LETTER

Electric vehicle adoption: can short experiences lead to big change?

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Abstract

Plug-in electric vehicles (PEVs) offer a promising pathway to decarbonizing the personal transportation sector, but PEV sales remains low. Prior research has found that direct experience with PEVs increases consumers’ stated purchase consideration, but these studies have used relatively long exposure times (days to months) with a PEV. To assess the effect of shorter exposure times (e.g. minutes) on stated purchase consideration, we conducted an experiment at the 2019 Washington D.C. Auto Show. Participants \( n = 6518 \) were asked to rate their level of consideration to adopt a PEV before and after riding in one of four different PEVs for just 3–5 min. We find that the experience of riding in a PEV on average had a significant, positive effect on participants’ consideration ratings. We also find that the vast majority of respondents were unable to correctly answer basic knowledge questions about refueling a PEV and federal subsidies available for purchasing a PEV. These results suggest that while consumer knowledge about PEVs remains low, short rides or drives in a PEV could be an effective, more scalable strategy for increasing PEV consideration across larger populations.

1. Introduction

Meeting the goals of the Paris Agreement will require massive decarbonization of the transportation sector—the largest contributor to anthropogenic greenhouse gas emissions in the U.S \([1]\). Plug-in electric vehicles (PEVs) offer a promising pathway to rapid decarbonization, provided they are charged on low-carbon energy sources. Despite a wide range of government incentives to increase PEV adoption, sales are still low compared to conventional internal combustion engine (ICE) vehicles \([2–4]\). In 2018, U.S. PEV sales comprised just 2.1% of total vehicle sales \([5]\), and with the exception of Tesla the combined monthly sales of battery electric vehicles (BEVs) sold by all other automakers have been flat for the past 5 yr (see figure 1).

Prior research has identified multiple barriers to achieving greater PEV adoption, including high purchase prices \([6, 7]\), insufficient recharging infrastructure \([8–10]\), and ‘range anxiety”—the fear that the driving range on a single charge will be insufficient to make it to a destination \([6, 8, 11–13]\). Researchers have also found that consumers often hold multiple misperceptions about PEVs, including that they are less powerful than ICE vehicles, have worse environmental benefits, and are inconvenient to recharge—perceptions that are inconsistent with actual PEVs available on the market today \([14, 15]\). Finally, researchers have found that most consumers lack basic knowledge about many aspects of PEVs, including their appearance, purchase price, acceleration performance, top speed, recharging time, driving range, recharging operation, electricity costs, and maintenance \([4, 16–18]\).

One potential strategy to help alleviate some of these barriers and misperceptions is to increase consumers’ direct experience with PEVs. Prior research has found that consumers who have had direct experience with PEVs were more comfortable with the technology, noticed more of the advantages that PEVs offer, and in general perceived PEVs more positively than those who lacked direct experience \([19–22]\). Experiments that measure differences in stated perceptions about PEVs before and after having a direct experience with a PEV have concluded that direct
experience results in a more positive perception and opinion about PEVs and their performance [23–30]. Other studies found that participants with more PEV experience could readily recognize the environmental and economic benefits of PEVs, such as lower refueling costs, and were more capable of assessing whether their true driving range needs would be met by a PEV [19–21, 31]. Finally, studies also found that after directly experiencing a PEV, participants had more favorable opinions about PEVs and higher stated purchase intentions [25, 27, 29, 30].

Nonetheless, these studies have all involved relatively long time frames—from days to months—during which participants experienced a PEV, which limited the feasible sample size (most studies have had less than 100 participants). The implications of these studies are also limited in their scalability; for example, it would be unreasonably costly for many thousands of customers to test drive a PEV for days or months in order to increase PEV adoption. Table 1 places this study in the context of this prior literature (a more detailed and comprehensive version can be found in section 4 of the comprehensive information (stacks.iop.org/ERL/15/0940c3/mmedia)).

