Learning by Charging: Understanding Consumers' Changing Attitudes Towards Vehicle-to-Grid

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Abstract

Vehicle-to-grid (V2G) charging, where vehicles can send power to the grid, can provide valuable services to energy systems and network operators. However, social acceptance is an essential and overlooked barrier which must be addressed if V2G is to be successfully deployed. This study investigates the factors that govern attitudes towards V2G, and how electric vehicle (EV) ownership and participation in V2G changes them. For the first time, this includes survey data from users who had experience using a V2G charger, comparing the response of V2G users ($n = 49$) with EV owners ($n = 520$) and non-EV owners ($n = 1091$). We show that time and EV ownership have lowered concerns around range anxiety, and that EV ownership and V2G trial participation leads to a 15-35% increase in stated willingness to participate in V2G or Smart Charging as compared to a 2013 baseline. Additionally, it is demonstrated that the strongest single predictor for V2G willingness is whether the consumer believes that V2G can contributes to a stable electricity system. These results suggest that education around V2G benefits and allowing consumers to test V2G before committing could be key factors in increasing adoption. We also highlight the importance of data privacy, which for some consumers contributes towards a negative attitude towards V2G. We release the raw survey data and code with this manuscript.

Keywords: Vehicle-to-Grid, Smart Charging, Consumer Acceptance.

1. Introduction

Global electric vehicle adoption has been accelerating rapidly – in 2022 it is estimated that there were 26 million plug-in electric vehicles (EVs) in use globally, representing a 10-fold increase since 2016 [1]. It is anticipated that a majority of EV owners will continue to have home or local charging so that the EV batteries can be charged to an appropriate level before departure whilst maximising behind-the-meter self-consumption (e.g., from rooftop solar). This residential charging of electric vehicles will present significant challenges to system operators, due to the large increase in load [2]. Smart charging (where the load from EVs is temporally shifted to match price or network congestion signals) is one solution, having potential to significantly reduce network reinforcement [3; 4]. However, the system benefits or smart charging are limited as the EV battery can only be charged but not discharged. This is addressed by using bi-directional charging [5], where a vehicle can also send power back to the grid – often referred to as vehicle-to-grid (V2G).

The cost-benefit analysis of V2G is more complicated than with smart charging – round-trip losses and additional battery cycling meaning that the user incurs additional costs [6]; whereas, with uni-directional smart charging, the user pays no penalty for shifting load (assuming that their departure deadline can still be met). Furthermore, it is well-known that individual consumers do not necessarily act only in their economic self-interest [7], and so it is not sufficient to only consider consumer's net financial gain. Therefore, the growing body of literature considering the economic case for V2G [8] demonstrates the potential system benefits, but will not in isolation be sufficient to understand if V2G will be socially acceptable in a given system. Instead, a deep understanding of the social factors and individual drivers of consumer participation in V2G schemes will be necessary. Without this understanding, the added value of V2G will not be realizable in energy systems [9], potentially jeopardising or slowing electrification efforts.

There have been several previous studies which focus on the public perceptions of V2G, but the majority of these focus on financial compensation and consumer fears. One of the most common concerns raised across the literature were financial. A workplace Australian survey found the greatest concern with V2G was the upfront cost and the unclear return rate [10]. Similarly, [11] found that consumers' willingness to pay for V2G was lower than the projected costs. Several studies highlighted range anxiety (worries that participating in V2G will mean they do not have enough charge) as a major concern [11; 12]. Focus groups from the Nordic countries identified that provided it does not upset their travel and they are appropriately compensated, V2G is not viewed negatively [13]. On other issues the literature is divided; in [14] expert interviews concluded that the addition of V2G does not change opinions about EVs, while [15] found that adding V2G capability can foster EV adoption. One study found that V2G more likely to be accepted by older population [16], while another found that younger men were more likely adopters [15].

These studies have been collected from across the globe and in different formats, so there may be underlying demographic differences between respondents. However, many of these studies used data collected before 2017 – at a time when the global number of electric vehicles is one tenth of what it was in 2022. In a 2013 survey, 87.7% of the respondents had never heard of V2G [12]. Ownership of an EV gives consumers a more tangible understanding of how controlled charging would affect them. Two recent works have sought to specifically target EV owners. In [17] interviews were conducted with 20 EV drivers in the Netherlands, and found that compensation and battery degradation were the biggest factors in V2G adoption. In [18] a mix of EV and non-EV drivers were surveyed and they found that EV users demanded higher compensation to participate in V2G compared to non-EV users. However, these recent efforts were smaller scale and targeted specific aspects of V2G.

