Promoting Sustainable Charging Through User Interface Interventions

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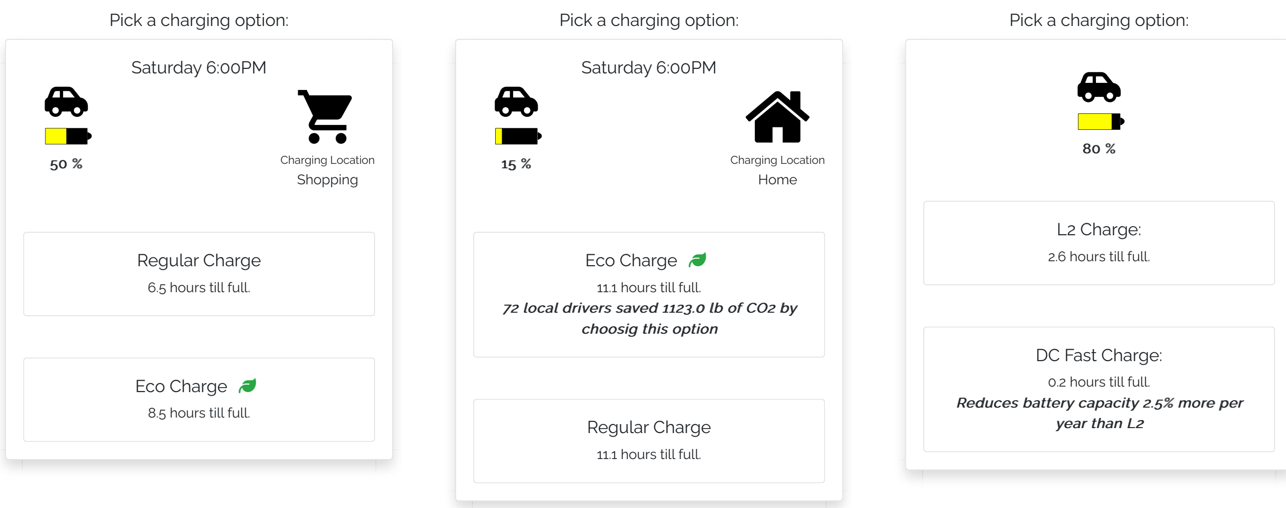

(a) Situational Factors **(b) CO_2 Interventions** **(c) Battery Degradation**

Figure 1: Three charging interventions tested: willingness to wait for charging given (a) location, remaining charge, and time, (b) CO_2 information, and (c) externalizing battery degradation.

ABSTRACT

With the rising popularity of electrified vehicles, emphasis has been placed on encouraging charging with renewable energy and maximizing battery longevity to improve vehicle sustainability. Many mobile applications offer tools to suggest charging times with more sustainable renewable energy and charging strategies that preserve battery health. However, these options often result in longer, less convenient charging times for drivers. Here we conducted three charging scenario studies to identify factors that influence willingness to wait for sustainable charging. Participants selected between faster but less sustainable charging options and slower charging options that either reduce charging emissions or improve battery longevity. We find people's willingness to wait for green energy is influenced by situational factors; further we find that information and battery longevity interventions can increase willingness to wait for sustainable charging. Finally, we provide design recommendations to promote sustainably in charging behaviors.

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CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **User studies**; *Interface design prototyping*; • **Applied computing** → Law, social and behavioral sciences.

KEYWORDS

Carbon Emissions; Electric Vehicles; CO_2 Emissions; Eco-Feedback; Ridesharing; Ride Hailing; Design Interventions; Automobiles; Carbon Neutrality; Behavioral Science

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1 INTRODUCTION

Eco-feedback vehicle interfaces have become commonplace in today's vehicles; for example, in-dash displays often coach individuals with driver scores, or real-time visualizations of fuel and/or battery usage [23, 54]. These eco-displays are used in-situ of driving or at ignition off and show anything from growing trees in hybrid vehicles to driver efficiency scores displayed at ignition off [65]. With the growing popularity of electrified vehicles (EV), user interfaces incorporate elements designed to promote more sustainable charging habits. These interfaces can be informed by systems like WattTime[1] to track local grid emissions and help EV drivers schedule charging at times when clean energy is more readily available. Some interfaces also allow users to control the amount of charge they put in their vehicle and the charging speeds, with the aim of helping drivers maximize battery health and increase their vehicle's longevity. Indeed, although direct current fast charging charges electrified vehicles more quickly, over-use can lead batteries to degrade twice as fast compare to slower alternating current charging [4, 69]. Together, using slower charging at times when more renewable energy is readily available can improve the carbon impact of electrified vehicles [11]. However, these green charging strategies also present a time cost, requiring drivers to wait for the availability of renewable energy to charge [43], or using slower charging speeds to reduce battery degradation.

In this article, we investigate factors and interventions that influence U.S. drivers' willingness to wait for more sustainable charging behaviors. As electrified vehicles sales are relatively low but rapidly increasing in the U.S. (growing from 1% to 5.8% of new car sales from 2016–2022 [32]), we focus on general willingness to wait amongst all U.S. drivers. Testing a more general population of drivers can help provide insights into the potential charging behavior of future adopters for whom interfaces will be built. First, we examine the extent to which situational factors (e.g., location, time of day) influence people's willingness to wait for green charging. Next, we test a series of information interventions added to the interface to examine which displays lead to an increase in willingness to wait for greener energy. Finally, we explore whether information interventions about accelerated battery degradation increase willingness to wait for slower, less battery intensive charging. We use our findings to discuss suggestions for the design of charging applications with green and/or battery-life preserving interventions.

[1] https://www.watttime.org (Accessed April 2023)

2 RELATED WORK

Battery electric vehicles (BEV) have the potential to dramatically reduce transportation-based greenhouse gas emissions (GHGs) [31], but their effectiveness depends on how they are used. Although BEVs do not emit tailpipe emissions, GHGs are often emitted to generate the electricity they use to charge. The energy sources used to charge BEVs have strong influence on their overall GHG emissions, potentially making them less environmentally friendly than gasoline-powered vehicles when charged with high emission non-renewable energy (e.g., coal, oil) [9, 60]. In the U.S., the availability of renewable energy varies considerably from region-to-region and throughout the day [9, 15] (e.g., between periods where solar energy is or is not available). However, this scenario offers an opportunity to use renewable energy sources to meet EV customers' charging needs [10, 30].

In addition to emissions from electricity, BEV manufacturing emits more GHG emissions than conventional vehicles due to the processes needed to manufacture lithium-ion batteries [45]. Because batteries contribute to BEV GHG emissions, efforts to maximize battery longevity can both help reduce the environmental impact and reduce the costs associated with battery production [69]. BEV battery longevity can be influenced by charging habits, with factors such as the frequency of direct current (DC) fast charging affecting how quickly a vehicle's battery degrades [4, 69]. Therefore, interfaces can promote charging behaviors that minimize battery degradation and allow a longer vehicle life cycle that will have lower overall environmental impacts [11].

2.1 Charging Practices

User–battery interaction is an important component of BEV users' understanding of their vehicle's range, driving utilization, and access to sustainable charging [21]. Charging logistics are currently a strong barrier towards EV adoption [17]. However, this barrier can be mitigated by interacting with a BEV, which can change perceptions by offering real world practice [8]. Unlike fueling combustion engines, which are often driven until empty before being refilled, EV drivers charge their vehicles more opportunistically, when charging becomes timely or more available [49]. Further, charging locations are important to EV owners, with highest preference given to home charging, followed by work, then public charging [28]. Public locations are often seen as less important because of their inconvenience and lack of reliability [35]. Additionally, decisions regarding where and when to charge can largely be driven by financial tradeoffs [13, 35].

