefore, to calculate these markets shares we rely on the model with the best estimators and goodness-of-fit, which is Model 4 for both gasoline and EVs. Table 6 presents the actual and predicted choices for both branches, for each type of road subset, as well as for the overall. The *t*-ratios and *p*-values show if the difference between actual and predicted choices is significant. For a better understanding, it is indicated when the different models significantly overestimate and underestimate.

Overall, the models overestimate the market shares of the gas alternative with the Eco-CACC while underestimate those of the EV with the Eco-CACC. When the shares are calculated by the type of road that the gasoline users drive, these are significantly overestimated for the *Arterial* group, and significantly underestimated for the *Highway* group. On the other hand, for the electric users, the predictions are more accurate, significantly underestimating only in the case of the *Both* group. Table 7 shows the conversion of the above figures to market shares. The prediction for vehicles that incorporate the Eco-CACC system is, overall, 50.79 % for gasoline cars and 58.67 % for EVs. These proportions are reasonably maintained for the different sub-groups of drivers, no matter the type of engine. It is interesting that the market shares of the alternative with and without the system diverge more in the case of the EV than in the case of the Gasoline vehicle, and yet the specific cost-benefit variables of the system are not relevant for that choice. This leads to the conclusion that users' decisions are mainly based on the strong influence of the attitude towards new technologies as well as on taste heterogeneity. As previously anticipated, the predisposition of individuals buying EVs towards new environmentally friendly technologies such as the Eco-CACC, makes them adopt the system regardless its lack of pecuniary profitability. Resorting to the classic taxonomy of Rogers (1962), we would consider individuals buying EVs as innovators or early adopters; i.e., people who, by nature, can afford and are excited by the possibilities that new technologies have to offer to improve environmental efficiency. Coupled with the relatively higher cost of the EV, they would not mind investing in a cruise-control feature whose high price is also a barrier to its widespread adoption. This suggests that those adopting the Eco-CACC would be wealthier and have easy access to finances. A socioeconomic characteristic that correlates with reasonably high levels of education and social status. Our results, however, do not concur with this stereotype in full. As shown in the Appendix 2, both individual and household average incomes are smaller for the EV

[7] The only ACTS close to Washington D.C., located in Arlington (VA), and based on the SCOOT system covering 200 intersections, has been decommissioned-see https://latom.eng.fau.edu/research-reports/. A list of current and previously existing ATCS, including deployments in phase 3, can be consulted in USDOT (2018: 36-38). A total of 224 adoptions are reported.

branch than for the gasoline branch. In particular, the average income in households buying EVs is $69,542 versus $78,033 for the gasoline car. However, it is observed that the buyers of the EV are indeed more educated than buyers of gas vehicles, i.e., educational degrees above high school are consistently higher in the EV branch.

4. Discussion: Policy and industry implications

The results reported in Tables 6 and 7 are key to understand the potential market penetration of connected and self-driving cars relying on V2I systems, whose benefit over conventional cars is undisputed despite potential drawbacks. However, consumers' willingness to adopt the new technology is a necessary but not a sufficient condition for its commercial success. This also requires the commitment of government agencies in the form of infrastructure investments, and of car manufacturers, which should adapt their production and commercial practices.

In order to raise awareness among these key stakeholders, we implement a Stated Choice Experiment, considering the particularities of the Eco-CACC system, its performance in field and simulated experiments, and apply known DCMs already tested in the literature and previous research. This exercise certainly fills a research gap since no other study applies these techniques to this technology using real data obtained from field tests. For the survey and data collection, the design has been divided into Gasoline and Electric in order to gather the possible different decision-making process of those potential consumers. The reason is that both types of cars belong to clearly differentiated markets segments, whose characteristics are steadily growing apart. For both branches an efficient design has been carried out, pre-defining the Eco-CACC attributes and their levels. With the data collected, several multinomial logit and mixed multinomial logit formulations have been tested, to achieve the best fit to the data and, therefore, to have a reliable base in which to calculate market shares.