In this paper, we present the results of a large online questionnaire in the UK that included non-EV owners ($n = 1,091$), fully electric battery electric vehicles (BEV) owners ($n = 520$), and (for the first time) those that had experience using a V2G charger ($n = 49$), who are also BEV owners. This allows us to study how BEV ownership and V2G experience influences consumers attitudes towards V2G. We also investigate the influence of users' attitude towards data privacy, which is not explored significantly in any previous study.

Studying multiple groups with varying levels of exposure to BEVs and V2G charging technologies allowed us to analyse empirically revealed preferences from actual V2G users while also considering the perceptions, potential barriers and incentives across the adoption spectrum.

Alongside this analysis, we release the full dataset and associated analysis scripts. This will enable researchers to explore other aspects of the data; and this baseline documentation provides a reference point for comparing and tracking shifts in perceptions and acceptance as and if V2G undergoes further adoption in the future.

2. Methods

2.1. Survey design and conduct

This research is carried out as part of a £30 million UK government investment program in V2G that ran between 2018 and 2022. The program supported the development of V2G chargers, trialling V2G grid services, and evaluating business models for domestic and commercial EV drivers. Throughout the program's duration, the only EVs with V2G capabilities were the Japanese cars which utilised the CHAdeMO protocol. Consequently, the program's efforts concentrated on developing V2G charging stations compatible with the CHAdeMO standard to work with the existing V2G-enabled EVs, namely the fully electric Nissan LEAF and e-NV models [19].

Despite the acceleration in EV adoption, it was still challenging to recruit BEV drivers for the V2G trial because of the limited availability of vehicles equipped with V2G functionality. During the initial phases of the program, which coincided with the COVID pandemic lockdown, it was not possible to recruit business fleet drivers for the V2G trial. Nonetheless, over two hundred private users were recruited to trial out V2G chargers installed free of charge at their homes; and a subset of these participants completed our online survey.

The V2G program's online survey was conducted to focus on exploring private car users' to attitudes and willingness to use V2G charging technologies compared to unmanaged- and smart charging. The survey data were collected between February 2021 and April 2022, and the analysed data were only from participants who passed at least two out of three attention checks in the survey.

To capture a comprehensive range of perspectives, the analysis included responses from three distinct groups of participants who completed the same questions. The first group consists of 1,091 non-EV drivers from the general population sourced from the Prolific database, a platform that helps researchers recruit participants for online research [20] – this is a common tool used in similar research (e.g. [21]). The second group consists of 520 fully electric BEV drivers without V2G experience sourced by posting the online survey link into EV drivers' social media forums and from Prolific; and the third group consists of 49 BEV drivers who have been using a V2G charger at home between 4 and 18 months as part of the V2G trials.

One pre-screener was applied to exclude UK prolific users with no driving licence and a quota approach was adopted to balance the Prolific participants across the UK household income distribution. To collect a sample that matches the distribution of the national population on household income [22], we ran the survey several times to ensure various income categories are proportionally represented. For example, as the UK Government's Office for National Statistics (ONS) data shows that 5% of people aged 18 and above in the UK make "Less than £10,000", then "Survey 1" was opened for a total of 100 participants (out of total 2000 participants that were recruited). This was achieved by using the Prolific household income prescreener corresponding to that ONS category (i.e. household income <£10,000).

As part of our analysis, we also included a direct comparison of the results from our survey with results to questions asked in a 2013 legacy study on V2G [12].

2.2. Survey details and limitations

The online survey was built using SoSci Survey [23] a tool that adheres to data privacy laws and offers customisable interfaces. The survey consisted of 10 sections with an estimated completion time of 15 to 20 minutes. The first section gathered information about participants' knowledge of different charging technologies, including V2G; if they are currently taking part in a V2G trial; commuting patterns; and household adoption of green technologies like solar panels. The second section provided participants with educational information about charging technologies. It included visuals such as pictures of V2G chargers, diagrams explaining how V2G chargers manage the time, power rate, and direction of energy flow, and screenshots from a V2G trial app demonstrating user control over charging preferences (e.g., setting a desired state of charge by a specific time). Subsequent sections covered various topics, including:

- General questions about EVs and charging requirements, including participants' willingness to allow an operator to temporarily stop charging during grid emergencies.
- Preferences for control over the charging process and the level of engagement desired.
- Attitudes, concerns, and incentives related to V2G adoption, such as concerns about battery impact and the importance of using the EV for backup power.
- Ranking participants' willingness to use different charging technologies.
- Participant information, including home ownership status, location (urban or rural), number of household vehicles, parking arrangements, and charging habits if they owned an EV.
- Privacy requirements regarding data sharing.

The complete survey, including the exact information presented to participants, is available in the paper's repository.