2.2 Sustainable Charging Practices

In recent years, various initiatives have emerged to support BEV charging with renewable energy, such as networks of stations powered by wind and solar, utility programs promoting off-peak charging, and co-locating BEVs with on-site solar energy systems and battery storage [2, 19, 30]. Managed BEV charging programs also offer customers the ability to adjust their charging schedules to align with clean energy availability and grid requirements [44, 64]. Incentivizing delays in charging EVs can not only minimize the impact on the grid and help in cost-savings, but also mitigate the need to create new power plants [43]. While consumers are largely driven by cost-savings, they have expressed preference for user-managed charging (UMC) over supplier-managed charging (SMC) due to perceived personal control and reduced risk of incomplete charging [14, 16]. Prior work has shown consumers delaying home deliveries up to 5 days when shown an environmental incentive (i.e., number of trees saved) [42, 63]. In this article, we study consumers' willingness to wait for sustainable charging and effective interventions that encourage delayed charging. Direct current fast charging options can also lead to quicker battery degradation than slower alternating current charging (e.g., L2 charging) [4, 68], while being potentially counterproductive towards sustainability goals [11]. We also explore consumers' willingness to wait for charging options that maximize battery longevity.

2.3 Eco-Feedback Interventions in Vehicular Contexts

Personal transportation is the leading source of carbon emissions in both the US and Europe [18, 31, 62]. To reduce driving-related emissions, some research has focused on providing carbon footprint feedback associated with personal transportation behaviors, such as commuting alternatives [22, 47] (e.g., carpooling, biking), energy-efficient driving [65], BEV adoption [59], and eco-friendly routes [37]. However, communicating CO_2 emissions can be challenging because metrics such as the weight of GHG emissions come across as too scientific or unactionable for consumers [1, 66]. To help people understand GHG emissions, the United States Environmental Protection Agency (EPA) offers a calculator[2] with over 20 equivalencies to "translate abstract measurements into concrete terms you can understand". Such equivalencies are meant to help people better understand measurements [33] and make better perspective analogies for numbers [29].

Recent research finds that although people find CO_2 equivalencies useful and relatable, vehicle-based interventions that communicate raw CO_2 emissions are more effective than equivalencies as a tool for behavior change [41]. However, raw CO_2 numbers are mainly effective when used for relative comparisons rather than in absolute terms, suggesting a gap in people's carbon literacy [40]. Valence can also play an impact on how eco-feedback information is perceived by users, with prior work showing that negatively framed eco-feedback is more effective at influencing behavior than positively framed messages [40, 53, 58].

Rewards and mobile embodiment can also effectively influence charging behavior [55]. Eco-charging incentives that focus on monetary rewards can effectively lead to greener charging behavior [67]. Moreover, rewards are not always necessary: informational interventions that highlight consequences of metrics like CO_2 can also motivate behavior change [34]. Similarly, studies have also shown promising results with eco-friendly behaviors when consumers are exposed to social interventions, such as collective feedback [20, 24, 40] or gamification [25]. Although there is a focus on eco-driving in most existing literature, here we explore the effectiveness of different feedback interventions for encouraging users to wait for sustainable charging.

[2]https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator (Accessed April 2023)

3 EXPERIMENTS

In this work we explore a motivating scenario in which a driver is plugging their car in to charge. At this point of plugging in, we provide a mock interface to ask the driver to choose between two charging options that vary in duration. Figure 1 shows the options presented for willingness to wait for (a) green energy depending on situational factors like time, location, and remaining battery, (b) green energy when CO_2 interventions are included, and (c) slower charging to save battery degradation. Currently, many existing apps either provide options to charge immediately or schedule the charge for a later, greener time. We conducted three studies to understand people's perception in these willingness-to-wait embodiment interfaces and provide design implications for greener charging systems.

3.1 Study 1: Waiting for Green Energy

Study 1. *Using a survey with a prototype design of a charging mobile app, we establish a base understanding of how situational factors (location, time, and remaining charge) influence people's willingness to wait for green energy. The situation of the study is that a driver has plugged in their vehicle and is choosing to charge immediately with higher emission electricity, or wait an equal or greater amount of time for cleaner electricity from renewable sources.*

In most charging situations, there are various situational factors that could affect a person's willingness to wait to charge. These factors include: location (home, shopping, work, etc.), time of day, and remaining battery [35, 50, 52] (Fig. 1a). For Study 1, we propose five hypotheses: **H1.1** People are more likely to wait for green energy when charging in a stable location (e.g., at home). **H1.2** People are more likely to wait additional time for green energy when they have higher remaining charge at the time of charging. **H1.3** People are more likely to wait for green energy when charging in the morning or at night rather than in the middle of the day. **H1.4** People are more likely to wait for green energy when charging on weekends than on weekdays. **H1.5** People are more likely to wait for green energy if they are given information about the CO_2 emissions saved. In addition to these specific factors, we conducted an exploratory comparison of BEV and non-BEV owners to examine whether owning a BEV affected the influence of situational factors on people's willingness to wait for green charging.

3.1.1 Methods. We designed an online survey in Qualtrics aimed at measuring the influence of different situational factors on people's willingness to wait for green charging. Participants were instructed to imagine that they owned a hypothetical BEV with a maximum range of 270 miles (the average range across U.S. BEV models sold in 2022 [32]) and were using an app to schedule charging. Participants used a simulated app user interface to select a charging method on each trial (Figure 1a).

The interface displayed information about four main situational factors: (1) **Charging Location:** The place where the charging would occur (*home*, *work*, or *shopping*), presented on the top right of the app screen using text and an icon. (2) **Remaining Battery:** The charge remaining in the battery before charging started (*15%*, *50%*, or *80%*), presented on the top left of the app as a numerical percentage written next to a battery icon. (3) **Day of Week:** The day of the week on which people were charging (any day of the week) included at the top of the app screen. (4) **Time of Day:** The time of day at which people were charging (*9:00am*, *12:00pm*, or *6:00pm*) written beside the day of the week at the top of the app screen.

With these situational factors, participants were instructed to pick one of two charging options: (1) **Regular Charge:** Charging starts as soon as the vehicle is plugged-in, irrespective of the source generating electricity. (2) **Eco Charge:** Charging starts once cleaner electricity is available to charge the vehicle. This option was always presented with a green leaf icon and took 0 to 5 hours more to charge than *Regular Charge*. Each option listed the time (in hours) it would take to charge the hypothetical BEV. The base charging time was calculated by first multiplying the hypothetical BEV's battery size of 86 kWh (average battery size of all BEVs sold in the U.S. in 2022 [32]) by the proportion needed to charge the battery to 100% (e.g., if the remaining charge was 15%, the remaining amount of battery to charge is calculated as $(1 - 0.15) \times 86 = 73.1$). We then divided this remaining charge by an L2 charging speed of 6.6kW—a typical charging speed found at home, work, and public charging locations in the U.S.—to calculate the number of hours needed to charge to 100% (from the previous example, $73.1/6.6 = 11.1$ hours).