In this study, we aim to assess the effect of short exposure times (e.g. minutes) on stated PEV purchase consideration. By limiting the exposure time to riding in a PEV for just 3–5 min, we were able to achieve a much larger sample size (n = 6518) compared to similar prior studies. We find that the short experience of riding in a PEV on average had a significant, positive effect on participants’ stated consideration ratings for adopting a PEV. Whereas longer duration experiences expose fewer participants to a wider variety of situations, our findings suggest that a single, shorter duration experience may be effective in increasing overall PEV adoption consideration across a larger population.

2. Methods

We collaborated with an industry partner, EZ-EV—a start-up subsidiary of Exelon Corp, one of the largest energy providers in the U.S.—to conduct a PEV ride along experience at the 2019 Washington DC Auto Show. The mission of EZ-EV is to simplify the process of consumer consideration and adoption of PEVs by providing educational and shopping tools about PEVs and hosting PEV events.

The PEV ride along experience was conducted inside the Walter Reed Convention Center from April 18 to 26, 2019 and was open to all attendees of the Auto Show, although individuals under 18 had to be accompanied by a parent or guardian. The PEV experience involved riding in a PEV with a professional driver around a short indoor course for approximately 3–5 min to experience some of the features of PEVs, including a 0–40 mph section to specifically highlight the acceleration performance and drivability of the vehicle. During the experience, the drivers answered questions specific to the vehicle and about PEVs in general. While they were not provided a script to follow, we know that some drivers provided basic information regarding the vehicle’s drivability, the charging process, and available incentives based on feedback from participants that we interviewed after the experience. It is certainly possible that some of this information could have influenced the participants’ survey responses, but isolating this effect is a limitation of the experiment. As a result, our results must be interpreted as the joint effect of riding in a PEV with an informative driver.

The available vehicles included three BEVs—the Audi e-tron, Hyundai Kona, and Nissan Leaf—which run entirely on electricity and can be recharged from the grid; one plug-in hybrid electric vehicle (PHEV)—the Toyota Prius Prime—which combines a conventional gasoline-powered engine with a battery that can be recharged from the grid; and one fuel cell electric vehicle (FCEV)—the Hyundai Nexo—which use fuel cells powered by hydrogen to produce electricity for the motor.

Data was collected at the driving experience booth through entry and exit surveys. All participants were required to take the entry survey and register for the event first, during which time they were given a unique ID code. The entry survey included three sections: (1) information about their current and future vehicle(s), (2) questions about their knowledge of PEVs, including the maximum available federal subsidy and vehicle refueling requirements, and (3) a Likert scale rating of two questions: (a) whether they would ‘consider’ a BEV and a PHEV for their next vehicle, and (b) whether they would ‘recommend’ either vehicle type to a friend. Respondents were not informed about whether their answers to the knowledge questions were correct or not. Table 2 summarizes the questions asked on the entry and exit surveys (a complete copy of the surveys can be found in section 6 of the supplementary information).

After taking the entry survey, participants were driven around the course in one of the vehicles by a professional driver. Participants were given the option to choose which vehicle to ride in, otherwise they were randomly assigned to one. After the driving experience was over, participants completed the exit survey, which captured the vehicle(s) the participants rode in as well as the same consideration and recommendation questions as shown in the entry survey.

The final dataset for our analysis was formed by using the unique respondent ID codes to match the entry and exit survey responses. To assess the impact of the PEV experience on the participants’ consideration and recommendation ratings for BEVs and PHEVs, we first tabulated the ratings provided before and after the experience. Then, to examine the effect of the experience on the probability of participants choosing each rating level, we estimated an ordinal
Figure 1. U.S. monthly sales of BEVs. Despite Tesla’s market success, PEVs comprised just 2.1% of vehicle sales in 2018. The authors developed this figure using vehicle sales data from hybridcars.com and insideEVs.com.