Some limitations should be considered when interpreting the results from the revealed preferences of the 49 V2G users, as it is possible that their positive perceptions of V2G technology led them to participate in the trial, rather than their positive perceptions being a direct result of their V2G experience. Nonetheless, the study findings demonstrate that these participants did not have a negative experience with V2G, as shown in Fig. 2, and they had been using their V2G chargers between 4 to 18 months at the time of the study. Moreover, the study design did not allow for pre-trial and post-trial measurements of attitudes.

Despite these limitations, the openly available data and analysis in this work serve as a record of the current attitudes towards V2G technology.

Moreover, despite the EVs in the V2G user group having smaller battery capacities (pre-2022 Nissan LEAFs and e-NVs with 24 or 30 kWh) compared to more recent EVs (50+ kWh), we believe the survey findings on topics such as willingness to allow charging management, required financial incentives, attitudes toward data privacy, and concerns about battery degradation remain applicable irrespective of EV battery size.

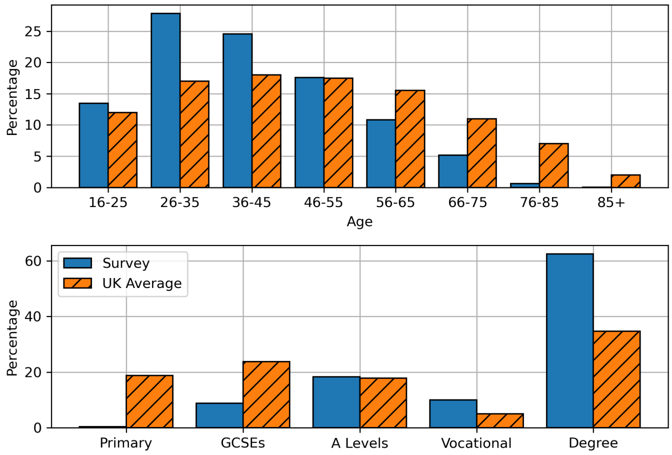

Figure 1: Survey participant age and education breakdown compared to the UK national average. GCSEs exams are taken universally aged 16 (a 'pass' constitutes five passes across ca. 10 subjects); A-levels are non-mandatory academic exams taken aged 18; 'vocational' refers to vocational diplomas, 'degree' includes undergraduate degrees (e.g., BA, BSc) or higher degrees (e.g., MA, MSc, PhD); respondents were asked to state their highest equivalent qualification (with lowest to highest considered in that order).

2.3. Participant demographics

The demographics of the survey participants with respect to the UK average are summarised in Fig 1. Good age coverage was achieved, albeit with the oldest age categories were under-represented; a common issue with web-based surveys. It should be noted that our survey participants were significantly more highly educated than the UK average. This is likely caused by a combination of our efforts to recruit EV users (who have higher incomes on average) and the technical nature of the topic and computer literacy required to participate. The gender balance of our participants was good, with 52.7% of participants identifying as male and 46.7% as female.

2.4. Regression Model

In order to analyze the contributing factors which led to V2G willingness, we develop a regression model to predict consumers willingness using their answers to other questions from the survey. The prediction target was respondents' answers to the question "Would you use V2G chargers?", which had five possible answers ranging from "definitely" to "definitely not". As prediction inputs we took answers to various demographic and opinion questions from the survey.

Linear regression attempts to find the linear function $f(x) = mx + c$ To study the link between outputs and inputs, we consider the use of logistic regression for target y against inputs x. For considering membership of a single class, logistic regression uses the logistic function,

$$f(x) = \frac{1}{1 + \exp\left(\frac{-(x-\mu)}{s}\right)}, \quad (1)$$

where μ is the location parameter and s is a scale parameter. Logistic regression is favored for classification tasks, where the function f is the probability that a data point belongs to a particular class.

In this case of multiple classes, the input data is x, the parameter μ, and the output of function f will be multi-dimensional, with one model (1) for each output. The function (1) remains the same, but there will be one set of parameters for each of the possible classes. Overall, there are therefore $N_y(1 + N_x)$ unknown parameters to determine, where N_y is the number of output variables, and N_x is the number of input variables.

Determining the best fitting parameters μ, s is non-trivial due to bias-variance tradeoff, and the non-convexity of the likelihood function under common loss functions. In general, an optimization problem is formed to determine the parameters which minimize a square error loss function ϵ,

$$\epsilon(\mu, s) = \sum_i (y_i - f(x_i))^2, \quad (2)$$

where x_i is the input data associated with target y_i. However, given the large number of parameters and (potentially) modest about of data this approach can lead to over-fitting – where the resulting model fits the data well but does not generalize well to unseen data. Regularization methods address this problem, altering the objective to favor smoother simpler models. In this case we use L_1 regularization, which alters the loss function (optimization objective) to the regularized error ϵ', as

$$\epsilon'(\mu, s) = \sum_i (y_i - f(x_i))^2 + \lambda (\|\mu\|_1 + \|s\|_1). \quad (3)$$

where (with slight abuse of notation) parameters μ, s are concatenated across all outputs y. The additional terms, weighted by the small constant λ, penalize large model parameters. The main alternative is to use L_2 regularization, which instead penalizes differences in magnitude of parameter weights. We chose L_1 because the input variables x_i may cover very different topics (and hence scales), so we do not necessarily want to penalize different sizes in our parameters

The model was trained iteratively to discover a reduced subset of the available data to use as inputs. This process is outlined in more detail in the Supplementary Information at the end of this paper.

