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National Renewable Energy Laboratory

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Abstract

In fall 2020, the Colorado Energy Office, as part of the State of Colorado’s “Can Do Colorado” initiative, initiated a project aimed at encouraging energy-efficient transportation during the COVID-19 pandemic. The initial mini-pilot provided e-bikes to 13 low-income households under an individual ownership model. This report assesses the impact of providing this additional mobility option on the travel behavior of participants. It also outlines the lessons learned from deploying a continuous monitoring platform to track the travel behavior. These lessons will influence the evaluation component for the full pilot, which will cover multiple geographic regions, start in summer 2021, and run for 2 years.

The continuous data collection was enabled by a customized version of the open-source e-mission platform, called *CanBikeCO*, configured with a behavioral gamification feature. The Colorado Energy Office used this system to collect a unique data set consisting of 3 months of partially automated travel diaries, combining sensed and surveyed data and linked with demographic information, from 12 participants. The data collection process worked well overall: users generally liked the app, appreciated the game, and did not complain about battery life. The long tracking period introduced behavioral challenges in user engagement, which we plan to address using repeated patterns and automated status checks for the full pilot.

The analysis results, based on the subset of trips with user-reported labels (68%), indicate that the e-bike was the dominant commute mode share (31%), in sharp contrast to the census bicycle commute mode share (<1%). E-bike trips primarily replaced single-occupancy vehicle (SOV) trips (28%), followed closely by walking (24%) and regular bike (20%). The nonmotorized mode replacement corresponds to lower travel time and increased productivity enabled by the program. The emissions impact analysis of the program, computed using trip-level energy intensity factors, indicates savings of 1,367 lbs. of CO₂. Although the results are strongly positive, the narrow demographic profile of study participants, their limited mobility alternatives, and nonuniform labeling indicate caution in broader interpretation.

These preliminary results do suggest that such programs, supported by real-time education and support from program managers, can simultaneously meet *equity* and *sustainability* goals. The planned full pilot, addressing the data collection challenges and broadening the geographic scope, will provide additional insights into the generality of this approach.

Introduction

Pathways to transportation energy efficiency and climate change mitigation include behavioral and technological innovations. Behavioral innovations include fostering shifts to more energy-efficient and climate-friendly modes of transportation while maintaining or improving overall mobility access.¹ *Micromobility* options, such as manual and electric-assisted human-powered vehicles, are often presented as a solution for reducing carbon emissions and improving energy efficiency for short-distance trips, especially in urban areas.² Although transportation researchers have studied *shared* micromobility usage extensively,³ they have not been able to assess *ownership* micromobility characteristics due to the lack of relevant data.

This report addresses that gap through the lens of the CanBikeCO project.⁴ As the COVID-19 pandemic increased transit avoidance, the resulting cuts to transit service led to increased transit wait times, potentially setting up a vicious cycle. As part of the State of Colorado’s “Can Do Colorado” initiative, the Colorado Energy Office explored the use of e-bikes to avoid a mass shift to single-occupancy vehicles (SOVs). Selected participants were essential workers or students, primarily from low-income portions of the population. These selection criteria aimed to provide greater mobility options to those with limited choices. The small-scale mini-pilot in fall 2020 was planned for 3 months with 13 participants. These initial insights will be used to design a full-scale, 2-year pilot in locations across Colorado.⁵

This report includes two novel components:

- It uses a novel, multi-month data set that collected *both sensed and surveyed patterns* of multimodal, end-to-end, individual human mobility, including non-commute trips and trips without the e-bike.
- The data set reflects a longitudinal view of *ownership* micromobility, the usage patterns of the new e-bikes, the purposes, and the modes that the trips replaced.