In the case of gasoline vehicles, both the additional cost of the system as well as the energy savings, have been found significant. This means that drivers perceive a trade-off between the cost of the Eco-CACC and the savings that it provides. This is not the case for the EVs, a result that is consistent in all models, which is due to the low cost of propulsion. The price of electricity per mile traveled is reduced and, therefore, the savings, in absolute amount, are reduced as well. Although the amount of fuel saving may seem attractive in percentage, when these are converted to annual savings in dollars this effect softens, so the expected cost-benefit analysis goes against the adoption decision. In short, as the results show, cost-benefit analyses yield results against adopting EVs with the Eco-CACC implemented, because savings are not still high enough to compensate the cost of the system. Moreover, since the system is activated in selected corridors with signalized intersections, and the share of driving time that occurs in them is currently limited to certain areas in the case of the gasoline car, and none for EVs in the state of Maryland (based on ATCS deployment and the limited range of the EV), the fact that the willingness to adopt the Eco-CACC is low should come as no surprise. This is an interesting finding that stands in contrast to the literature, in general, where the attributes related to the good at hand are significant in most of the cases. The inclusion of more characteristics of the Eco-CACC system might shed some light on this; however, this cruise control is still under development and there were no additional features that could be incorporated at the time this analysis was conducted. Nevertheless, regarding the attitudinal aspects, our results point in the same direction as other studies, like those reviewed in the Introduction. Although these works follow a different methodological approach, they highlight the importance of indicators of environmental concern and technology inclination.

These results are key for infrastructure planning purposes. As internal combustion cars are increasingly banned in urban areas to curb polluting emissions (particularly, in Europe, where specific phase-out dates are being considered), and it is in these arterial areas where the Eco-CACC is more cost effective, it means that drivers of gasoline cars will be discouraged to adopt it, as their use will be mainly reserved to long distance travelling in highways. On the contrary, the use of EVs is increasingly promoted in urban areas by adopting environmentally friendly regulations (e.g., tax breaks, free parking, etc.), where the private benefits of adopting the Eco-CACC are dubious. Our results regarding the adoption incentives of Eco-CACC initially mirror those already obtained for EVs. On the one hand Kim et al. (2018) show that EVs diffusion would only be successful if consumers perceive the monetary savings of adopting the new technology. However, since the cost benefit analysis yields a negative outcome, this requires strong government subsidies in the early stages of market penetration. This is confirmed by Axsen and Wolinetz (2018) in the Canadian case, stressing the high government expenditure that would be required for EVs to reach a 30 % share of new sales by 2030; around $CDN 6,000/vehicle, totaling $CDN 15–48 billion under different scenarios, or 1 %-3% of the Canadian GDP in 2017. On the other hand, to the extent that government agencies cannot realistically commit these figures to reach these goals, these authors conclude that it will be technological progress in the form of lower costs (e.g., $/kWh for batteries, or the Eco-CACC device in our case) what can ultimately ensure that these environmentally friendly technologies are widely adopted. That is, once economies of scale reducing the cost of EVs and the Eco-CACC take place in mature stages of market penetration. This does not preclude that, to be finally successful, agencies must show a long run commitment to subsidies (or infrastructure investments implementing ATCS in the case of the Eco-CACC), because financial incentives produce little long-term impact on technology adoption if only implemented for a short period of time; i.e., not long enough for the market to develop without government help.

Thus, regarding the Eco-CACC system, state and federal agencies face the dilemma of investing in ATCS, which would implement the adoption of V2I systems at a sizable cost over time, but demand would not follow rendering this investment useless. Thankfully, as a relevant qualification obtained in our study, the positive attitude of buyers of EVs towards new technologies resulting in higher environmental efficiency dominates the adoption choice despite the adverse cost-benefit result. In consequence, and quite unexpectedly, the market shares for the EV equipped with the Eco-CACC are the highest among both branches. This is a reassuring result for government agencies, as it implies that the deployments of ACTS systems enhanced with V2I technology will be matched by demand. Also, being contamination an externality, these agencies (as social planners) could regulate its adoption as part of a future package of safety and environmental features to be mandatory in connected cars. Knowing the positive attitude of consumers towards the Eco-

CACC, which translates into high market shares, this regulation should not face a general opposition.

As for the industry, it seems that the drive for the autonomous car is not waiting for ATCS investments. Car manufactures are using different types of active and passive sensors to deploy their self-driving vehicles, but they are not actively seeking partnerships with public officials. Hence the installation of the Eco-CACC is not currently a priority for them, and if it were to be adopted, it would be eventually bundled in packages allowing V2V and V2I communications. Our results show that while they should not be particularly eager to offer the system in EVs, if they were to look at consumers' willingness to pay in terms of pure cost-benefit level, their attitude is clearly favorable towards the adoption of features such as the Eco-CACC. This is consistent with observed long-run trends in the industry that will result in the abandonment of internal combustions cars.