2.5. Source Data and Code

The anonymised survey data is hosted at `https://github.com/constancecrozier/V2G_survey`. The download folder includes a `csv` file with the data and two `pdf` documents showing the questions and the variables listing of the survey. The Python code used to read in the data and produce the analysis in this paper is available (to be released on the date of publication).

3. Results

3.1. Changing Perceptions

In the last 10 years the number of EVs on the roads globally has grown more than 100-fold, from less than 200,000 to more than 26 million in 2022. The vast majority of this EV stock is in China, Europe and the United States [1]. This means that many consumers in these regions now either own an EV or know someone who does. This practical knowledge of EVs means that they can feel more confident and informed in their opinions on EV charging. Here we analyze the effect of time, BEV ownership, and participation in a V2G trial on willingness and fears associated with V2G.

Figure 2 (upper) shows the willingness of consumers to participate in various charging strategies, comparing the results of our survey (2021) with the results from [12] (2013). We also show separately the subset of our respondents who own a BEV and those who have participated in a V2G trial. It can be seen that willingness to use unmanaged charging (where EV begins charging immediately after being plugged in) has decreased, while both smart charging and V2G charging willingness has increased. Notably smart charging is now the charging mode that respondents were most likely to use. BEV ownership and V2G trial participation both increased likelihood of smart charging, while for V2G charging only trial participation did.

Also shown are the answers to three questions regarding respondents' fears around the use of V2G. Neither time nor BEV ownership has reduced fears that V2G will accelerate battery degradation, while they have both led to lower concerns around range anxiety. Concerns that V2G will affect data privacy have increased in the general population (although it should be noted that the phrasing of this question was not identical between surveys – as detailed in the Methods section). Participation in a V2G trial was the only factor which led to significant reductions in all three fears. This demonstrates that while increasing general knowledge and adoption has improved willingness of consumers, some fears are only addressed with experience.

3.2. Data Privacy Concerns

Data privacy has not been previously addressed in literature concerning attitudes towards V2G. However, Fig. 2 suggests that many consumers have concerns around the

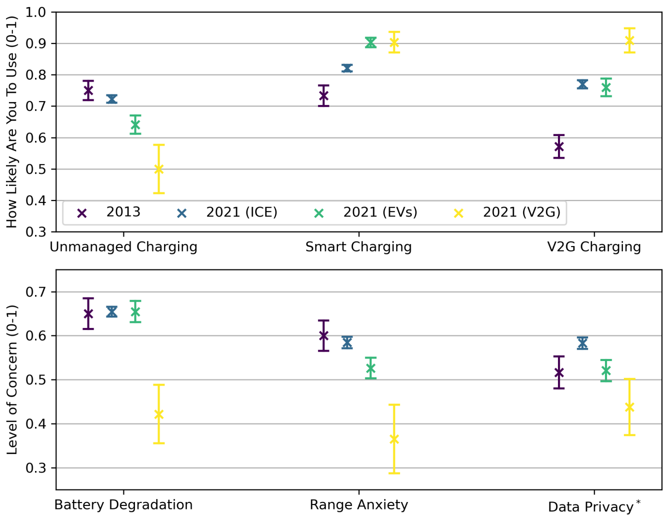

Figure 2: A direct comparison of the results from our survey with questions asked in [12]. The mean response is shown alongside a confidence interval which shows ± two standard errors. (Top): How likely respondents are to use each charging type. (Bottom): How concerned respondents are about issues related to V2G. Our survey results are broken down into internal combustion engine users, BEV owners, and V2G trial participants. *Different wording in 2013