The data set was collected through a custom deployment of the open-source e-mission⁶ platform, with polar bear-based gamification and leaderboard components from the TripAware⁷ study. Combining sensed and labeled data was significantly better than a survey-only evaluation approach, both in response rate and collection duration. However, this pilot was marred by initial technical glitches, and the long tracking period introduced additional behavioral challenges such as users not using the app properly, uninstalling the app, and not providing even the limited trip-specific labels requested. This experience indicates that similar future data collection efforts will benefit from both strategies to monitor and track all aspects of user engagement and iterative improvement to data collection processes.

Because this exploratory analysis is based on user-reported labels, it largely reflects the travel of the eight users whose labeling rates are high (70%–100%). Over the 3-month analysis period, e-bikes were the dominant mode share overall (30%), followed by shared rides at 29%. SOV mode share was only 20%. This pattern far exceeds the Denver Mobility Action Plan⁸ goals for 2030 (15% walk/bike, 15% transit). E-bike trips primarily replaced *drive alone* trips (28%), followed closely by active transportation such as walk and bike. Unlike *shared micromobility*, in which one-third of trips were for transit access,⁹ *ownership micromobility* seems to be used for end-to-end trips similar to the use of larger private vehicles such as cars. This automobile trip replacement ensured that overall impact on both energy and emissions was positive. Although active trip replacement leads to increased energy and emissions in exchange for the convenience of an e-bike, the high efficiency of e-bikes ensures that such increases are small.

Data collection methodology and results

The primary mode of data collection was a custom configuration of the open-source e-mission platform.⁶ e-mission is an open-source, customizable platform for instrumenting human travel data. To support the specific needs of this Colorado Energy Office project, we made the following changes to the e-mission user interface:

- In addition to the existing mode and purpose labels (Figure 1) for each trip, we added a new input variable to capture the “replaced mode” of the trip. Along with route information, the replaced mode variable enables energy and emissions estimates to be derived by comparing the mode used to the mode replaced for a given trip.
- We used the polar bear and leaderboard elements (Figure 1) of the TripAware study.⁷
- We introduced in-app demographic and weekly surveys to capture qualitative feedback about the experiences of using the e-bikes or the app.

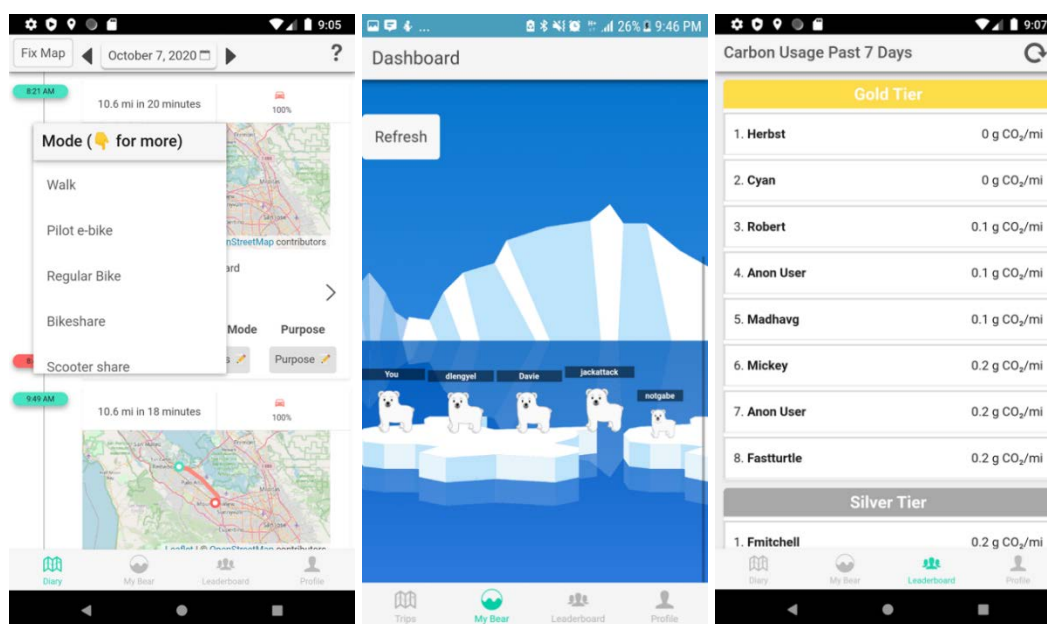


Figure 1: CanBikeCO app customizations (left to right): trip labels, polar bear, and leaderboard