Table 1. Summary of studies on the effect of direct PEV experience on PEV perceptions.

| Author       | Year | Location          | Year Time Frame | Sample Size | Change in Perception |
|--------------|------|-------------------|-----------------|-------------|----------------------|
| Gärling      | 2001 | Sweden            | 1998–2000       | 42          | No change            |
| Carroll      | 2010 | UK                | 2010            | 69          | +                    |
| Turrentine et al | 2011 | LA, NY, NJ        | 2009–2010       | 102         | +                    |
| Burgess et al | 2013 | UK                | 2008–2012       | 55          | +                    |
| Jensen et al | 2013 | Denmark           | 2012            | 369         | ±                    |
| Bühler et al | 2014 | Berlin            | 2009–2010       | 77          | +                    |
| Franke       | 2014 | Germany           | 2014            | 29          | No Change            |
| Wikström et al | 2014 | Sweden            | 2011–2012       | 50          | +                    |
| Skippon et al | 2016 | UK                | 2016            | 393         | ±                    |
| Schmalfuß et al | 2017 | Germany           | 2017            | 30          | +                    |
| This study   | 2019 | Washington D.C.   | 2019            | 6518        | +                    |

Table 2. Summary of entry and exit survey questions.

| Survey-specific questions | Exit survey |
|---------------------------|-------------|
| Entry survey              | Exit survey |
| Survey-specific questions | Exit survey |
| Demographics:             | Brands considering for next purchase. |
| Current vehicle (year, make, model, age) | |
| Time to next vehicle purchase | |
| Number of vehicles owned | |
| Home parking access | |
| Whether neighbor owns PEV | |
| PEV knowledge questions: | |
| Vehicle types that can be fueled with gasoline | |
| Vehicle types that can be plugged in | |
| Maximum available federal subsidy | |
| Questions asked in both surveys | |
| ID Code | |
| Consideration and recommendation ratings for BEVs & PHEVs | |

logistic regression (also known as the ‘proportional odds’ or ‘log odds’ model), which incorporates the inherent ordering of the consideration ratings that participants could choose, from ‘Definitely not’ to ‘Definitely yes.’

To explain the model, let $Y$ be an ordinal outcome with $J$ categories, corresponding to each rating level in the survey. If $P(Y \leq j)$ is the cumulative probability of $Y$ being less than or equal to rating level $j = 1, \ldots, J − 1$, then the odds of being less than or equal to rating
level \(j\) is defined as
\[
P(Y \leq j) = \frac{P(Y \leq j)}{P(Y > j)}, \text{ for } j = 1, \ldots, J - 1.
\]

The log odds, also known as the ‘logit,’ is then defined as
\[
\log \frac{P(Y \leq j)}{P(Y > j)} = \logit[P(Y \leq j)], \text{ for } j = 1, \ldots, J - 1.
\]

The ordinal logistic regression model defines a linear relationship between equation (2) and a series of independent variables. The specific model we use is given by the following equation:
\[
\logit[P(Y \leq j)] = \alpha_j - \beta x - \sum_{i} \gamma_i z_i - \sum_{i} \delta_i z_i x,
\]
where \(j = 1, \ldots, J - 1\) and \(i = 1, \ldots, M\) independent variables. The \(\alpha_j\) coefficients in equation (3) are intercepts that represent the dividing points between each level of the ordered ratings. The \(\beta\) coefficient determines the significance and magnitude of the main effect of interest: the before/after effect of having the PEV experience, where \(x\) is a dummy variable for the time period (0 for ‘before’ and 1 for ‘after’ the experience). Thus, if \(\alpha_j\) determines the probability of choosing each rating \(j\) before the PEV experience, then \(\alpha_j - \beta x\) determines the probability of choosing each rating \(j\) after the PEV experience. The \(\gamma_i\) coefficients reflect the effect of other independent variables, \(z_i\), on the before experience rating. These include the experience, knowledge, and demographic variables listed in table 3, such as correctly answering a knowledge question or having parking access at home. Finally, the \(\delta_i\) coefficients reflect the interaction effect between the independent variables \(z_i\) and the time period variable, \(x\). These terms reflect how much the main before/after effect (given by \(\beta\)) changes based on the independent variables \(z_i\). For example, participants that rode in a more premium vehicle, such as the Audi e-tron, might be expected to have a larger change in their ratings than those that rode in less premium vehicles, all else being equal.