We also tested if providing CO_2 emission information increases the likelihood of choosing *Eco Charge*, as seen in similar ride-sharing and rental contexts [40, 41]. On half of the trials, we added the text "This option saves x lbs of CO_2" to the *Eco Charge* option under the charging time. The pounds of CO_2 were estimated from an analysis of hourly grid emissions data collected by the U.S. Energy Information Administration across 76 U.S. balancing authorities [15]. Using data from January 1st to December 31st, 2022, we computed the average grid emission intensity for each balancing authority (in pounds of CO_2 per kWh), and computed the median value across balancing authorities, resulting in a median grid emission intensity value of 0.97 $lbCO_2$/kWh. To compute the difference between *Regular Charge* and *Eco Charge*, we first computed the average emission intensity for each hour of the day for each balancing authority, then computed the percent difference between the hours of day with the lowest and highest grid emissions. Across balancing authorities, the median percent difference in grid emission intensity was 22%. With these values, we computed the CO_2 emissions of the *Regular Charge* option as the kWh needed to charge multiplied by 0.97, and then computed the emissions saved by Eco Charge as 22% of this result.

Each trial contained a scenario permutation of charging location, time of day, day of week, remaining battery, and CO_2. Given the high number of scenario permutations, we used a mixed study design in which each participant responded to a randomly selected 30 out of a possible 648 possible scenarios (i.e., not all subjects saw all possible permutations). Attention checks were included after the 15th and 30th trial where people answered "yes" or "no" to the prompt "Have you been paying attention to each question?". After completing the trials, participants answered a questionnaire about the extent to which each situational factor, charging time, and CO_2 information influenced their decisions (using a 5-point Likert scale ranging from *Disagree* to *Agree*) and a demographic questionnaire.

Before starting the task, participants indicated the type(s) of vehicle(s) they owned. They did this by selecting the options that applied from the following list: "Gas Vehicle", "Hybrid Electric Vehicle (hybrid that CANNOT be plugged in)", "Plug-in Hybrid Vehicle (hybrid that CAN be plugged in)", "Battery Electric Vehicle (electric vehicle that can ONLY be plugged in and DOES NOT run on another fuel)", "Hydrogen Fuel Cell Vehicle", and "Other". Any participant who selected "Battery Electric Vehicle" was identified as a BEV owner to measure the influence of BEV experience on willingness to wait for green charging.

3.1.2 Participants. A total of 1005 participants were recruited from Prolific [46]. All participants were U.S. residents, 18 years of age or older, spoke English, have a valid drivers' license, and had driven a vehicle within the last month. Participants had also completed at least 100 previous tasks with a $\geq$ 95% approval rating to ensure good quality responses [48]. We excluded 4 participants who answered "no" to at least one of the attention checks, leaving a final sample of 1001 participants (responses from all 50 states; gender identity: 43% women, 56% men, 1% genderqueer or non-binary; mean age = 40.7 years, SD = 13.0 years).

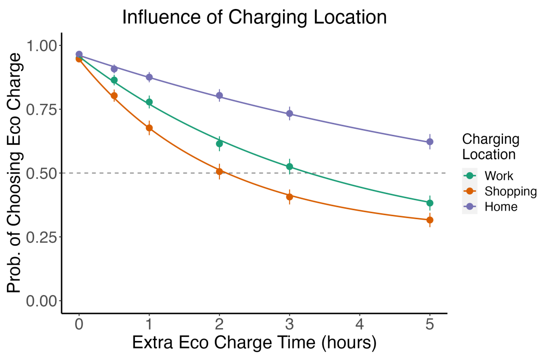
3.1.3 Analysis. Because our study is a mixed design and contained both within and between participant variance, we used mixed-effects logistic regression models implemented by the lme4 package in R [6] to evaluate the influence of different situational factors and the CO_2 information intervention on the likelihood that people would choose *Eco Charge*. The model included difference in charging time, location, time of day, day of week, remaining charge, and CO_2 information as fixed effects, and participant ID and question order (i.e., the order in which each question appeared to the participant) as random intercepts. To test for the presence of interactions between factors, we compared the difference in Bayes Information Criterion values (BIC) between the main effects model described above and models that included the specific interactions, with lower BIC values indicating more parsimonious fits. Effect sizes for our regression analyses are computed as Cohen's d for mixed-effects models by dividing the beta weight for a particular effect by the square of the sum of the variances of the random effects [7].

3.1.4 Results.

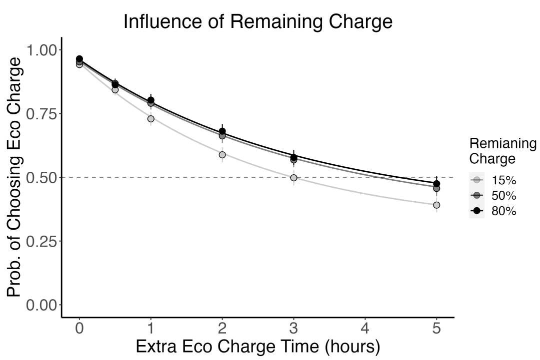
Situational factors influenced willingness to wait for green energy. Overall, participants were more likely to choose *Eco Charge* than *Regular Charge*, choosing this option on 70% of trials. However, they were also less likely to choose *Eco Charge* as the difference in waiting time increased between charging options (influence of additional charging time on likelihood of choosing *Eco Charge*: $\beta = -0.74, 95\%\text{CI} = [-0.76 - -0.71], p < .001, d = .44$).

Situational factors also influenced people's willingness to wait for green energy. Location had the largest effect, with participants much more likely to choose *Eco Charge* if charging at home compared to charging at work or while shopping, and more likely to choose *Eco Charge* at work than while shopping (contrast comparing likelihood of choosing *Eco Charge* at home vs. at work: $\beta = 1.17, 95\%\text{CI} = [1.08 - 1.25], p < .001, d = .70$; home vs. shopping: $\beta = 1.72, 95\%\text{CI} = [1.64 - 1.81], p < .001, d = 1.03$; work vs. shopping: $\beta = 0.56, 95\%\text{CI} = [0.48 - 0.63], p < .001, d = 0.33$; Fig. 2a).

Remaining charge also influenced people's choices. Participants were more likely to choose *Eco Charge* if the remaining charge



(a)



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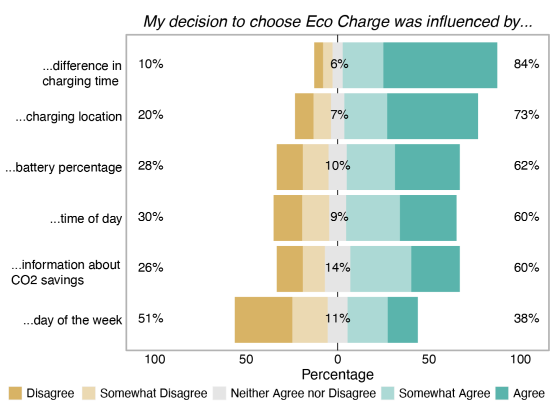


(c)

Figure 2: Influence of (a) location and (b) remaining charge from Study 1. Other conditions (time of day, day of the week, and CO_2) savings had minimal effects on the likelihood that participants chose *Eco Charge*. Points indicate the mean proportion of *Eco Charge* response for each difference in charging time across all subjects and error bars indicate between subject 95% confidence intervals. The lines joining the points indicate best fitting exponential decay curves. (c) Proportion of participants responses to questionnaire asking about the importance of different factors on their decision to choose *Eco Charge*.

was 50% or 80% compared to 15% (contrast comparing likelihood of choosing *Eco Charge* with 50% vs. 15% remaining charge: $\beta = 0.39$, 95%CI $= [0.31 - 0.47]$, $p < .001$, $d = 0.24$; 80% vs. 15% remaining charge: $\beta = 0.50$, 95%CI $= [0.40 - 0.56]$, $p < .001$, $d = 0.29$; Fig. 2b). Participants were also slightly more likely to choose green charging with 80% remaining charge compared with 50% remaining charge, but the effect size was very small (80% vs. 50% remaining charge: $\beta = 0.50$, 95%CI $= [0.01 - 0.17]$, $p = .037$, $d = 0.05$).