Smartphone usage characteristics

All participants in the mini-pilot were required to have a smartphone. The distribution of phone models for the selected participants indicates that iPhones predominate slightly (Figure 2). An overwhelming majority of the phones are running recent Android (9 and 10) and iOS versions (14+), indicating fairly recent models. This is an interesting finding because of the focus on recruitment among low-income groups and an initial concern of whether likely participants would own a smartphone.

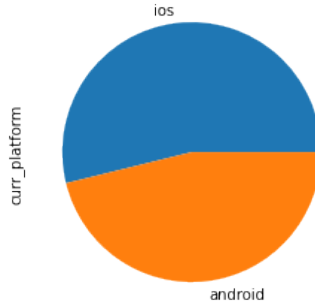


Figure 2: Participant smartphone models

Trip labeling rates

Although trip labels support the rich analyses outlined below, they remain challenging to collect. Passive data collection was robust—we expected the number of active days (days with at least one trip per user) to be around 90, and in fact, the median is 63. However, only six users (~50%) initially labeled even half their trips, and nobody was at 100%. The response rate for the weekly surveys was worse than the labels. We expected the number of weekly survey responses per user, after skipping holiday weeks, to be around 10. However, the median is 4, and only two users answered a significant percentage of surveys. Even worse, four users did not answer **any** weekly surveys—there were only nine unique respondents.

We then offered a monetary incentive of \$25 for labeling all 3 months of trips and modified the leaderboard to display the expected amount for gamification. When this was insufficient, we also added a new labeling screen to provide a multiday, infinite scroll list along with buttons to filter only unlabeled or invalid trips (Figure 3). The combination of the monetary incentive and the improved ease of use increased the labeling rate to over 90% for over 50% of the users. This indicates that achieving high labeling rates involves a balance between improving ease of use and providing more traditional incentives.

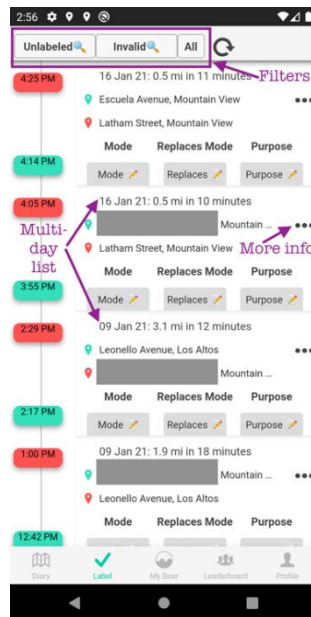


Figure 3: Newly added screen to improve labeling

Ongoing program monitoring

We originally planned to follow the classic pattern of deploying the system, collecting data, and then analyzing them. However, the long-term data collection made it challenging to observe any ongoing issues with the data collection. To mitigate these concerns, we adapted the dashboard (Figure 4) developed by University of New South Wales.¹⁰ This allowed us to discover several issues caused by unexpected user behavior.