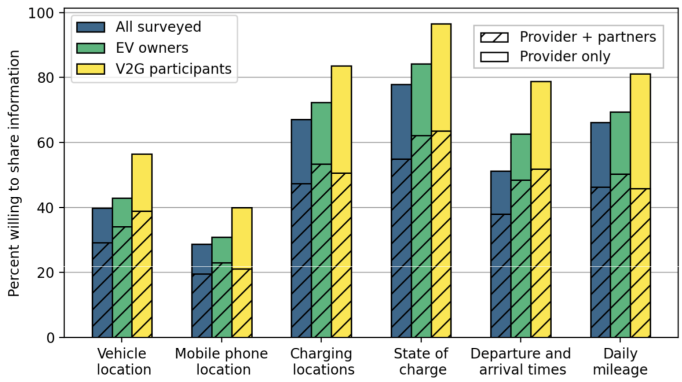

Figure 3: The percentage of respondents who would be willing to share various pieces of information with both their V2G provider, and the partners of their provider. Again we break down respondents who have owned an BEV or participated in a V2G trial.

privacy aspect of V2G. Our survey included deeper questions about which personal information users were comfortable sharing with either their V2G provider, or third-party partners of that provider (e.g. an aggregator who co-ordinates flexible devices), as summarized in Fig. 3. Across all categories, consumers were more willing to share their data with their V2G provider than their third-party partners. Willingness to share information also increased with BEV ownership and V2G participation, perhaps due to deeper understanding of the need to share data. There was the most hesitance to share personal or vehicle location, while the majority of respondents were comfortable to share where they charged, the vehicle state of charge, and their daily mileage. For smart charging, state of charge and departure time are the most salient pieces of information. Departure and arrival times showed the greatest change in opinion with BEV ownership and V2G participation – perhaps due to consumers better understanding why this information is important. The survey also asked users about their current location sharing practices. Notably, 44% of those who were unwilling to share their mobile phone location with V2G providers reported that they 'rarely' or 'never' disabled location sharing on their phones. Whereas, 58% of those willing to share their location rarely disabled location. This demonstrates the expected trend in attitudes towards privacy, although it's worth noting that many consumers reporting to be unwilling to share location do not take active steps towards preventing this.

3.3. What influences willingness to participate?

We can assess the factors contributing towards respondents willingness to participate in V2G by building predictive models. If a factor is a strong predictor we can say that it may influence consumers' decision. We considered a range of demographic factors, as well as their answers to opinion questions. All opinion questions were expressed on a scale of 1–5, from strongly disagree (1) to strongly agree (5). Demographics questions were categorized in order of increasing quantity. All of these variables were numerically scaled to lie between 0 and 1; for example for education 0 would be the lowest level of education (GCSEs or lower) while 1 would be postgraduate education.

These factors were then used to form a predictive model using a multinomial logistic regression-based approach (as outlined in Section 2.4). As described, the model was trained iteratively to discover a reduced subset of the available data to use as inputs. It should be noted that highly correlated variables may be removed from the input set – not because they are not good predictors alone, but because only one of the variables contains the predictive potential of both. Figure 4 visualizes the parameters of the resulting model. The chosen variables are shown on the horizontal axis, ordered left to right from most significant to least significant predictor. The vertical axis shows the five possible answers to the question "How likely are you to use V2G chargers" and the cell shading indicates the parameter weighting; a large positive weighting (green) demonstrates that a factor has a large positive influence, while a large negative influence (red) indicates that the factor has a strong negative influence.

This suggests that by far the most contributing factor is a belief that V2G contributes towards a more stable electricity network. This worked as both a positive and negative predictor; those who strongly agreed were more willing to use V2G chargers, while those who strong disagreed were significantly less likely to. The second predictor was primary vehicle type and this had a divisive effect. Those with more electrified primary vehicles were more likely to have a strong opinion on V2G (either positive or negative). This highlights that, while on average BEV ownership improves attitudes towards V2G, for some consumers it makes them less willing to participate. Concerns

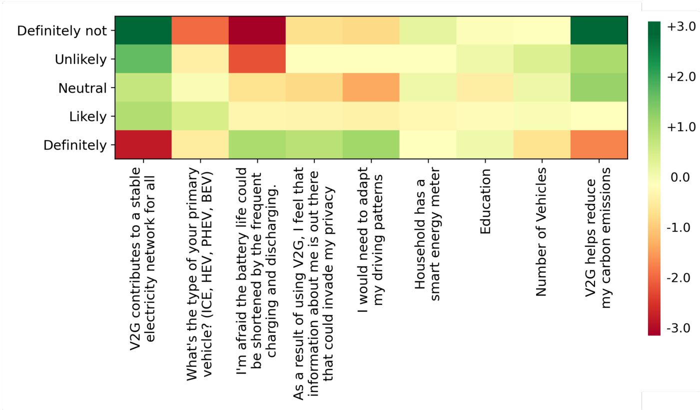

Figure 4: A visualization of the weighting parameters used in the logistic regression model. A large positive weighting (green) demonstrates that a factor has a large positive influence, while a large negative influence (red) indicates that the factor has a strong negative influence.

about battery degradation and privacy are also predictors. Education, number of vehicles, and ownership of a smart meter were included in the model but were not weighted strongly. A belief that V2G would reduce carbon emissions had a strong relationship with V2G willingness, but was selected last – meaning that it only marginally improved the accuracy of the model compared to not using it. This is likely because it is strongly correlated with some of the other variables, meaning much of the dataset variability can be explained without that variable.