Other situational factors had a much smaller influence on participant choices. Participants were slightly more likely to choose *Eco Charge* in the morning than at noon or in the evening, and slightly more likely at noon than in the evening (contrast comparing likelihood of choosing *Eco Charge* in the morning vs. noon: $\beta = 0.14$, 95%CI $= [0.06 - 0.22]$, $p < .001$, $d = 0.08$; morning vs. evening: $\beta = 0.23$, 95%CI $= [0.15 - 0.31]$, $p < .001$, $d = 0.14$; noon vs. evening: $\beta = 0.08$, 95%CI $= [0.01 - 0.16]$, $p = .038$, $d = 0.05$; Fig. 2c).

However, the influence of time of day depended on the charging location (comparison of main effect model and model with interaction term for time of day and location: $BIC_{me} = 25478$, $BIC_{int} = 25423$). When charging at home, participants were equally likely to choose *Eco Charge* in the morning or at noon, and slightly more likely to choose this option when charging in the evening (contrast comparing likelihood of choosing *Eco Charge* at home in the morning vs. noon: $\beta = -0.08$, 95%CI $= [-0.09 - 0.25]$, $p = .373$, $d = 0.04$; evening vs. morning: $\beta = 0.23$, 95%CI $= [0.06 - 0.41]$, $p = .010$, $d = 0.10$; evening vs. noon: $\beta = 0.31$, 95%CI $= [0.13 - 0.49]$, $p < .001$, $d = 0.14$). When charging at work, participants became less likely to choose *Eco Charge* as the day progressed (contrast comparing likelihood of choosing *Eco Charge* at work in the morning vs. noon: $\beta = 0.43$, 95%CI $= [0.28 - 0.58]$, $p < .001$, $d = 0.24$; morning vs. evening: $\beta = 0.78$, 95%CI $= [0.63 - 0.93]$, $p < .001$, $d = 0.44$; noon vs. evening: $\beta = 0.35$, 95%CI $= [0.11 - 0.28]$, $p < .001$, $d = 0.20$). When charging away from home, time of day did not have any influence on people's choice to choose *Eco Charge* (all $\beta < 0.11$, all $p > 0.157$, all $d < 0.06$).

Day of the week exerted the smallest influence on participant choices. Participants were slightly more likely to choose *Eco Charge* when charging on a weekend than on a weekday, but this effect was very small (weekend vs. weekday: $\beta = 0.07$, 95%CI $= [0.01 - 0.14]$, $p = .025$, $d = 0.04$; Fig. 2d).

CO_2 messaging slightly increased willingness to wait for green energy. Similar to previous reports, providing information about CO_2 savings below the *Eco Charge* option made participants slightly more likely (28% greater odds) to wait for green charging than cases where no information was provided (i.e., when *Eco Charge* only had a green leaf icon; contrast comparing the likelihood of choosing *Eco Charge* with information vs. a simple green leaf: $\beta_{CO_2} = 0.25$, 95%CI $= [0.18 - 0.31]$, $p < .001$, $d = 0.11$; Fig. 2e). However, the effect was much smaller than in previous reports [40]. Additionally, the effect of CO_2 messaging did not interact with any situational variables (all differences in BICs between interaction models and main effect models ≥ 10).

Self-reported influence of different factors. Participants' self reported influence of different factors were consistent with their responses on the choice task (Fig. 2f). When asked which factors exerted the strongest influence on their decision to choose *Eco Charge*, participants were most likely to respond "agree" or "somewhat agree" to the additional time required to charge, followed by charging location, remaining battery, time of day and CO_2 information, with day of the week rated as the factor with the least influence.

Experience with BEVs had little influence on participant choices. Although our focus was on general U.S. drivers, 60 participants (6%) reported owning a BEV. We took this opportunity to measure the influence of BEV experience on willingness to wait. Overall, BEV owners were not more likely to choose *Eco Charge* than non-BEV owners (contrast comparing likelihood of BEV owners of choosing *Eco Charge* over other drivers: $\beta = 0.32$, 95%CI = $[-0.14 - 0.80]$, $p = .165$, $d = 0.19$) and were overall not more likely to wait additional time for green charging (interaction of additional charging time and BEV ownership: $\beta = 0.07$, 95%CI = $[-0.02 - 0.05]$, $p = .149$, $d = .04$). Of all the situational factors, BEV owners were slightly more willing to wait for green energy at work (contrast measuring influence of BEV ownership on willingness to wait at work: $\beta = 0.62$, 95%CI = $[0.06 - 1.18]$, $p = .030$, $d = 0.35$), but no more likely to wait at home or while shopping (all $|\beta| < 0.23$, all $p > .543$, all $d < 0.10$). No other situational factors influenced willingness to wait for BEV owners compared to non-BEV owners (contrasts comparing the influence of remaining charge, day of week, and time of day on likelihood of choosing *Eco Charge*: all $|\beta| < 0.45$, all $p > 0.09$, all $d < 0.27$).

Together, these results demonstrate that situational factors, particularly charging location and state of charge, can influence willingness to wait for green charging. We additional find that interventions involving messaging about carbon savings can also increase willingness to wait but these have much smaller effects than location and state of charge. Last, we show that our results do not depend on experience with BEV ownership. Next, we explore the influence of different intervention types on people's willingness to wait for green charging.

3.2 Study 2: Interventions to increase waiting for Green Energy

Study 2. *Here we ad interventions on top of the existing contextual factors. The motivating charging scenario remains the same as Study 1. These interventions are: (1) CO_2 Savings with negative or positive valence, (2) social collective messaging with negative or positive valence, (3) and extrinsic rewards.*

To motivate participants to wait for green energy, we chose interventions shown to influence people's choices in other vehicular contexts [41] (Fig. 1b). Here we specifically test the following two hypotheses: **H2.1** Information about CO_2, social collective actions, and extrinsic rewards increase the likelihood that greener options are selected. **H2.2** Negatively valenced information interventions increase the likelihood that greener options are selected.

3.2.1 Methods. We took the same mixed study design approach used in Study 1 except that participants were exposed to one of six interventions on each trial: (1) **Baseline:** A green leaf was presented next to *Eco Charge* with no additional information. (2) **CO_2 savings (positive valence):** text added below the *Eco Charge* option indicating the pounds of CO_2 this option saves (same as the CO_2 intervention condition from Study 1). (3) **CO_2 emissions (negative valence):** text added below the *Regular Charge* option indicating the additional pounds of CO_2 emitted by this option. (4) **Social collective CO_2 savings (positive valence):** text added below the *Eco Charge* option indicating the total pounds of CO_2 saved by local people who also selected this option. The number of local people on each trial was randomly chosen between 40 and 90 people and the emission savings were calculated by multiplying to estimated carbon savings for one person by the number of local people selected for that trial. (5) **Social collective CO_2 emissions (negative valence):** text added below the *Regular Charge* option indicating the total additional pounds of CO_2 emitted by local people who also selected this option. (6) **Extrinsic rewards:** text below the *Eco Charge* option indicating that selecting this option would result in "2x points". Similar to Mohanty et al. [40, 41], participants were deliberately not given any information about what these points represented nor how they could be redeemed. Participants completed the same open-ended questions and post-study questionnaires as the participants in Study 1.