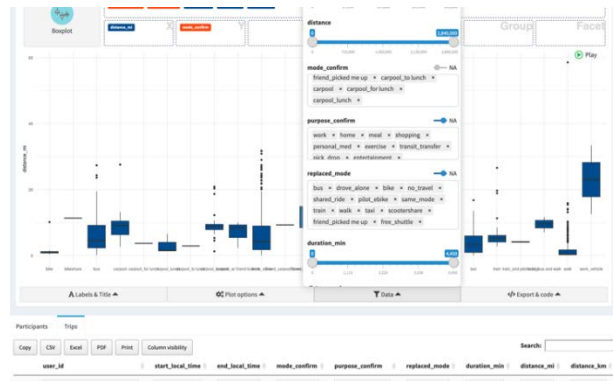


Figure 4: Dashboard with mode-specific distance boxplots

Unexpected user behavior

The data collection is robust **if users:** (i) keep the app installed, (ii) give it the “always” permission, (iii) don’t force-stop it on iOS, and (iv) stay with the same, unmodified phone throughout the data collection period. Unfortunately, we discovered during the mini-pilot that these conditions were not met consistently. Users sometimes switched phones during the program, or, ignoring the FAQ (Figure 5), force-stopped the app. The dashboard allowed us to quickly identify such users and follow up with them to troubleshoot their issues. We also had to overcome some initial technical glitches and data loss related to the lack of backup storage and Google Forms survey regressions. Unlike prior related projects, there were no complaints about battery life.

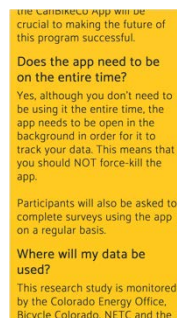


Figure 5: FAQ indicating no force-kill

Sketch of behavior impacts

We used the data set collected above to sketch the travel behavior impacts of providing this additional mobility option to a low-income population without significant alternatives.

Methodology highlights include:

- Although the e-mission platform infers the travel mode automatically, we use only trips with user-provided labels for the analysis. The analysis uses the *purpose* and *replaced mode* labels as well, and those are harder to infer automatically. These user labels are used as *ground truth*, except for the code book-based mapping below.
- The user labels are not uniformly distributed—six of the participants had at least 90% of their trips labeled, two had at least 70%, and the remaining four had <50%. The current results accurately reflect the travel patterns of only a subset of the participants.
- In addition to predefined labels, users had the ability to specify custom labels. Participants frequently availed themselves of this option, resulting in a long tail of labels. We had to develop a static code book to consolidate the responses into the standard categories.
- We used a trip-level energy impact analysis in which we determine the energy and emissions intensities for the mode and replaced mode for each labeled trip. The impact is then the difference of the two, multiplied by the trip length. We obtain energy intensities primarily from the Transportation Energy Data Book (TEDB).⁸ The emissions intensities are from the U.S. Energy Information Administration (EIA)¹¹ and the U.S. Environmental Protection Agency (EPA).¹²

Mode share

The e-bike was the dominant trip mode in the data set, with 30%–35% mode share (Figure 6). The second-most-common mode was “shared ride,” which was ~6%–8% more than “drove alone.” This may be because some participants do not have access to a private automobile. Traditional transit is poorly represented, ~2%–3% below walking. This could be due to improved tallying of walk trips enabled by the data collection method. It could also be due to transit avoidance during the pandemic, or replacement by e-bikes due to their improved convenience. In comparison, the 2017 National Household Travel Survey (NHTS) has a 1% overall bicycle mode share.¹³ If we count carpooling as a shared mobility mode similar to transit, the current mode share for these travelers significantly exceeds the targets of the Denver Mobility Action Plan (15% walk/bike, 15% transit).¹⁴