3.4. Demographics

Demographics have played a central role in existing literature on V2G acceptance. It is important to understand the differences in attitudes across demographic groups, as these can be used to build targeted policies which increase adoption in these groups. Figure 5 shows the standard error of the mean for various demographic groups compared to the population average. This indicates how many standard deviations of the expected value that group's average is – this measure adjusts for sample size; otherwise we would likely see larger departures for the smaller groups. The larger the standard error (and darker the shading), the more statistically significant the effect. Red indicates that the group is more willing compared to the population average and blue indicates less willingness.

While there exists a large number of interesting effects, here we limit our discussions to those with high statistical significance. For unmanaged charging, a significant gender difference can be observed, with men more likely to report using unmanaged charging and women less likely. Conversely, women appear more likely to use both smart charging and V2G, but this effect is much less significant. Those whose main vehicle is an internal combustion engine or hybrid were much more likely to use unmanaged charging. While those whose primary vehicle was a battery electric vehicle were more likely to use smart charging. Although BEV owners were more likely to use V2G, this effect was not as significant, again highlighting that for a minority of consumers owning an BEV makes them less willing to participate in V2G. Those with more vehicles available are more likely to participate in both smart charging and V2G, which is consistent with previous literature suggesting that the security of additional vehicle makes consumers less concerned about range. Those with high incomes were more likely to participate in both unmanaged and smart charging, but not V2G charging. No significant difference was found for different ownership models. This is perhaps surprising, given that a degraded battery reduces the value of the vehicle – a loss which is only suffered by EV owners (those who lease vehicles do not suffer any financial loss as the car depreciates). This could indicate that the influence of battery degradation was small compared to other factors which are felt uniformly by ownership models (such as range anxiety). However, the effect could have a number of explanations – including that those who leased the vehicles were planning to purchase the vehicle down the line.

3.5. Financial incentives

Although the response of consumers to various financial incentives has been more widely studied, we include a small analysis for comparison of our survey respondents attitudes towards financial compensation. Figure 6 summarizes the answers to those questions. Around 80% of respondents felt that compensation was necessary for them to participate in V2G. The majority of the respondents felt that a 5% energy bill saving would be sufficient to participate in V2G, while over 95% said they would for a 10% reduction. BEV owners and those who had participated in a V2G trial on average demanded more compensation than those who do not own an EV. This means that the findings from our survey were consistent with those in [18]. For trial participants this is likely because they have become used to receiving an incentive for their managed charging, including receiving a V2G charger for free worth several thousands pounds. Most respondents agreed that they would be happy for an operator to stop their charger for up to to hour in an emergency. There was a lot of variation in the answer around on-peak pricing; most would not pay extra to charge at peak times but many would, showing that this option may be useful for some lifestyles.

4. Discussion and Conclusions

In this study, we investigated the attitudes of more than 1,500 survey respondents to vehicle-to-grid (V2G) technologies; around one third of respondents owned an EV and 49 had participated in a V2G trial. This allowed us to investigate, among other things, the effect of experience driving and (bi-directional) charging on attitudes towards V2G. Our study also included questions around commonly attributed contributing variables (such as battery degradation, range anxiety, and incentives) as well as

Figure 5: The standard error from the mean of various demographic groups, when answering how likely they were to use each method of charging. The darker the shading the more significant the difference of that group compared to the population average was. Green indicates a positive departure (more likely) and red indicates the converse.