Since the outcome variables in this model (the log odds) is not immediately intuitive to interpret, we convert them into probabilities of choosing a rating by taking the inverse logit:
\[
P(Y \leq j) = \exp \left( \alpha_j - \beta x - \sum_{i} \gamma_i z_i - \sum_{i} \delta_i z_i x \right) \frac{1}{1 + \exp \left( \alpha_j - \beta x - \sum_{i} \gamma_i z_i - \sum_{i} \delta_i z_i x \right)}.
\]

We then use the values of each \(P(Y \leq j)\) level to compute the individual probabilities of choosing each rating level. For example, the probability of choosing rating level 1 (‘Definitely not’) is \(P(Y \leq 1)\), and the probability of choosing rating level 2 (‘Probably not’) is \(P(Y \leq 2) - P(Y \leq 1)\), and so on, with the probability of choosing rating 5 (‘Definitely yes’) being equal to 1 minus the sum of the others.

We estimate a series of models to assess how different variables influence the probability of choosing a rating before and after the PEV experience. Each model is estimated using the polr() command from the MASS package in R [32]. The first model tests the main effect of interest: the time period before and after the experience. We also estimate models to control for each of the vehicle metrics we captured in the survey as well as the knowledge questions. The full set of variables is shown in table 3. In the results section, we only report results for models that had non-negligible outcomes on the consideration ratings for BEVs. While we did also collect ratings on PHEVs, the results do not vary substantially compared to those from the BEV ratings. We include these results and other additional model results in section 3 of the supplementary information.

3. Results

3.1. Participant sample and consideration ratings

Out of the 7509 people that participated in the experience, 6518 respondents completed both the entry and exist surveys—a completion rate of 86.8%. To keep the survey short and facilitate throughput, respondents were only asked about their current vehicle (age and make), when they plan to purchase a vehicle next, and which vehicles they rode in during the experience. The majority of participants had vehicles that were less than 10 yr old, which aligns with the average light duty vehicle age in the US of 11.8 yr [33]. The most common brands owned in the sample were Toyota, Honda, Ford, Chevy and Nissan, and most respondents stated not being in the market for a new vehicle. A total of 7787 total rides were taken during the experience (some participants rode in more than one vehicle). Despite having five vehicles available, 90% of respondents rode in either the Audi e-tron or the Hyundai Kona as they were available every day of the event. The other cars were not always available due to various factors, such as driver availability or technical issues with the vehicle. We summarize this information about the sample in table 4.

While we asked respondents to rate both their consideration to purchase a PEV and whether they would recommend a PEV to a friend, we only present results for the consideration questions here because (1) the recommendation ratings were similar to the consideration ratings, and (2) our primary interest is consumer adoption of PEVs. Furthermore, because results were similar for BEVs and PHEVs, we only show results for BEV ratings (results for PHEVs can
Table 3. Summary of model variables.

