# Pick Your CARbon: User Perceptions of Equivalencies for Carbon Emissions when Selecting Rideshares


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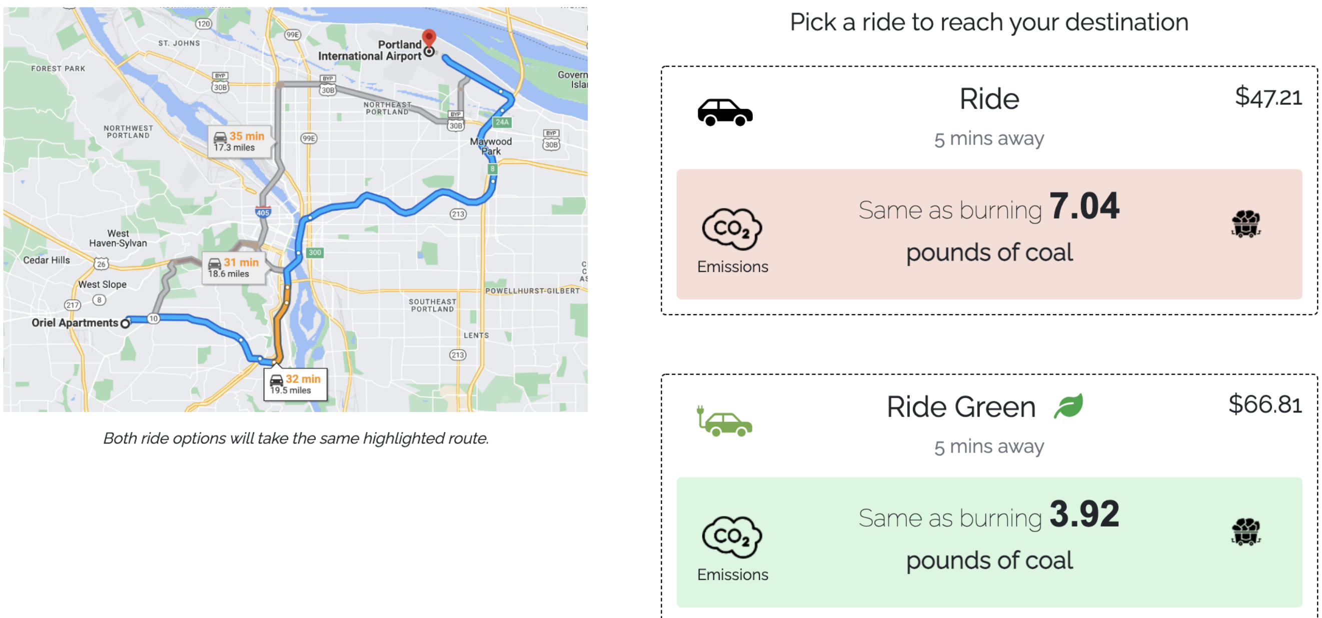


**Figure 1: An example "Pick your Rideshare" survey question showing information about $CO_2$ emissions in equivalent terms (*coal* here) for two ridesharing options—a standard ("Ride") and an eco-friendly alternative ("Ride Green").**


## ABSTRACT

Ridesharing is a popular choice for personal transportation needs. Although more ecologically-friendly than single-occupancy vehicles, there is an opportunity to further reduce $CO_2$ emissions by offering green choices. Here we examine whether providing people with information about $CO_2$ emissions nudges them to make more eco-friendly rideshare decisions. Our study tested what kind of information works best to inform people about carbon emissions, comparing direct $CO_2$ values with more relatable carbon equivalents (e.g., trees). We conducted an online study with 1000 participants who picked between regular and eco-friendly ride options that detailed various carbon-output equivalency interventions (e.g., pounds of coal, number of smartphones charged, etc.). We found that participants are more likely to choose a green ride when presented with information about direct $CO_2$ emissions than when presented with carbon-equivalencies. This study aims to inform future information-based interventions more broadly, beyond the context of ridesharing.