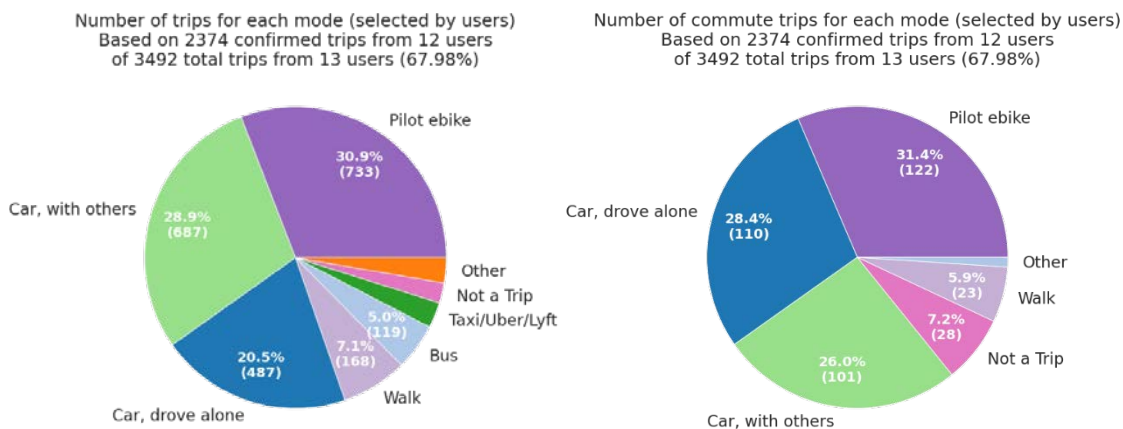


Figure 6: Trip count for all trips (left) and commute trips (right)

Trip purpose

Participants used the e-bike for a variety of purposes beyond commuting, including shopping, recreation, and entertainment (Figure 7). The distribution of trip purposes is more uniform than the mode share, with the top-seven purposes in the 8%–20% range. The dominant mode for e-bike trips is “Pick-up/Drop off.” Because the e-bikes were not designed for passenger transport, we assume that the trips were to pick up or drop off items. That is still disproportionately high compared to the NHTS, in which work and home dominate. Given the increased need for delivery services during the pandemic, these may actually represent work trips, albeit not to a single fixed workplace. The “transit transfer” category is significant enough to appear in the general purpose list for all trips but not the e-bike specific one. This indicates that the e-bikes are being used for end-to-end travel instead of bridging last mile/first mile to other transportation modes.

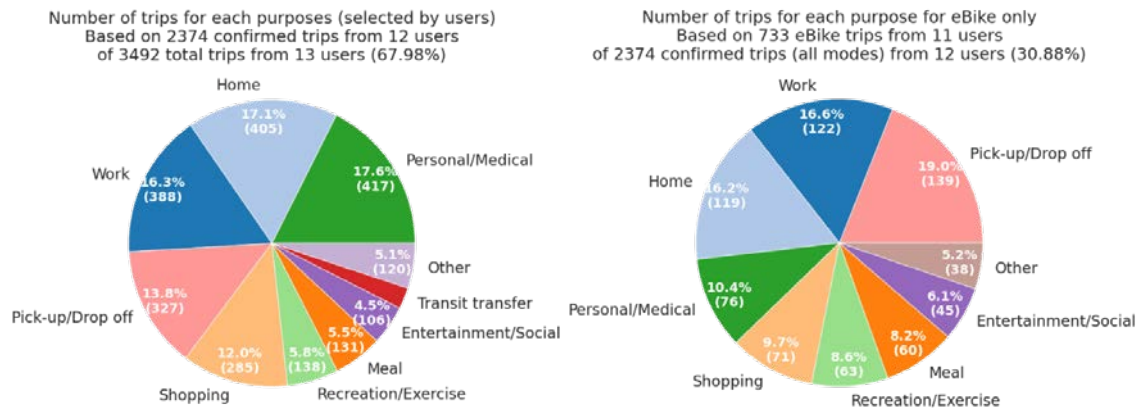


Figure 7: Purposes for all trips (left) and e-bike trips only (right)

Emissions impact

The emissions impact of the program is overwhelmingly positive (Figure 8). The bulk of the savings come from replacing SOV trips. The second- and third-highest replacement modes are walk and bike trips. Although the e-bike provides increased productivity in those cases, it does consume greater energy and emissions. Fortunately, the energy intensity of e-bikes is very low, so the energy loss from the replacement is small and the overall impact is overwhelmingly positive.