5. Conclusions

The goal of this study is to evaluate the potential penetration of the Eco-CACC system, a cruise control that automatically adjusts the speed of a vehicle in the vicinity of signalized intersections with the aim of providing energy savings. This brings the economic dimension to the analysis of the Eco-CACC technology, which mainly focuses on the technical improvements that the system provides. Based on consumers' environmental attitudes and willingness to pay for the new technology, reflected in the potential market shares of vehicles equipped with this system, we conclude that if a concerted action between public agencies and industry manufactures is taken, the commercial growth of the Eco-CACC can be very successful. The overall attitude of individuals in favor of adopting the system is capable of overturning the lack of private (cost-benefit) profitability. Naturally, lower prices for the cruise system resulting from scale economics as market shares grow in time will translate in even higher adoption rates. If in future the Eco-CACC can be implemented at a lesser cost, the benefits may be more evident for the users. In this respect, we acknowledge that the reduction in price has not been included in the adoption model due to the difficulty of forecasting the cost elasticity of the system associated to larger production scales. But again, our models already predict remarkable market shares for the alternatives that include the Eco-CACC technology to the tune of 51 % for gasoline cars and 59 % for EVs.

Finding reliable estimations of market shares is a complicated process, especially in this case, since the Eco-CACC is a disruptive technology for which no prior information exists in terms of willingness to adopt it, which implies an inherent uncertainty. However, following previous literature on similar cases, we have shown that the SCE approach, coupled with multinomial regression analysis, represents an appropriate tool to model this uncertainty, so as to obtain relevant conclusions regarding the future adoption of this technology; conclusions that are quite relevant for stakeholders. Possible extensions of this study that would increase the robustness of our results may consist of exploring aggregated diffusion models, like those initiated by Bass (1969) and extended by other authors such as Weerahandi and Dalal (1992) and Jun and Kim (2011). These authors combine Bass diffusion models with multinomial logits, aiming to capture simultaneously both the diffusion and replacement processes.

Finally, it is fair to mention the limitations of any study using stated preferences. Since the information gathered is hypothetical, i.e., referred to what users state they would do in a given situation, there is no factual information against which compare the obtained results. Although this limitation is inherent to any study that explores products that do not yet exist, it is necessary to keep it in mind. Consequently, SCEs require specific and careful design, which may be subject to several iterations until the appropriate trade-offs that users evaluate are fine-tuned. This is a process that requires a significant investment of time and resources; including efforts aimed at addressing sample issues that may arise from the data collection (such as selection error or participation bias). Overall, we believe that the approach that we have developed overcomes these potential weaknesses, offering reliable results that go beyond the common applications of these methodologies to calculate the willingness to pay for existing products or services, rather than proofs of concepts as we do here. In this respect, we also unveil relevant behavioral elements underlying the decision-making process of individuals when they face the decision to adopt new environmentally friendly technologies like the Eco-CACC.

Declaration of ethics approval.

The University of Maryland College Park (UMCP) IRB has determined that this project, which involves human participants is EXEMPT FROM IRB REVIEW according to federal regulations. Exemption category #4; Consent Waiver: 45CFR46.117(c)(1).

Financial disclosure

This research was sponsored by the Urban Mobility & Equity Center (UMEC), based at Morgan State University, project number UMEC-018. UMEC is a federally funded Tier 1 research center through the Fixing America's Surface Transportation (FAST) Act. José L. Zofío thanks grant EIN2020-112260 funded by Ministerio de Ciencia e Innovación/ Agencia Estatal de Investigación /https://doi.org/10.13039/501100011033.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

Appendix 1. On-line survey questions for the choice experiment.

See Figs. A1-A3.

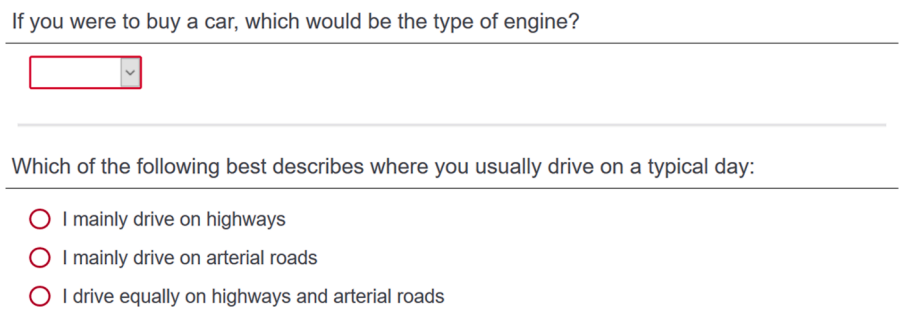

Fig. A1. Screenshot. Vehicle choice and roads driven on a typical day.