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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; CO2 Emissions; Eco-Feedback; Ridesharing; Ride Hailing; Design Interventions; Automobiles; Carbon Neutrality; Behavioral Science

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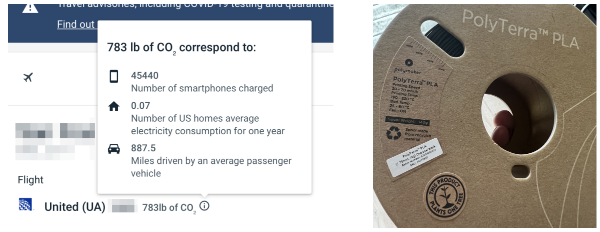
## 1 INTRODUCTION

As concern for climate change grows amongst consumers, intervention interfaces have been designed to communicate the environmental impact of different products and services. These interventions can take the form of direct information about carbon emissions (e.g., pounds of $CO_2$; Figure 2a), or information about incentives or offsets associated with a product (e.g., tree planting; Figure 2b). Although information about $CO_2$ emissions has grown steadily, less is known about how effectively this information influences customer decisions: do consumers have an understanding of direct $CO_2$ emissions? Do they prefer simpler heuristic interventions (e.g., green logos) or more relatable $CO_2$-equivalent activities?

In this article we focus on the user interface of ridesharing services. Eco-friendly options have steadily grown in this space (e.g., Uber Green, Lyft Green Mode), providing customers with options to ride in eco-friendly vehicles. Our study examines which types of information make people more likely to choose eco-friendly ridesharing options.

A number of tools exist that help people calculate their carbon footprint [2, 6, 15]. These tools aim to provide context for emissions by linking emissions directly to everyday activities. To help provide relatable information to consumers, the Environmental Protection Agency (EPA) created tools [5] to help contextualize $CO_2$ emissions into $CO_2$-equivalent activities (e.g., pounds of $CO_2$ converted to miles driven).

These tools have also permeated the transportation sector. Personal transportation is a leading cause of emission for US-based drivers [9]. As such, emission calculators have been created to help people track the impact of their transportation habits [1]. Additionally, numerous interventions have been aimed at motivating consumers towards more sustainable options through social interventions (e.g., on social media [7, 8]) and reward/incentive programs [10]. More recently, $CO_2$-related information has been provided alongside transportation options, with the intention of informing people's choices (e.g., $CO_2$ from flying, Monroney window stickers). However, less is known about how effectively this information resonates with consumers and influences their choices.




(a) (b)

**Figure 2: Equivalencies in the wild. (a) While booking a flight, carbon equivalencies are shown to the buyer. (b) A spool of 3D printer filament with a sticker denoting "This product plants one tree."**

In this study we examine whether information about $CO_2$ influences people's decisions to make green rideshare choices. Specifically, we explore the following research questions:

(1) Does information about the $CO_2$ emissions for available ride options affect a passenger's choice?
(2) Does communicating $CO_2$ emissions in measurable equivalent actions influence choice more than providing direct $CO_2$ emission numbers?
(3) How do these interventions compare with other non-$CO_2$ related intervention types (e.g., social motivators)?