| Effect          | Variable                  | Description                                                                 | Units/Values      |
|-----------------|---------------------------|-----------------------------------------------------------------------------|-------------------|
| PEV experience  | timePeriod                | Rating given before or after PEV experience.                                | Before (0); After (1) |
| PEV metrics     | etron, kona, leaf, nexo   | Variable for each vehicle model rode in (base level is the Toyota Prius Prime). | For each vehicle model: Yes (1); No (0) |
| PHEVpowertrain  |                           | Variable for powertrain of vehicle rode in (base level is BEV).              | Yes (1); No (0)    |
| FCEVpowertrain  |                           |                                                                              |                   |
| countCarsDriven |                           | Variable for number of vehicles ridden in.                                  | 1 to 5            |
| Respondent      | homeParking               | Dedicated home parking spot (i.e. accessible for home charging).             | Yes (1); No (0)    |
| demographics    | neighborPEV               | Whether respondent’s neighbor owns a PEV.                                   | Yes (1); No (0)    |
| PEV knowledge   | multicar                  | Owns more than 1 vehicle.                                                    | Yes (1); No (0)    |
| bothFuels       |                           | Correctly answered both refueling questions.                                | Yes (1); No (0)    |
| pluginFuel      |                           | Only correctly answered plug-in refueling question.                         | Yes (1); No (0)    |
| gasFuel         |                           | Only correctly answered gasoline refueling question.                        | Yes (1); No (0)    |
| subsidy         |                           | Correctly answered subsidy question.                                        | Yes (1); No (0)    |

Table 4. Summary of sample demographics.

| Current Car Age | NA | 1 yr or less | 2–5 yr | 6–10 yr | 11–20 yr | 21+ yr |
|-----------------|----|--------------|--------|---------|----------|--------|
| Total Responses: | 366 | 1132 | 2694 | 1805 | 1329 | 183 |
| Complete Responses: | 298 | 968 | 2336 | 1593 | 1164 | 159 |
| Current Vehicle Make | Toyota | Honda | Ford | Chevrolet | Nissan | Other |
| Total Responses: | 897 | 887 | 541 | 473 | 410 | 4301 |
| Complete Responses: | 779 | 776 | 465 | 414 | 355 | 3729 |
| Time to next purchase | Not in Market | 0–6 Months | 6–12 Months | 12+ Months |
| Total Responses: | 4809 | 432 | 695 | 1573 |
| Complete Responses: | 4140 | 370 | 671 | 1391 |
| Vehicle rides taken | e-tron | Kona | Leaf | Nexo | Prius Prime | Total |
| Complete Responses: | 3117 | 3925 | 597 | 135 | 13 | 7787 |
| Neighbor has an PEV | Yes | No | I am not sure |
| Total Responses: | 1458 | 4249 | 1802 |
| Complete Responses: | 1275 | 3681 | 1562 |
| Number of cars in Household | 0 | 1 | 2 | 3 | 4 | 5 |
| Total Responses: | 410 | 3487 | 1762 | 973 | 508 | 369 |
| Complete Responses: | 332 | 3010 | 1535 | 858 | 449 | 334 |
| Dedicated home parking | Yes | No |
| Total Responses: | 4420 | 3089 |
| Complete Responses: | 3872 | 2646 |
| Number of Vehicles Ridden | 1 | 2 | 3 | 4 | 5 | NA |
| Complete Responses: | 5284 | 1100 | 92 | 3 | 36 |

be seen in section 1 of the supplementary information). Figure 2 shows the change in BEV consideration ratings before and after the PEV experience.

3.2. Modeling consideration rating choices
We estimated six different ordinal logistic regression models to assess the impact of the PEV ride along experience and other factors on the BEV rating choices. Model 1 includes only the main effect of interest—the time period (before/after the PEV experience); models 2a and 2b include effects for whether participants correctly answered the knowledge questions for PEV refueling (2a) and the maximum available federal PEV purchase subsidy (2b); model 3 includes an effect for whether the participants stated having a neighbor who owns a PEV; model 4 includes effects for which vehicle models they rode in during the experience; and model 5 includes all of the effects from models 1–4. Table 5 shows the estimated coefficients from each model.