3.2.2 Participants. A total of 1000 participants were recruited Prolific for Study 2 using the same criteria as Study 1 with an additional filter ensuring that they had not participated in Study 1. Three participants were excluded for failing our attention checks, leaving a final sample of 997 participants (responses from all 50 states; gender identity: 45% women, 53% men, 2% genderqueer or non-binary; mean age = 41.4 years, SD = 13.0 years).

3.2.3 Analysis. We used the same mixed effects logistic regressions as in Study 1, including the six interventions tested. In our analysis of "valence", we replaced the fixed effect of intervention and replaced it with a "valence" fixed effect. Similar to previous work, any interventions that included mention of CO_2 "savings" were labeled as "positively valenced", and those mentioning additional CO_2 "emissions" were labeled as "negatively valenced" [40].

3.2.4 Results. The influence of situational factors in Study 2 were largely consistent with the results from Study 1. Participants were more likely to choose *Eco Charge* at home over work and shopping, and more likely to choose *Eco Charge* at work than while shopping (contrast comparing likelihood of choosing *Eco Charge* at home vs. at work: $\beta = 1.08$, 95%CI = $[0.99 - 1.17]$, $p < .001$, $d = 0.68$; home vs. shopping: $\beta = 1.56$, 95%CI = $[1.49 - 1.67]$, $p < .001$, $d = 1.00$; work vs. shopping: $\beta = 0.50$, 95%CI = $[0.42 - 0.58]$, $p < .001$, $d = 0.32$). Participants were also less likely to choose *Eco Charge* if they had lower remaining charge (15%) than if they had higher remaining charge (50% or 80%; contrast comparing likelihood of choosing *Eco Charge* when remaining charge is 50% vs. 15%: $\beta = 0.30$, 95%CI = $[0.22 - 0.38]$, $p < .001$, $d = 0.19$; 80% vs. 15%: $\beta = 0.34$, 95%CI = $[0.26 - 0.42]$, $p < .001$, $d = 0.22$). There were no differences between higher remaining charges (80% vs. 50%: $\beta = 0.04$, 95%CI = $[-0.04 - 0.13]$, $p = .303$, $d = 0.03$). Participants were additionally more likely to choose *Eco Charge* on a weekend than on a weekday, although this effect was again very small (contrast comparing likelihood of choosing *Eco Charge* on a weekend vs. weekday: $\beta = 0.09$, 95%CI = $[0.03 - 0.16]$, $p = .007$, $d = 0.06$).

When examining time, participants were more likely to choose *Eco Charge* in the morning or evening than at noon, but unlike Study 1, there were no differences between morning and evening (contrast comparing likelihood of choosing *Eco Charge* in the morning vs. at noon: $\beta = 0.12, 95\%CI = [0.04-0.12], p = .004, d = 0.08$; evening vs. noon: $\beta = 0.12, 95\%CI = [0.01-0.17], p = .034, d = 0.06$; morning vs. evening: $\beta = 0.03, 95\%CI = [-0.05-0.11], p = .429, d = 0.02$).

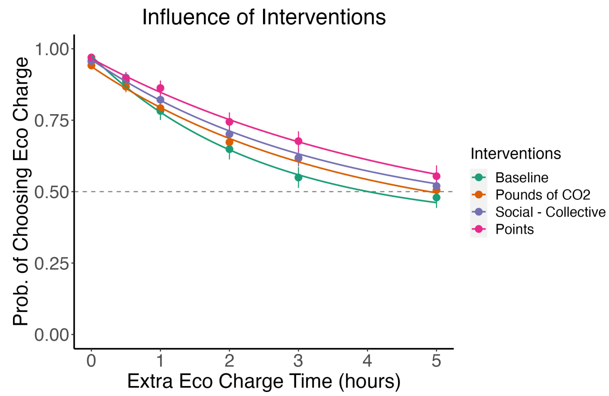
We find results that are generally consistent between studies, particularly the effects of location and remaining charge, which showed the largest effects in both studies. Next we examine how the different information interventions influenced people's willingness to wait for green energy.

Interventions increased willingness to wait for green energy. Overall, when compared to the baseline condition, interventions that presented information about CO_2, social information, and points all succeeded in increasing people's likelihood of choosing *Eco Charge* (contrast comparing the influence of CO_2 information vs. baseline on the likelihood of choosing *Eco Charge*: $\beta = 0.10, 95\%CI = [0.01-0.20], p = .038, d = 0.06$; social collective vs. baseline: $\beta = 0.31, 95\%CI = [0.21-0.40], p < .001, d = 0.19$; points vs. baseline: $\beta = 0.58, 95\%CI = [0.46-0.70], p < .001, d = 0.37$; Fig. 3a). However, some interventions worked better than others (Fig. 3b). Providing extrinsic rewards in the form of arbitrary "points" had the strongest effect on people's choices, outperforming raw and social collective CO_2 information (contrasts comparing the influence extrinsic reward intervention vs. CO_2 information on the likelihood of choosing *Eco Charge*: $\beta = 0.48, 95\%CI = [0.38-0.58], p < .001, d = 0.30$; extrinsic rewards vs. social collective: $\beta = 0.27, 95\%CI = [0.17-0.38], p < .001, d = 0.17$; Fig. 3b). Social collective interventions were also overall more effective than CO_2 information interventions (contrasts comparing the influence social collective interventions vs. CO_2 information on the likelihood of choosing *Eco Charge*: $\beta = 0.21, 95\%CI = [0.13-0.29], p < .001, d = 0.13$).

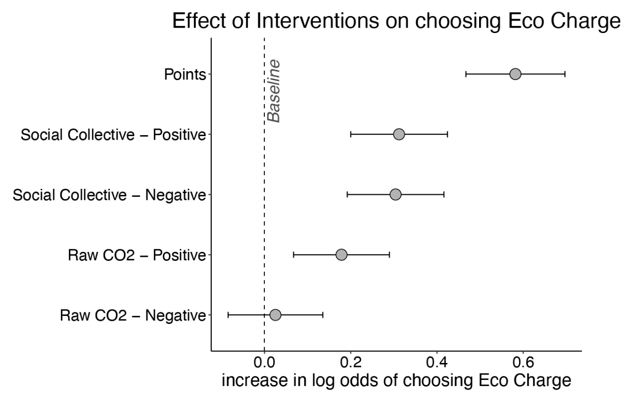
Influence of interventions did not depend on experience with BEVs. A total of 53 participants (5% of Study 2 participants) reported owning at least one BEV. Similar to Study 1, BEV owners were not more likely to choose *Eco Charge* than non-BEV owners (contrast comparing likelihood of BEV owners of choosing *Eco Charge* over other drivers: $\beta = -0.02, 95\%CI = [-0.45-0.49], p = .935, d = 0.01$), but were willing to wait slightly more time for green charging (interaction of additional charging time and BEV ownership: $\beta = 0.09, 95\%CI = [0.01-0.18], p = .0.039, d = .05$). However, none of the interventions influenced BEV owners any differently than non-BEV owners (contrast comparing likelihood of BEV owners of choosing *Eco Charge* over other drivers in any intervention condition: all $|\beta| < 0.41$, all $p > .210$, all $d < 0.25$).