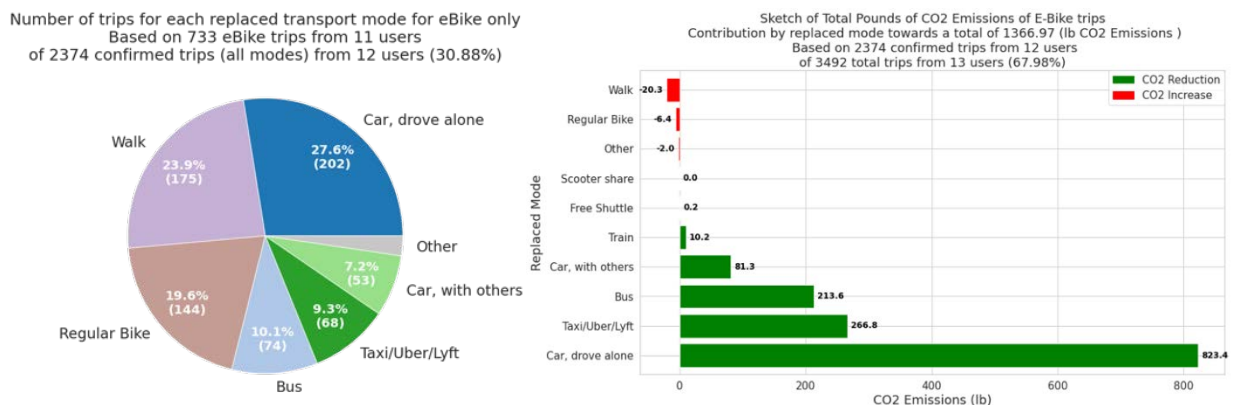


Figure 8: E-bike replaced modes (left) and emissions impact (right). The energy impact chart is very similar to emissions.

New research questions

The analysis of the mini-pilot data collection raises interesting research questions around the intersection of computational and social sciences in the context of long-term data collection. They include:

- **Efficient labeling:** Although monetary incentives were shown to be effective in increasing labeling rates, requiring participants to label every trip is inefficient. However, some labels (e.g., “replaced mode”) cannot be inferred using sensor data alone. Can we leverage the long-term data collection to identify repeated patterns (e.g., home to work) in participant travel and only prompt users for novel trips?
- **Improved label quality:** The data collection process supports user-defined labels for each field. This results in a long tail of similar responses (*carpool*, *carpool_to_work*, *carpool_with_friend*) or responses in other languages (*iglesia*, *pago_de_aseguranza*) that necessitated the use of a static codebook for mapping. However, a static codebook is not a viable option for ongoing, long-term data collection. Can we automate codebook creation to encourage label reuse and develop a process for periodic manual updates to the codebook when necessary?
- **Incorporating inferences:** In addition to direct user labels, we can infer labels from multiple sources, using multiple inference techniques. These techniques could include: (i) inferred mode and purpose from sensed data, (ii) inferred labels from common patterns for individual users, and (iii) inferred labels from common demographic characteristics. Can we develop a rigorous technique to combine these labels for the final automated analysis? How can we estimate the error factors?

Conclusion

As part of the CanBikeCO mini-pilot, the Colorado Energy Office was able to collect a novel data set that included 3 months of end-to-end, multimodal data from 12 participants, labeled (~68%) and linked to demographic information.

A preliminary analysis of the data set indicates that the “Can Do Colorado eBike Mini-Pilot Program” enabled participants to shift their mobility patterns toward more sustainable choices with energy and emissions benefits. We can reasonably conclude that e-bikes are an attractive option to other modes and represent an effective, energy-efficient alternative, able to be used for a wide variety of travel purposes.

The data set can be expanded to additional analyses that provide a richer picture of the impact. Examples include: (i) demographic factors, (ii) seasonal and time-of-day factors, or (iii) user-level analysis that can highlight variability in impact across participants.