## 2 STUDY

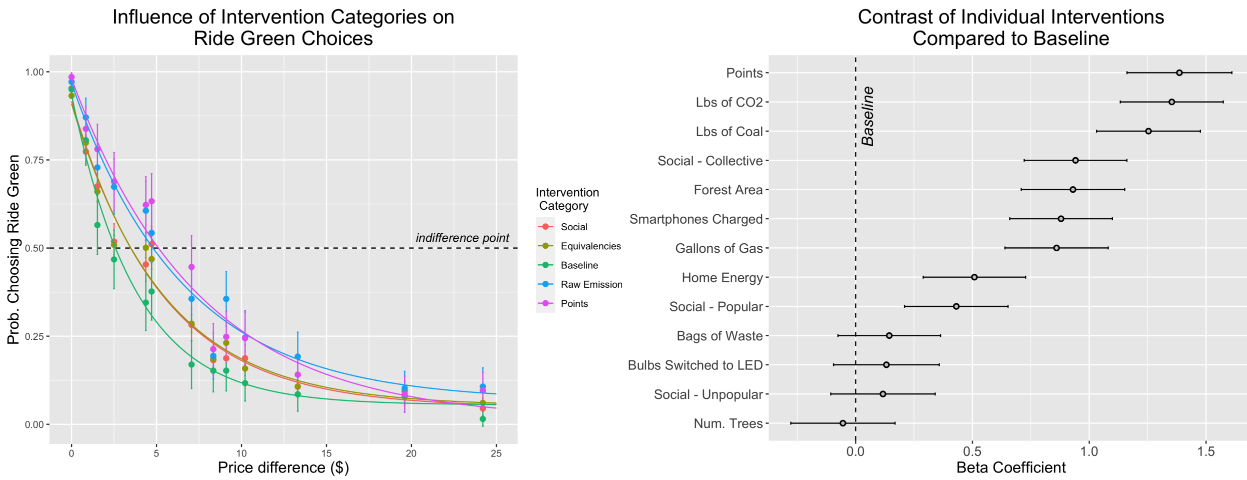
### 2.1 Experiment Design

To address these questions, we designed an online experiment to simulate choices made in a rideshare app. On each trial, participants saw a map with a hypothetical trip and chose between two rideshare options: *Ride* and *Ride Green*. The prepared study dataset consisted of 15 trips based in 15 major US cities that were distributed evenly across short (< 15 miles), medium (< 25 miles), and long ranges (> 25 miles), overall varying between 5–44 miles. The *Ride* option was always presented with a black car whereas the *Ride Green* option was presented as a green car with a green leaf icon (Figure 1). The price for both options was either identical or higher for the *Ride Green* option (between \$0.50–\$24.00 more), and ride option choice positions were randomized (i.e., whether *Ride Green* appeared on top/bottom). Each participant completed 30 trials, each consisting of a randomly picked trip from the dataset and a randomly picked intervention from the following list:

**Baseline:** No additional information provided about the ride other than a green leaf icon on the *Ride Green* option.

**Raw Emissions:** $CO_2$ emissions (in pounds) for both ride options was provided. We used the US Fuel Economy calculator [4] to calculate the emissions of a gas vehicle (i.e., *Ride*) and an electric vehicle (i.e., *Ride Green*) for a given trip distance.

**Equivalencies:** Information about the $CO_2$ emissions for both ride options was provided in terms of *measurable actions* that would either emit (e.g., charging smartphones, daily energy usage of houses, and burning pounds of coal or gallons of gasoline or barrels of oil) or sequester (e.g., recycling bags of waste, switching incandescent lamps to LEDs, growing trees




(a) (b)

**Figure 3: (a) Influence of different intervention types on probability that participants chose the *Ride Green* option for different price differences. Colored dots indicate average probabilities across subjects, error bars indicate 95% confidence intervals, and trend lines indicates the best fitting exponential decay curve. (b) Logistic mixed-effects contrast coefficients comparing the influence of individual intervention types compared to the Baseline condition (dashed line). Error bars indicate 95% confidence intervals.**

or forests) an equivalent amount of $CO_2$ emissions (using the EPA calculator [5]).

**Social:** Information about hypothetical social trends was provided, including a "popular" condition in which participants were told that 75–99% of other riders chose the *Ride Green* option and an "unpopular" condition in which 1–25% of rider chose the green option. We also displayed a "collective action" condition, where participants saw how many other riders had picked the green option and the collective environmental impact across all riders (e.g., *16 trees were saved by 318 passengers who rode this today*).

**Points:** Participants were told that they would "receive 2x points" for choosing the *Ride Green* option (versus "1x points" for *Ride*). Participants were deliberately not given any additional information about the points.

After completing 30 trials, participants answered a survey questionnaire that included questions related to their demographics and attitudes about climate change, renewable energy, and electric vehicles. They also answered a MaxDiff questionnaire [12] about the usefulness and relatability of the different equivalencies presented during the main experiment, and open-ended questions about their choice process.

## 2.2 Analysis

We measured the effect of each intervention using a logistic mixed-effects model (LME) implemented with the `lme4` library in `R` [3]. This model predicted the likelihood of making *Ride Green* choices using the difference in price between the *Ride Green* and *Ride* options and intervention type as fixed effects, and random intercepts for participants and city. This model provided a better fit than one that considered a "Price Difference by Intervention Type" interaction ($\Delta BIC_{Int-ME}$: 92), and so we used the main effects model for all subsequent analyses.