These results demonstrate that all interventions we tested increased the likelihood that participants would wait for green energy, with points working most effectively, followed by social collective information, and then information about CO_2. These effects also did not depend on participants' experience with BEVs.

Valence had little effect on willingness to wait for green energy. Valence played only a small role in influencing people's choices when presented with CO_2 information. Contrary to **H2.2**, participants were slightly *less* likely to choose *Eco Charge* in the negative valence condition than in the positive condition ($\beta = 0.15, 95\%CI = [0.03-0.17], p < .001, d = 0.10$; Fig. 3b). However, valence did not influence choices in the social collective interventions ($\beta = 0.01, 95\%CI = [-0.11-0.12], p = .890, d = 0.01$; Fig. 3b). These results suggest that valence plays little to no role in influencing people's choice to wait for green charging.



(a)



(b)

Figure 3: Influence of different interventions on the likelihood that participants chose *Eco Charge*. (a) Points indicate the mean proportion of *Eco Charge* response for each difference in charging time across all subjects; error bars indicate between subject 95% confidence intervals. The lines joining the points indicate best fitting exponential decay curves. (b) Beta weights for each intervention from a logistic regression model measuring the influence of each different intervention on the likelihood of choosing *Eco Charge*. Points indicate beta weights; errorbars indicate 95% confidence intervals.

These first two studies demonstrate that willingness to wait for green energy is (1) influenced by situational factors, primarily location and state of charge, and (2) can be increased with interventions that focus on extrinsic rewards, social collective messaging, and, to a lesser extent, information about CO_2. Our last study explores the extent to which charging speed and battery degradation influence willingness to wait for charging. Whereas Studies 1 and 2 focused on reducing grid emissions related to charging itself, Study 3 examines people's willingness to wait for charging that promotes better battery longevity.

3.3 Study 3: Choosing lower charging to reduce battery degradation

STUDY 3. *Using a mock charging app, we test the effect of externalizing battery degradation from DC Fast Charging versus Level 2 (L2) charging. The situation embodiment follows the same as Study 1 and 2. Specifically, we test (1) Simple negative or positive valence labels stating a charge is worse or better for battery health, (2) displaying battery degradation as a projected yearly percentage, (3) and projecting yearly degradation as a ratio between the two options.*

The first two studies examined the role of context and interventions on reducing people's charging emissions. Study 3 focuses on vehicle ownership and people's willingness to trade-off charging speed with battery health. As highlighted in the introduction, battery production emits a considerable amount of GHG and efforts to minimize battery degradation reduce the need for more new batteries [69]. Here, we focus on people's interest in waiting for slower L2 charging versus DC charging, which is faster but can increase battery degradation (Fig. 1c).

We first test the influence of remaining charge and extra charging time on people's willingness to wait for L2 charging. Results from Study 1 show that people are more willing to wait for charging if they have higher remaining charge. We therefore expected this influence to apply in the context of choices between charging speeds. We additionally test the influence of two different informational interventions to increase willingness to wait for slower charging: (1) information valence, since degradation can be construed as a negatively valenced "loss", and (2) absolute versus relative differences in degradation, as research in cognitive psychology demonstrates that decision makers undervalue absolute comparisons and overvalue relative comparisons [5, 61]. With Study 3 we specifically hypothesize: **H3.1** People are more willing to wait for slower charging if they have higher remaining charge. **H3.2** Negatively valenced messaging will increase willingness to wait for slower charging. **H3.3** Absolute percentage of degradation is not effective as owners do not have a baseline of normal degradation. However, stating a ratio (in this case 2:1) is an effective intervention as it provides information about relative degradation that is easier to understand.

3.3.1 Methods. Similar to Study 1 and 2, participants first completed a behavioral task in which they imagined that they owned a hypothetical BEV and were using an app to choose the type of charging they were going to use. On each trial participant were told the remaining charge in the battery before charging (15%, 50%, or 80%) and given two charging options: (1) **L2 Charge:** slower charging that charges a vehicle from 0% to 100% in 4 to 13 hours depending on available charging speed, can be found at home and at public charging stations, and was better for battery health. (2) **DC Fast Charge:** faster charging that charges a vehicle from 0–100% in 20 minutes to 3 hours depending on available charging speed, is only available at public charging stations, is typically more expensive to charge, and worse for battery health.

The estimated charging times were obtained from the U.S. Department of Transportation (DOT)[3], which provides charging times for a BEV with a 60 kWh battery (4 to 10 hours for L2 charging and 20 minutes to 1 hour for DC Fast Charging). Because we used the same average BEV specifications as in Studies 1 and 2 (86 kWh battery), we adjusted the upper limits of DOT charging times for both L2 and DC Fast Charging to reflect realistic charging times in our study. We note that DC fast charging speeds are not constant and drop after a battery reaches 80% state of charge [12]. However, the rate of dropoff varies considerably across BEV models [12]. For this study, charging times assumed that charging speeds would remain constant throughout the charging period.

Under each charging option participants were given the estimated time (in hours) of charging. Charging time was computed by dividing the kWh needed to fully charge the battery by the charging speed (measured in kW). The L2 charging time was always calculated using 6.6 kW as the charging speed, a typical speed found for home and public L2 chargers in the U.S. DC fast charging speeds vary more considerably from charger to charger and throughout the day. To simulate this variability, the DC fast charging speed was randomly chosen on each trial to be either 24 kW, 50 kW, 100 kW, or 150 kW, all of which are common DC fast charging speeds.

We additionally tested four information interventions intended to increase the likelihood that people chose *L2 Charge*: (1) **Simple positive:** The text "Better for battery health" was added under the time estimate of the *L2 Charging* option. (2) **Simple negative:** The text "Worse for battery health" was added under the time estimate of the *DC Fast Charging* option. (3) **Percentage yearly battery degradation:** The text "Reduces battery capacity 2.5% more per year than L2" was added under the time estimate of the *DC Fast Charging* option. This percentage is near the average impact of DC fast charging on battery degradation. [4, 69] (4) **Ratio of yearly battery degradation:** The text "Reduces battery capacity twice as fast as L2" was added under the time estimate of the *DC Fast Charging* option. This information was similar to the percentage provided, but provided as a ratio instead of as an absolute number [69]. Participants were told that the number corresponds to the percentage lost from the battery's maximum state of charge and given the example that, if their hypothetical BEV has a maximum range of 270 miles, a 1% reduction per year would correspond to a 2.7 mile loss of maximum range per year. Using the same mixed design as Studies 1 and 2, participants completed 30 trials in which each trial had a random permutation of remaining charge and DC Charging speed.

After completing the behavioral task, participants completed a number of *additional questionnaires* relating to their task performance and their attitudes towards the tradeoff between battery degradation and charging speed: (1) The maximum percentage of the battery's full capacity that participants deem is acceptable to lose per year (10 point likert scale ranging from "1%" to "10%+"); (2) Two open-ended questions asking participants to list the factors that were most and least likely to choose *L2 Charge* instead of *DC Fast Charge*; (3) 5 point Likert scale asking the extent to which participants agreed or disagreed with the statements: "If I

[3] https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds (accessed April 2023).