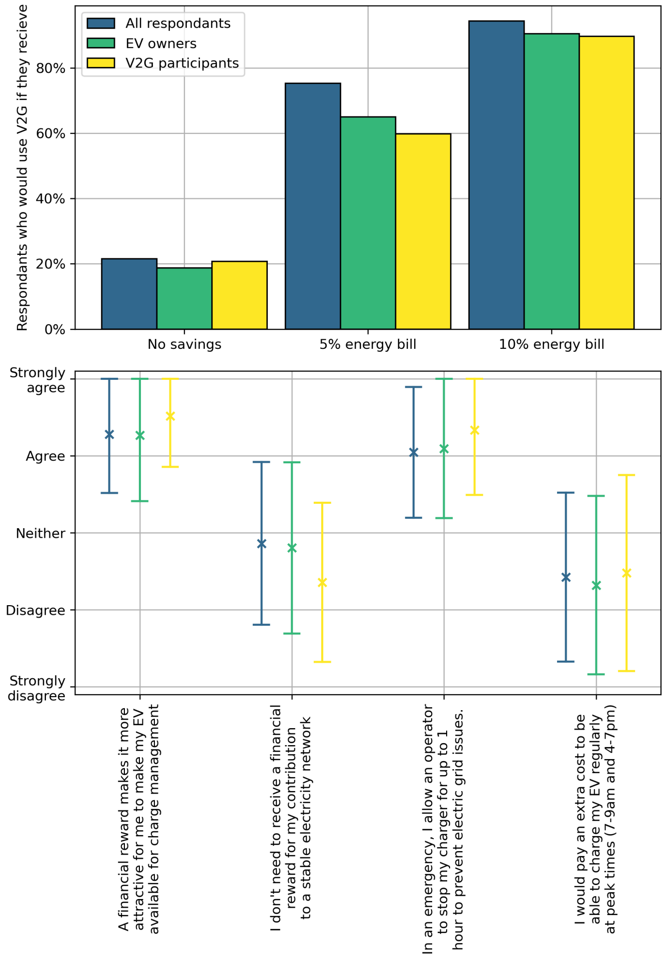

Figure 6: (Top) The percentage of respondents who would use V2G in response to varied levels of savings. (Bottom) The mean and standard deviation of respondents answers to various questions about incentives. In both cases respondents with electric vehicles and those who have participated in a V2G trial are also shown separately.

less studied variables (such as data privacy concerns and education). Our study respondents were based in the UK and covered a broadly representative age profile, although skewed towards higher levels of education.

Attitudes to new technologies evolve as consumer exposure increases, either through direct or indirect (societal) interactions with the technology. For the first time, we have studied the attitudes of a sample of participants in a large-scale V2G demonstration project ($n = 49$), comparing their responses with those of BEV owners, the wider non-EV owning population, and also legacy attitudes from previous research. Although individual consumers are not tracked, the results nonetheless provide an invaluable insight into the attitudes of consumers at different stages of the transport electrification journey.

Compared to legacy studies, conducted when most consumers had little or no real experience with EV charging, we find that the general attitude towards smart charging and V2G has improved significantly across the three major demographic splits (non-EV owners, BEV owners, or trial participants). This suggests levels of trust around EVs is improving across the population. BEV owners and V2G participants may be subject to some 'early adopter' bias in their responses (and also due to some demographic skew, particularly with regards to high income levels), but nevertheless it is shown that those consumers do continue to report much higher levels of willingness to use smart charging or V2G than the general population.

V2G was more divisive than smart charging, with a larger variance in responses across all groups. Deeper analysis showed that, despite average BEV ownership increasing likelihood of showing willingness to use V2G, some BEV owners were *less* willing to use V2G. In contrast, BEV ownership had a much more consistent improvement on willingness to participate in smart charging. We hypothesise that this is due concerns around battery degradation, which may become more tangible once a consumer owns an electric vehicle.

As with prior works, concerns around battery degradation and range anxiety were also found to be significant explanatory factors, although these were less significant than BEV ownership and/or trial participation.

Concerns about battery degradation are challenging to address, regardless of EV battery size, due to conflicting information on V2G's impact. Some studies have quantified degradation impacts [24; 25], while others have demonstrated that V2G can actually extend battery life by mitigating degradation associated with prolonged storage at high charge levels [26; 27]. However, current datasets on degradation are not yet comprehensive. More studies are needed to include various real-world operating conditions and battery chemistries [28]. These studies should provide a more holistic understanding of V2G's long-term effects on battery health. While V2G trial participants exhibit lower concerns regarding battery degradation compared to non-participants (Fig. 2), the potential impact on battery life should be carefully monitored and factored into V2G cost-benefit analyses. This may include considering compensation for customers to address potential degradation risks.

The vast majority of respondents believed they should be compensated for V2G, and those who owned a BEV or participated in the V2G trial demanded more compensation on average than those who did not.

While V2G trial participants expected higher compensation for V2G services, we cannot definitively link this expectation to concerns about battery degradation, as we did not specifically ask participants to explain their compensation requirements. The higher compensation expectations of V2G triallists may be influenced by their exposure to significant incentives (e.g., free chargers) as early adopters of this new technology.

We find that the effect of V2G usage is a highly significant explanatory factor for stated willingness to participate in V2G. Furthermore, across all factors, it was found that the belief that V2G contributes to a more stable electricity network was most significant in predicting willingness to use V2G.

Data privacy was a significant concern, although BEV ownership and trial participation correlated with consumers being more willing to share their data with an operator.