Across all models, the main effect—the before/after effect of the PEV experience—is large, statistically significant, and robust to the inclusion of other effects. All other statistically significant effects in each model are smaller in magnitude than the before/after effect. To make this effect easier to interpret, we use equation (4) to convert the estimated coefficients in model 1 into probabilities of choosing each rating level before and after the PEV experience.
Table 5. Estimated coefficients from ordinal logistic regression models of BEV ratings.

| Description                  | Model # | 1                                      | 2a | 2b                                      | 3                                      | 4                                      | 5                                      |
|------------------------------|---------|----------------------------------------|----|----------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| N:                           | 13 036  | 13 036                                 | 13 036 | 13 036                                 | 13 036                                 | 13 036                                 | 13 036                                 |

| Main effects                |         | timePeriod                             | pluginFuel | gasFuel | bothFuel | Subsidy | neighborPEV | Etron | Kona | Leaf | Nexo | pluginFuel | gasFuel | bothFuel | Subsidy | neighborPEV | Etron | Kona | Leaf | Nexo |
|------------------------------|---------|----------------------------------------|------------|---------|----------|---------|-------------|-------|------|------|------|------------|---------|----------|---------|-------------|-------|------|------|------|
| N:                           |         | 1.033 (0.036) ***                      | -0.034 (0.080) | 0.115 (0.084) | 0.47 (0.071) *** | 0.785 (0.074) *** | 0.620 (0.064) *** | 0.098 (0.065) | 0.029 (0.067) | 0.219 (0.097) | -0.031 (0.184) | -0.114 (0.109) | -0.028 (0.114) | -0.205 (0.095) * | -0.253 (0.100) * | 0.093 (0.088) | 0.081 (0.091) | 0.154 (0.097) | -0.015 (0.133) | 0.168 (0.125) | 0.155 (0.125) | 2.682 (0.037) *** | 2.780 (0.043) *** | 2.811 (0.039) *** | 2.828 (0.040) *** | 2.768 (0.078) *** | 3.005 (0.082) *** |

| Interaction effects          |         | definitelyNot | probablyNot | probablyNot | maybeNotSure | probablyYes | definitelyYes | 3.232 (0.056) *** | -3.151 (0.060) *** | -3.146 (0.057) *** | -3.131 (0.057) *** | -3.149 (0.089) *** | -3.003 (0.091) *** | -1.937 (0.033) *** | -1.860 (0.039) *** | -1.854 (0.034) *** | -1.835 (0.035) *** | -1.855 (0.076) *** | -1.711 (0.078) *** | 1.365 (0.029) *** | 1.456 (0.036) *** | 1.478 (0.031) *** | 1.498 (0.032) *** | 1.450 (0.075) *** | 1.655 (0.078) *** | 2.682 (0.037) *** | 2.780 (0.043) *** | 2.811 (0.039) *** | 2.828 (0.040) *** | 2.768 (0.078) *** | 3.005 (0.082) *** |

| Intercepts                  |         | probablyYes | definitelyYes | 2.682 (0.037) *** | 2.780 (0.043) *** | 2.811 (0.039) *** | 2.828 (0.040) *** | 2.768 (0.078) *** | 3.005 (0.082) *** |

Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Figure 2. Change in BEV consideration rating before and after ride along experience. While the majority of respondents chose the same rating before and after riding in a PEV (gray ribbons), those who changed their rating were far more likely to choose a more positive rating (blue ribbons) than more negative rating (red ribbons). Before the PEV experience, nearly 70% of respondents chose ‘Maybe/not sure’, 11% chose negative ratings, and 20% chose positive ratings. In contrast, the post-PEV experience responses show a shift away from the ‘Maybe/not sure’ rating (down to 51%) coupled with a shift towards positive ratings (up to 43%) and a decline in negative responses (down to 6%).

Figure 3. Predicted probabilities of BEV consideration rating choices before and after PEV experience. The predicted ratings shift towards more positive ratings after the experience. Error bars represent a 95% confidence interval reflecting uncertainty in the model parameters, computed using simulation (see section 2 of the supplementary information).