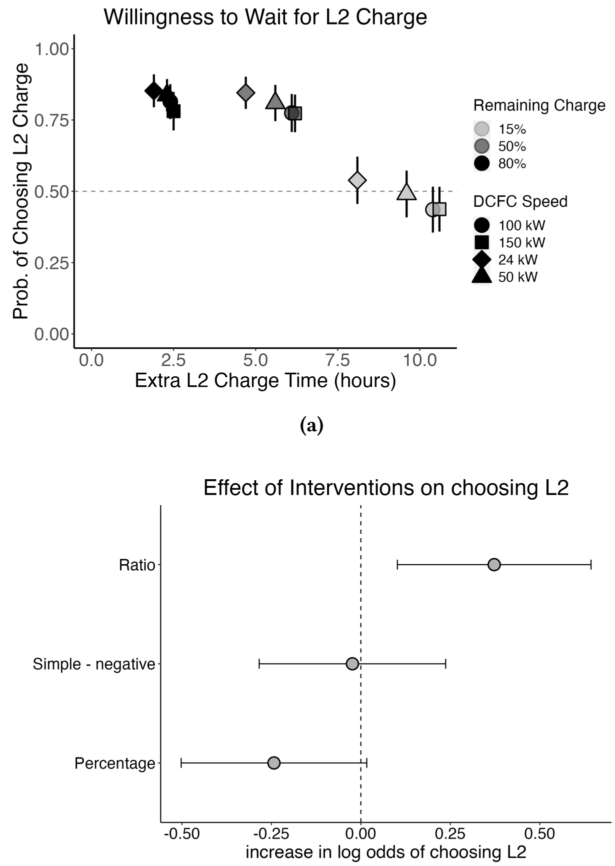
owned a battery electric vehicle, it would be important for me to..." (a) "...use DC Fast Charging" and (b) "...preserve battery health"; (4) 10 point scale asking participants to rate the extent to which DC Fast Charging or Preserving Battery Capacity were more important, with 1 indicating "I would only care about DC Fast Charging", 5 indicating "Both would be equally important", and 10 indicating "I would only care about battery capacity" Participants also completed the same demographic questionnaire asked in Studies 1 and 2.

3.3.2 Participants. Overall, 124 participants from Prolific participated in Study 3 and all passed attention checks. The same criteria as Studies 1 and 2 were applied and participants had not participated in either previous study (gender identity: 45% women, 52% men, 3% genderqueer or non-binary; mean age = 37.2 years, SD = 12.6 years). Only 2 participants reported owning a BEV; hence we did not compare responses from BEV and non-BEV owners in Study 3.

3.3.3 Analysis. We used a mixed effects logistic regressions to estimate the influence of different factors on participants' likelihood of choosing *L2 Charge*. This model included the remaining charge before charging, the DC fast charging speed, and interventions as fixed effects. We did not include differences in charging time between options as these were entirely determined by the combination of remaining charge and DC fast charging speed. Participant identifiers and question order were included as random intercepts.

3.3.4 Results. Overall, participants preferred *L2 Charge* over *DC Fast Charge* when the remaining charge was 50% or more (contrast comparing the likelihood of choosing *L2 Charge* when the remaining charge is 50% vs. 15%: $\beta = 2.36, 95\%\text{CI} = [2.11 - 2.60], p < .001, d = 1.53$; 80% vs. 15%: $\beta = 2.56, 95\%\text{CI} = [2.30 - 2.80], p < .001, d = 1.66$; 50% vs. 80%: $\beta = 0.20, 95\%\text{CI} = [-0.05 - 0.44], p = .115, d = 0.13$; Fig. 4a). *DC Fast Charge* speed also had an influence on participant choices. Participants were less likely to choose *L2 Charge* when the DC Fast Charging speed was 100 kW or 150 kW than when the charging speed was 24 kW or 50 kW (contrasts comparing the likelihood of choosing *L2 Charge* when DC Fast Charging speed is 100 kW or 150 kW vs. 24kW or 50kW: all $\beta > 0.44$, all $p < .002$, all $d > .28$). Participants were also slightly less likely to choose *L2 Charge* when DC Fast Charging speed was 50 kW instead of 24 kW ($\beta = 0.28, 95\%\text{CI} = [0.01 - 0.56], p = .040, d = 0.19$) but equally likely when DC fast charging speeds were 100 kW or 150 kW ($\beta = 0.16, 95\%\text{CI} = [-0.10 - 0.41], p = .232, d = 0.10$).

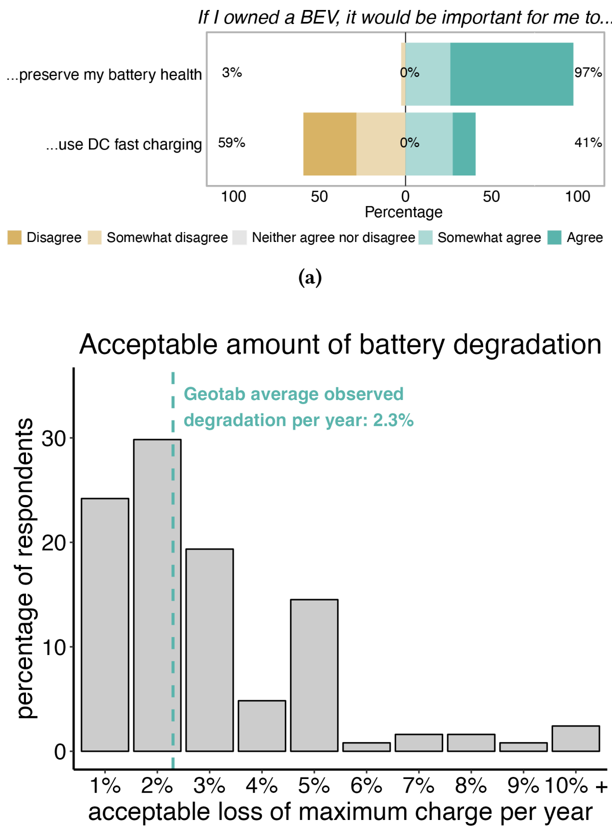
Ratio-based information interventions were most effective. Of the four interventions tested, the ratio intervention made participants most likely to choose *L2 Charge* (contrast comparing the likelihood of choosing *L2 Charge* with the ratio intervention vs. all other interventions: all $\beta > 0.37$, all $p < .007$, all $d > .24$; Fig. 4b). The simple interventions did not differ from one another ($\beta = -0.02, 95\%\text{CI} = [-0.24 - 0.28], p = .859, d = 0.01$), and although the percentage intervention tended to be *less* effective than the simple interventions, these did not differ significantly (percentage vs. simple positive: $\beta = -0.24, 95\%\text{CI} = [-0.50 - 0.02], p = .067, d = 0.11$; percentage vs. simple negative: $\beta = -0.22, 95\%\text{CI} = [-0.48 - 0.04], p = .094, d = 0.10$).



(b)

Figure 4: Influence of different factors and interventions on the likelihood that participants chose *L2 Charge*. (a) Points indicate the mean proportion of *L2 Charge* choices for each difference in charging time across all subjects. Error bars show between subject 95% confidence intervals. (b) Beta weights for each intervention from a logistic regression model measuring the influence of each different intervention relative to the "simple—positive" intervention on the likelihood of choosing *L2 Charge*. Points indicate beta weights and error-bars indicate 95% confidence intervals.