Taken together, it is concluded from the results that policies to increase V2G are likely to be self-reinforcing once V2G becomes available and cost-effective for consumers. Practical, low-regret approaches for consumers that expose them to V2G technology could prove fruitful, such as low-commitment 'taster' tariffs, guaranteed remuneration rates to reduce payback risk, or even EV showroom demonstrators. Furthermore, education and awareness around the pro-social aspects of V2G in support of grid stability and resilience could help to 'nudge' consumers towards the V2G solution. This is a particularly valuable point as many countries transition towards much more variable supply provided by renewables–large renewable penetrations correlate with more variable market prices, and therefore increased opportunities for reduced payback periods required for V2G infrastructure and system benefits provided by V2G. Future research could validate the results with increased representativeness (internationally and demographically within the UK), or directly follow the changing V2G perceptions of individual consumers over time to understand these effects and potential future interventions further.

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Supplementary Information

This section provides further details on the logistic regression model that was discussed in Section 3.3.

We used a logistic regression model, with L_1 regularization. The model was trained using the *scikit-learn* package [29]. The parameter selection was found using the following algorithm. First, we searched over all of the variables for the single best predictor – in other words we looked at the prediction score of MLR models with a single input variable and chose the best one. This variable was then added permanently to the predictors. We then searched over the remaining variables for the best single additional variable, and if best variable improved the prediction score by more than a threshold we added it to the predictors. This process was repeated until no single remaining variable improved the score significantly. For this

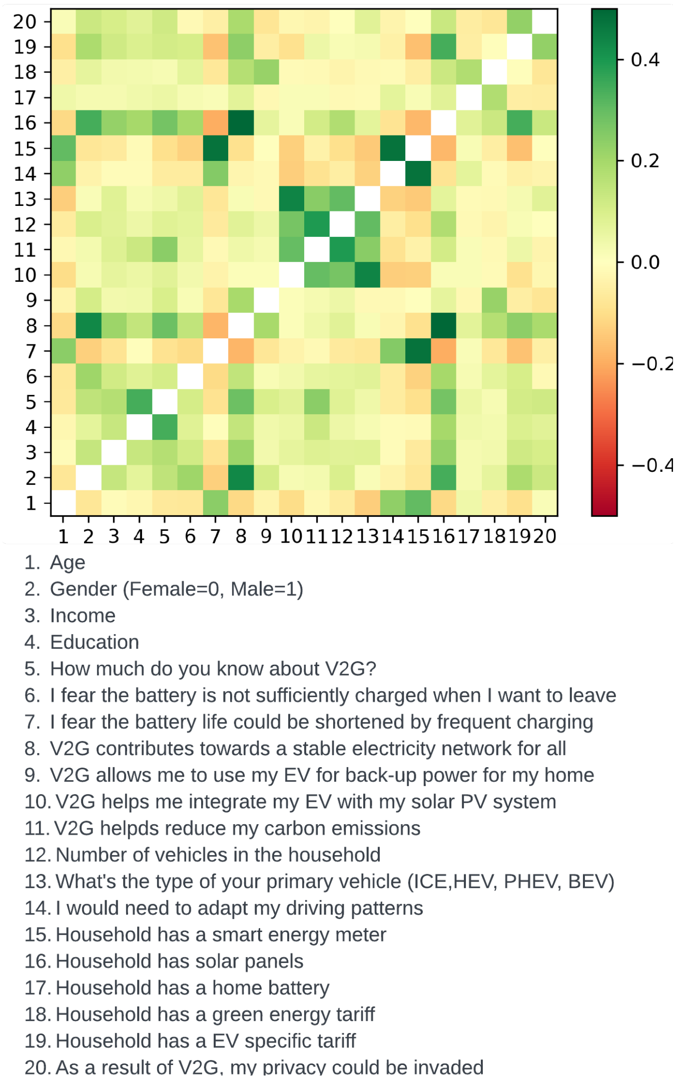

Figure 7: A map showing the correlation between the considered input variables. Green indicates a positive correlation, and red a negative correlation. Some variables are strongly correlated and are therefore unlikely to both be selected in our regression model.

case we chose a prediction threshold of 10^{-5} – although it's worth noting that in our case a threshold of 0 returned the same result.

These scaled values were all considered as potential inputs for a predictive logistic regression model. However, may of these factors are correlated with each other. Figure 7 shows the factors considered in the model and their cross-correlation. The cell (i, j) expresses the strength of the correlation between variable i and variable j. Darker shading indicates a stronger relationship with pink indicating a positive correlation and green a negative correlation. For example, it can be observed that there is a strong correlation between gender and respondents who agreed with the statement "V2G contributes towards a stable electricity network", with men more likely to agree.

The resulting model predicts 52% of the responses exactly and 90% of the responses within one classification (e.g. predicts definitely instead of likely). However, the first variable is by far the most significant; using just that single variable we can predict 46% correctly and 85% within one.

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