In addition to the BEV rating questions, participants were asked three questions assessing their knowledge about PEVs: two pertaining to the refueling requirements of different vehicle types and one regarding the maximum federal subsidy available for purchasing a PEV. The responses indicate that most participants were not knowledgeable about these aspects of PEVs. Only 30% of respondents correctly answered either the plug-in or gasoline...
Figure 4. Knowledge question results (correct response highlighted in green). Only 30% of participants correctly answered either the plug-in or gasoline refueling questions, with just 18% correctly answering both (A). Only 14% of participants were able to correctly answer the question about the federal PEV subsidy, with 80% stating they were not sure (B).

Figure 5. Predicted probabilities of BEV consideration rating choices before and after PEV experience. Respondents with greater knowledge about PEV refueling (A) and subsidies (B) had higher predicted ratings both before and after the experience. Error bars represent a 95% confidence interval reflecting uncertainty in the model parameters, computed using simulation (see section 2 of the supplementary information).
refueling question (with only 18% correctly answering both refueling questions), and only 14% correctly answered the subsidy question, with 80% stating they were not sure. Figure 4 summarizes the responses to these questions.

Although the majority of respondents did not correctly answer the knowledge questions, those that did chose higher BEV consideration ratings both before and after the PEV experience. Those who knew the maximum federal PEV subsidy available in particular had higher ratings than those who correctly answered the refueling questions, though this may be expected as respondents who knew the subsidy may already be considering purchasing a PEV. Nonetheless, these results suggest that even those with more knowledge about PEVs were still on average chose more positive ratings after the PEV experience. Figure 5 shows the results of models 2a and 2b converted to probabilities of rating choices.

Results of model 3 suggest that respondents that stated they had a neighbor that owns a PEV chose higher BEV consideration ratings both before and after
after the PEV experience (this effect is similar in size to that of those who correctly answered the subsidy knowledge question). This corresponds with prior research on the ‘neighbor effect,’ which suggests that people are more likely to consider adopting a PEV if their neighbors have also adopted a PEV [34, 35]. Figure 6 shows these results.

Finally, results from model 4 suggest that the particular vehicle model that participants rode in did not have a substantial effect on their rating choices, as shown in the overlapping error bars in figure 7. This is important as it suggests that a short ride in a much more affordable PEV, such as the Nissan Leaf, could potentially be just as significant as riding in a luxury PEV in terms of influencing peoples’ consideration about adopting a PEV.

Model 5 provides a comprehensive model including all variables from models 1–4. While we did estimate additional models to control for other factors, such as having dedicated at-home parking and how many cars the participant owned, none of these models had statistically significantly different results. Results from these additional models can be found in section 4 of the supplementary information.

4. Discussion and conclusions

In this study, we conducted a large-scale experiment investigating how a short, direct exposure with a PEV could impact participants’ stated consideration of adopting the technology. Overall, results indicated that the experience had a positive impact on their stated consideration of recommendation for PEVs. Our results show a 118% increase in the number of participants that stated they would ‘probably’ or ‘definitely’ consider purchasing a BEV for their next vehicle—from 1268 participants before the experience to 2762 after. These results agree with previous studies that used substantially longer exposure times in their experiments [23–30]. For example, in Carroll et al [25], 72% of participants stated they would use a PEV as their regular car after the test drive experience compared with just 47% before the test drive [25], and in Turrentine et al [29] 67% of respondents changed their opinion about PEVs after the end of their leases, with 71% of respondents stating they would be more likely to purchase a PEV after the experience than before. Part of why this short exposure experience may have had such an impact on participants’ consideration of PEVs is that it familiarized participants with an otherwise foreign vehicle technology. Rogers (2003) suggests that knowledge and experience acquisition of a new technology leads to lower perceived risk from it and more favorable intentions towards it [36]. The short, scalable experience provided in our experiment may have helped address some of the known knowledge and risks issues associated with PEV adoption [13].