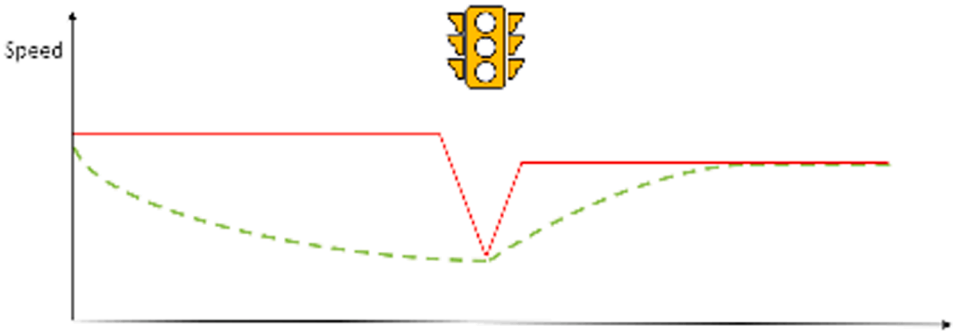

Fig. A2. Screenshot. Information about the Eco-CACC system.(Link to the explanatory video on the Eco-CACC system can be found at https://www.youtube.com/watch?v=EcnxTFFEkew&feature=youtu.be).

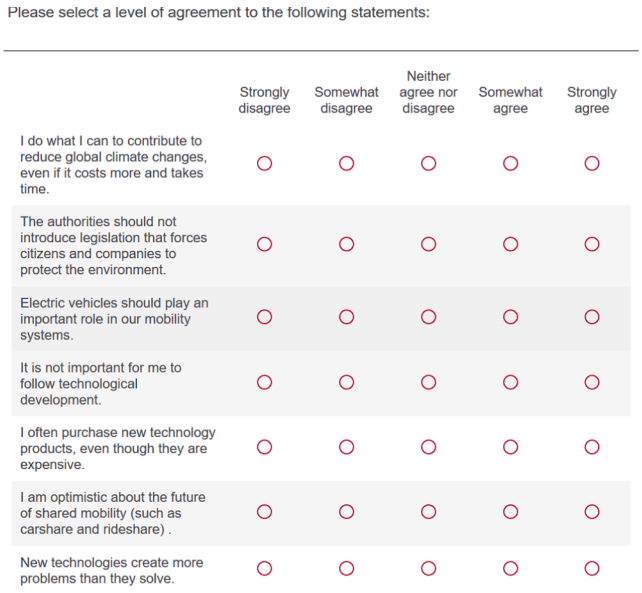

Figure 4. Attitudinal questions.

Fig. A3. Screenshot. Questions surveying ecological attitudes.

Appendix 2. Socioeconomic characteristics of the surveyed individuals residing in the state of Maryland.

	Overall	Gasoline	Electric (EV)
Age			
Min	18	18	18
Max	78	78	72
Ave	38	38	38
Gender			
Female	70.32 %	71.25 %	68.31 %
Married			
Yes	42.89 %	43.96 %	40.59 %
Employment status			
Government full time	5.99 %	4.63 %	9.79 %
Government part time	0.63 %	0.93 %	0.00 %
Private full time	52.03 %	55.53 %	44.55 %
Private part time	7.88 %	6.48 %	10.89 %
Self-employed	6.62 %	5.09 %	9.90 %
Retired	9.46 %	10.64 %	6.93 %
Student	4.10 %	2.78 %	6.93 %
Unemployed	9.15 %	9.25 %	8.91 %
Other	4.10 %	4.63 %	2.97 %
Education degree			
Less than high school	1.26 %	1.39 %	0.99 %
High school	19.87 %	21.75 %	15.84 %
Graduate or professional degree	17.66 %	12.03 %	20.79 %
Bachelor's degree	22.70 %	23.60 %	29.70 %
Some college	38.47 %	41.18 %	32.67 %
Individual gross income			
Min	0	0	1,000
Max	300,000	300,000	180,000
Ave	52,364	52,756	51,525
Household gross income			
Min	1,000	1,000	1,000
Max	800,000	800,000	300,000
Ave	75,327	78,033	69,542
% Income living expenses*			
Min	2	1	6
Max	99	99	99
Ave	56.52 %	55.96 %	57.71 %

*Income share spent in Housing, Healthcare, Insurance, Food and Education.

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