## 2.3 Participants

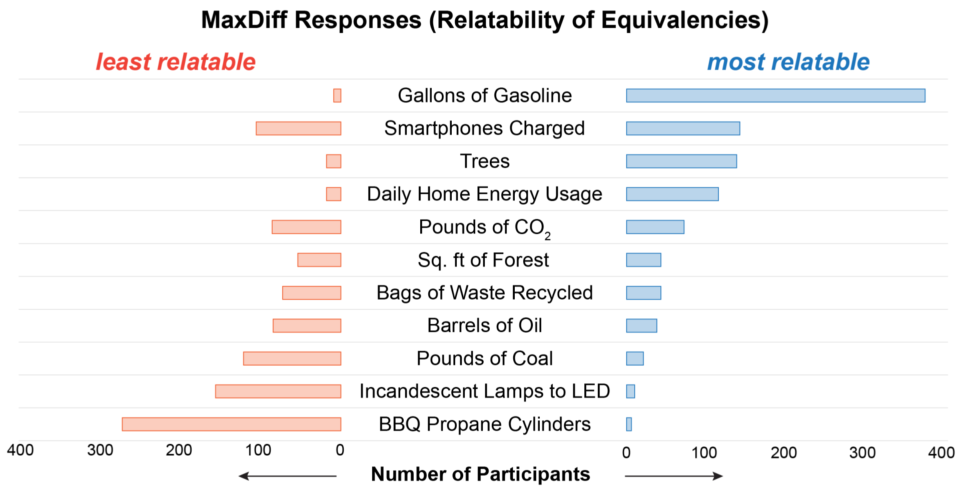
For this study, we recruited 1000 US-based participants from Prolific [11] (responses from all 50 US states; 47% women, 50% men, 2% genderqueer or non-binary, and 1% preferring not to answer; mean age = 37 years, SD = 13 years). Participants were all at least 18 years of age, fluent in English, and had used Uber and Lyft (the two most popular US ridesharing options). All participants provided informed consent before beginning the task.

# 3 PRELIMINARY FINDINGS

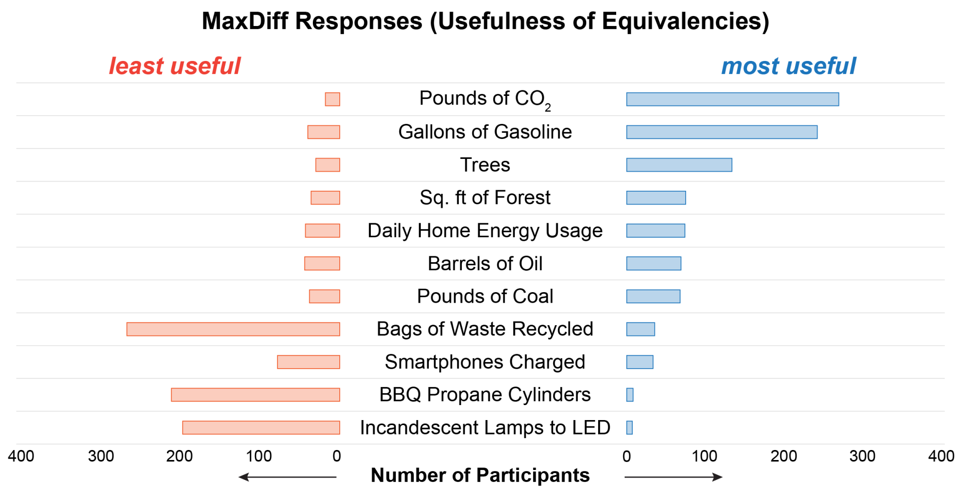
## 3.1 Interventions increase *Ride Green* choices

Overall, interventions with some form of information increased the likelihood of participants picking the *Ride Green* option compared to the Baseline condition (Figure 3a). Interventions using Raw Emissions were highly effective, increasing the likelihood of choosing the green option by 3.7x, followed by Equivalencies and Social interventions (each increasing the likelihood by 1.6x; LME contrasting intervention types with Baseline condition: $\beta_{RawEmissions} = 1.31$, $\beta_{Equivalencies} = 0.49$, $\beta_{Social} = 0.49$, all $z > 5.39$, all $p < 0.001$). P126 emphasized the usefulness of these interventions:

> "Metrics that would be useful for me need to be both relatable/tangible and have a direct correlation to environmental impact that I understand. For example, I find pounds of $CO_2$ (which directly indicates carbon emissions) and number of trees needed to counteract




(a)




(b)

**Figure 4: MaxDiff responses for the (a) relatability and (b) usefulness of different equivalencies.**

> the impact particularly helpful in understanding the environmental impact of daily activities."