People value battery health over charging speed. Participant follow-up questionnaire responses made it clear that they valued battery health over faster charging. Overall, 69% of participants answered 6 or above out of 10 when asked whether battery capacity was more important than DC Fast charging. Moreover, 97% of participants answered "agree" or "somewhat agree" when asked whether it was important to preserve their battery health, compared to only 41% who answered "agree" or "somewhat agree" when asked if it was important to use DC Fast Charging (two sample proportion z-test: $\chi^2(1) = 103, p < .001$; Fig. 5a). Participants also reported being willing to accept a mean 2.9% loss of maximum battery capacity each year, more than the 2.3% reported on average by a Geotab



(a)

(b)

Figure 5: (a) Likert responses from Study 3 highlighting the importance of battery life. (b) Reported acceptable battery loss per year with the majority reporting 2% per year.

analysis[4] (signed rank test comparing participant responses to 2.3%: $p = 0.028$), but also below the 4–5% reported by Geotabs if DC Fast Charging was used regularly (signed rank test comparing participant responses to 4%: $p < .001$; Fig. 5b).

These results confirm that participants value battery health and are willing to spend more time charging unless their remaining charge is too low. We additionally find that interventions were not particularly effective at promoting slower charging, with ratio information providing a marginal increase in the likelihood that people chose slower charging.

4 DISCUSSION & FUTURE WORK

The goal of these studies was to understand people's willingness to wait for charging under greener, more sustainable scenarios. Although many in-vehicle or in-app interventions offer metrics such as eco-scores for driving (see Fig. 6a) or charge scheduling (see Fig. 6b), our studies highlight the role eco-friendly charging prompts could play to promote more sustainable green charging. Using surveys to understand eco charging [34, 67], these studies used interfaces presented when plugging in the vehicle and address contextual, interventional, and battery preservation facets.

Study 1 found that people are generally interested in waiting for green energy, provided the added wait time is not too long. Additionally, this willingness to wait depends on situational factors we had hypothesized, particularly charging location (**H1.1**) and remaining battery (**H1.2**). These findings suggest that interfaces encouraging people to wait for green charging are likely to be effective when the wait time is short, the driver is in a stable location (e.g. at home), and/or when they have enough remaining battery. We found much weaker influences of time of day (**H1.3**) and day of the week (**H1.4**), suggesting these play less of a role than location and remaining charge. One embodiment could be interfaces that dynamically adjust recommendations based on people's location and/or remaining charge, providing people with options they want in situation where they would be most likely to accept longer charge times.

Study 2 found that information interventions increased the likelihood of green choices (**H2.1**). Consistent with prior work [40], all of our tested interventions encouraged participants to wait for eco-charging, with rewards (points) providing the strongest increase, followed by social collective information, CO_2 emission numbers, and a simple green leaf (baseline). These results fit well with what Sanguinetti et al. call "information" intervention frameworks to promote greener behaviors [53].

We observed that rewards can motivate people to adopt more sustainable behaviors [23, 40]. A challenge with rewards is ensuring that people's motivation transfers from the reward itself (extrinsic motivation) to the green behavior (intrinsic motivation). Although this transfer can be a challenge, previous work shows that it is amenable for green behaviors if people become motivated by the environmental benefits of a behavior instead of solely by the rewards [36, 38]. We also found that social collective feedback nudged people's behaviors towards sustainable decision-making, consistent with prior work on social norm theories [3, 56, 57]. The collective benefits of delayed charging could be related to network effects [43], inspiring and motivating individuals to contribute to a larger, shared goal of promoting sustainable energy use and potentially reducing issues related to collective action problems [27].

However, unlike prior work [40, 53, 58], CO_2 emission numbers and negatively valenced messaging did little to increase eco-charging choices (**H2.2**). This suggests that although CO_2 emission numbers and negative valence may work in some contexts (e.g., ride-sharing or rental choices [40]), these may not work ubiquitously across all vehicle-based contexts.

Last, Studies 1 and 2 found little influence of BEV ownership on the situations and interventions influencing green choices. This is not to say that BEV owners are the same as non-BEV owners, and care should be taken to assess whether differences arise in other contexts. However, as BEV adoption is still low in the U.S., it is important not just to take the perspective of new, early BEV adopters, but also how these may differ from future BEV owners.

Instead of focusing on directly reducing charging emissions, Study 3 examined interfaces to promote charging practices that improve battery longevity. We found that people were willing to wait longer for charging to preserve battery health. Remaining state of charge and charging time played the largest roles in people's

[4] https://www.geotab.com/blog/ev-battery-health/ (Accessed April 2023)

willingness to wait for slower charging (**H3.1**). negatively valenced messaging did not increase eco-charging choices (contrary to **H3.2**). The interventions we tested were much less effective, with people slightly more likely to wait for slower charging when degradation was presented as a ratio rather than as an absolute number (**H3.3**). Ratios may help contextualize battery degradation in ways that are easier for users to understand [29, 33]. Ratios are processed more efficiently than numerical values [5, 39] and could prove more effective when communicating effects of battery degradation or carbon emissions, particularly when people are less familiar with the units being used. We note Study 3 is less comparable to Studies 1 and 2; however, the green behavior change observed is still positive to the planet's overall perspective by maximizing the return on carbon investment spent in battery production [51].

These studies are not without limitations. All three studies were done via online survey tools and the insights derived will be best confirmed in real-world contexts. This limitation is known and shared across other short and longitudinal survey studies [34, 67]. As these results are survey based, there is an attitude-behavior gap where participants may make green choices in surveys but make other choices in-situ [26]. However, as the area of green charging is still relatively new, our results provide research directions for more intensive real-world studies.

Additionally, the charging and degradation parameters we chose for our studies are relatively narrow. We chose 6.6 kW L2 charging speed as this is the most common L2 speed in the U.S., but L2 charging speeds vary widely around the world (with some speeds reaching 22 kW[5]). Moreover, the degradation numbers we chose for our study are based on observations from older BEV models that may differ from BEVs sold today. We additionally did not model drop-offs in DC fast charging speed at higher states of charge. Future research could examine the influence of factors such as faster L2 charging, degradation rates, and variable DC charging rates on people's willingness to wait for L2 charging. Given people's clear interest in preserving battery health, we expect that factors like faster L2 charging speed and variable DC charging rates would only increase people's willingness to wait for L2 charging.

5 CONCLUSION

We conducted three studies to gather insights into factors that encourage sustainable charging behaviors. Our findings showed that situational factors and interventions can influence greener charging habits aimed at using green energy and improving battery longevity. Adopting tools and methods that promote greener charging habits will help maximize the carbon saving potential of BEVs and move us closer to a more sustainable future.

ACKNOWLEDGMENTS

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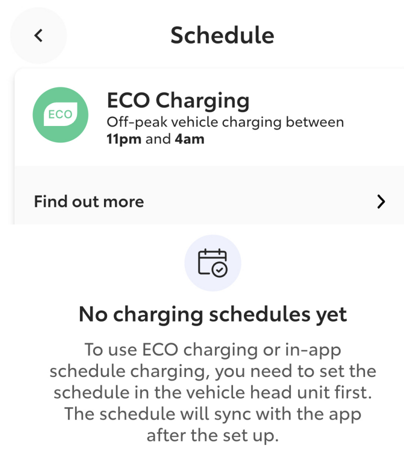
[5]https://www.power-sonic.com/level-2-ev-chargers/ (Accessed June 2023)

(a)



(b)

Figure 6: (a) An eco-driving score delivered at ignition off. (a) A vehicle charging interface offering suggestions for green times to charge.

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