Participants generally liked the data collection functionality and had thoughts on making it better. Although surveyed data is an important component of the novel analyses enabled by this data set, collecting it remains challenging. We were able to distill four key insights from these challenges: (i) use sensed data to request targeted surveyed data, (ii) real-time monitoring is essential, (iii) notifications help for quick inputs, and (iv) behavioral factors for both the program and the data collection are intertwined.

A helpful aphorism in computer science is that every time the input scales by an order of magnitude, the system needs to be redesigned. The mini-pilot already scaled the time dimension by an order of magnitude from previous e-mission deployments. The full pilot will scale the time dimension by multiple orders of magnitude, so we expect we will need to redesign components multiple times. At the end, however, we will have learned many lessons on the behavior of long-term data collection that can inform multiple domains.

References:

- ¹ California Air Resources Board. 2019. *California Air Resources Board 2017 Scoping Plan-Identified VMT Reductions and Relationship to State Climate Goals*.
<https://ww2.arb.ca.gov/resources/documents/carb-2017-scoping-plan-identified-vmt-reductions-and-relationship-state-climate>.
- ² American Public Transit Association. n.d. “First Last/Mile Solutions.”
<https://www.apta.com/research-technical-resources/mobility-innovation-hub/first-last-mile-solutions/>.
- ³ Daniel J. Reck, He Haitao, Sergio Guidon, and Kay W. Axhausen. 2021. “Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland.” *Transportation Research Part C: Emerging Technologies* 124: 102947.
<https://www.sciencedirect.com/science/article/pii/S0968090X20308445>.
- ⁴ “Can Do Colorado eBike program.” <https://www.canbikeco.org/>
- ⁵ Colorado Energy Office. n.d. “Can Do Colorado eBike Pilot Program.”
<https://energyoffice.colorado.gov/zero-emission-vehicles/can-do-colorado-ebike-pilot-program>.
- ⁶ K. Shankari, Mohamed Amine Bouzaghrane, Samuel M. Maurer, Paul Waddell, David E. Culler, and Randy H. Katz. 2018. “e-mission: An open-source smartphone platform for collecting human travel data.” https://rise.cs.berkeley.edu/wp-content/uploads/2018/10/emission_mobilityscope.pdf
- ⁷ Jesse Zhang, Jack Sullivan, Vasudev Venkatesh P.B., Kyle Tse, Andy Yan, John Leyden, and Kalyanaraman Shankari. 2019. “TripAware: Emotional and Informational Approaches to Encourage Sustainable Transportation via Mobile Applications.” *BuildSys*, November 13–14 2019, New York, NY. <https://dl.acm.org/doi/pdf/10.1145/3360322.3360871>.
- ⁸ “Mobility Action Plan - City and County of Denver”,
<https://www.denvergov.org/Government/Departments/Mayors-Office/Programs-and-Initiatives/Mobility-Action-Plan>
- ⁹ Stacy C. Davis and Robert G. Boundy. 2021. *Transportation Energy Data Book, Edition 39*. Oak Ridge, TN: Oak Ridge National Laboratory, Figure 7.05. <https://tedb.ornl.gov/data/>.
- ¹⁰ Amarin Siripanich, Taha Rashidi, and K. Shankari. 2021. “asiripanich/emdash: v1.2.3.”
<https://doi.org/10.5281/zenodo.4456315>.
- ¹¹ U.S. Energy Information Administration. 2016. “Carbon Dioxide Emissions Coefficients.”
https://www.eia.gov/environment/emissions/co2_vol_mass.php.
- ¹² U.S. Environmental Protection Agency. n.d. “eGRID Power Profiler.”
<https://www.epa.gov/egrid/power-profiler#/RMPA>.
- ¹³ National Household Travel Survey. 2017. “Popular Person Trips (PT) Statistics.”
<https://nhts.ornl.gov/person-trips>.
- ¹⁴ City and County of Denver. n.d. “Mobility Action Plan.”
<https://www.denvergov.org/Government/Departments/Mayors-Office/Programs-and-Initiatives/Mobility-Action-Plan>.