As anticipated, participants became less likely to select *Ride Green* as it got more expensive (LME estimating the influence of price on probability of choosing *Ride Green*: $\beta_{\text{PriceDifference}} = -0.41$, $z = -7.62$, $p < 0.001$). However, they were willing to pay more for *Ride Green* as long as it was no more than \$4.37 over the *Ride* option (Figure 3a). In the words of P755:

> "I looked at the information on how much more efficient it was from an energy/fuel perspective and as long as the price wasn't too different I would choose the green option. The only time I would pick the non-green option was if there was a significant price difference."

## 3.2 Raw $CO_2$ is effective

Contrary to our predictions, providing raw $CO_2$ emission number was more effective than presenting emissions in terms of carbon equivalencies (LME contrasting Equivalencies with Raw Emissions: $\beta_{\text{RawEmissions}} = 0.82$, $z = 10.06$, $p < 0.001$). P482 described what $CO_2$ emission numbers meant to them: *"I would want to know how much $CO_2$ (carbon dioxide) I use up each day since this has a pretty direct correlation to the harm one does to the atmosphere."*

## 3.3 People like points

Surprisingly, even though points were not tethered to any rewards, assigning 2x points for *Ride Green* was as effective as providing raw $CO_2$ emission information, increasing the likelihood of choosing the green option by 3.9x over the Baseline condition (LME contrasting interventions with Baseline condition: $\beta_{\text{Points}} = 1.35$, $z = 11.92$, $p < 0.001$). P371 highlighted the appeal of accumulating points:

*"…getting more points for doing so is great, so I liked that as well"*. When asked about what information was used to make choices, P830 added: *"…points…might lead to future discounts"*.

### 3.4 Not all equivalencies were effective

Not all equivalencies increased the likelihood of participants picking green options (see Figure 3b). Among the equivalencies, "burning pounds of coal", "growing forest cover", "charging smartphones", "burning gallons of gasoline", and "daily energy usage of homes" all increased the likelihood that participants chose the green option above the Baseline condition. All equivalencies except "pounds of coal" aligned with participants' self-reports about how useful and relatable they found equivalencies (Figure 4). Conversely, sequestering equivalencies—"recycling bags of waste", "switching incandescent bulbs to LEDs", and "growing number of trees"—were less effective than other interventions. Except "number of trees", participants also rated these equivalencies as the least relatable and useful.

### 3.5 Not all social interventions are equal

Displaying social interventions yielded mixed results. Although better than Baseline, they performed worse than Points or Raw Emissions (LME contrasting interventions with Social condition: $\beta_{\text{Points}} = 0.85$, $\beta_{\text{RawEmissions}} = 0.82$, all $z > 9.18$, all $p < 0.001$), but were similar to Equivalencies ($\beta_{\text{Equivalencies}} = 0.002$, $z = 0.05$, $p = 0.958$; Figure 3a). Among the individual social interventions, " Social–Collective" and "Social–Popular" both increased the likelihood of green choices over baseline whereas "Social–Unpopular" did not result in any change (Figure 3b).

## 4 DISCUSSION AND FUTURE WORK

Our findings showed that information interventions were overall effective in nudging riders towards making green ridesharing choices. However, it was unclear why some interventions performed better than the others. As part of future work, we aim to uncover the underlying reasons behind the effectiveness of certain interventions, which can open doors for designing newer intervention types.

While prior work has shown extrinsic rewards and social influence as strong motivators for sustainable decision-making [13–15], it requires deeper exploration to understand why they were highly effective in the current context. Further, we also hypothesized that presenting equivalencies would be more effective than raw $CO_2$ numbers (in pounds) as it is difficult to comprehend the meaning of these raw numbers, but our findings suggested otherwise. To follow up on these unexpected findings, we aim to conduct future studies to understand better how people interpret points and raw $CO_2$ emission numbers and explore how goal-setting (i.e., acceptable $CO_2$ emissions per day), an approach previously used in the context of sustainability [14, 15], can improve the effectiveness of current interventions. Building on these insights, we aim to design newer data-driven, user-centered interventions for nudging users to make green/greener choices in different automotive contexts, including car rentals and purchases.

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