An important observation of these results is that even a short exposure time with a PEV may lead to a significant increase in positive PEV perceptions—a result that has important practical implications for increasing PEV adoption. The type of short, experimental event that we conducted is well within the scope of the types of events vehicle manufacturers and dealers currently conduct with conventional vehicles in the form of promotional events. This structure could be utilized by automakers and dealers to promote PEVs in a cost- and time-effective manner to increase consumer acceptance of PEVs on a much larger scale. Fleet operators such as taxi and ride hailing companies could also potentially impact a much larger portion of the general public by operating PEV fleets and exposing riders to the technology. Policymakers could support PEV usage in fleets and other forms of short-term direct exposure events.

In terms of the general public’s knowledge about PEVs, our results corroborated prior research on large gaps in PEV knowledge and misperceptions that exist [4, 16–18]. Research in this area also found that greater PEV knowledge was associated with more positive perceptions of PEVs, lower perceived risks of PEVs, positive evaluation of PEV attributes, and a higher intent to pay a premium for renewable fuel—all of which are associated with a great overall intention to adopt a PEV [4, 18, 22, 37, 38]. Our study suggests similar results. Participants that correctly answered the knowledge questions on the survey—in particular, the federal subsidy question—had higher PEV consideration ratings both before and after the experience, suggesting that knowledge about the technology may be important for shifting public opinion and willingness to consider adopting a PEV. More research in this area is needed to determine effective means for conveying this knowledge to consumers and what kinds of knowledge might have the biggest impact.

Although this experiment was successful in capturing a substantially larger sample size than prior research on direct experience with PEVs, the experiment design is potentially susceptible to response biases that can be present in survey-based studies. In particular, because respondents were shown the same rating questions on both the before and after surveys, there is a chance that some of the shift to more positive ratings after the experience is due to response bias. We acknowledge this potential as a limitation of the study, and thus the main before/after experience effect should be interpreted with this potential bias in mind. Nonetheless, other aspects of the study suggest that response bias alone would not likely explain the results. For example, verbal responses from participants during short interviews conducted immediately after the PEV experience were overwhelmingly positive towards PEVs and frequently involved statements of surprise about PEVs, in particular about the high acceleration performance of the PEV. In
addition, some respondents stated more negative ratings after the experience than they did before. Finally, some of the results should be robust to response bias. For example, the association between having greater knowledge about PEVs and stating higher consideration ratings could still be concluded as the difference between the more and less knowledgeable participants should not be affected by response bias.

Some limitations in the data collection process include the lack of more detailed demographic data (a trade-off made between the time required to complete the surveys and participant throughput) and the self-reported nature of the demographic data collected. For instance, 20% of the complete sample reported that their neighbor owns a PEV, which is likely higher than reality given the historically low PEV sales rate. Given that few participants correctly answered the knowledge questions about PEVs, we suspect that many who responded ‘yes’ likely had neighbors with vehicles that they mistook for a PEV, such as a hybrid vehicle. Nonetheless, while it is not possible to determine the accuracy of their responses, it may still be valuable to gauge the difference in the perceptions of those who believe they encounter PEVs on a daily basis with those that do not.

Finally, it is important to address potential limitations in the generalizability and longevity of the effects noted in this study. Participants in this study were individuals who opted to attend the DC Auto Show and participate in the EV ride along experience, presenting a limited sample. However, the DC auto show is open to the general public with thousands of attendees and attracts a wide range of individuals. In addition, other ride and drive events for specific automakers were also present at the event, including Jeep, Jaguar, and Land Rover. Based on responses to our knowledge questions and results from the study, there was a similar lack of knowledge and experience with PEVs that is consistent with the general population. Unfortunately, we are unable to assess the longevity of the effects captured in this study as we did not obtain identifiable information about the respondents necessary to contact them at a later time. This is an important consideration for future related work.

Electrifying the vehicle fleet to meet carbon goals will require PEV adoption are far greater rates than have historically occurred. This will require solutions that go beyond attracting early adopters and scale to attract the general public. Our study shows that having a direct experience—even for just a few minutes—with a PEV could be important for changing public opinion about PEVs on a mass scale.

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.3962516.

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