Evaluating the Effectiveness of E-Bicycle Incentives in North Carolina

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RESEARCH & DEVELOPMENT

Evaluating the effectiveness of E-Bicycle Incentives in North Carolina

FINAL REPORT

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16. Abstract

This report evaluates the City of Raleigh's e-bike voucher program, which awarded 150 randomly allocated vouchers to support e-bike adoption among residents. Using a natural experiment design with panel surveys, trip-tracking via the OpenPATH app, and interviews, the study assessed impacts on travel behavior, vehicle miles traveled (VMT), and transportation insecurity. Results show voucher recipients were over ten times more likely to acquire an e-bike, with a 174% increase in daily cycling trips compared to controls. While no statistically significant reductions in car use or VMT were detected, transportation insecurity declined substantially among recipients. Interviews revealed strong appreciation for the program alongside challenges, including supply shortages, unanticipated costs, and limited infrastructure. Participants emphasized e-bikes' positive effects on independence, affordability, and well-being. Findings suggest that while financial incentives successfully increase e-bike ownership and use, complementary investments in safe infrastructure, supportive policies, and clear program communication are essential to maximize sustainable and equitable transportation outcomes.

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Executive Summary

Electric bicycles (e-bikes) can overcome critical limitations of conventional bikes, enabling more people to travel farther, faster, and with less physical strain. However, high upfront costs have remained a major barrier to adoption, particularly among low- and moderate-income households. In response, the City of Raleigh launched an e-bike voucher program initially offering 150 vouchers—75 worth $1,500 to lower-income applicants and 75 worth $500 to higher-income applicants—to make e-bikes more attainable.

Research Objectives and Methods

This study evaluated the program's impact on travel behavior, vehicle miles traveled (VMT), and transportation insecurity using a **natural experiment design**. Researchers surveyed applicants before voucher allocation and in two follow-up waves, leveraging the program's random lottery as a basis for causal inference. The research combined:

- Panel surveys measuring travel frequency, transportation insecurity, and attitudes
- Real-time travel data via the OpenPATH smartphone app
- In-depth interviews with voucher recipients

Pre-registered hypotheses guided the analysis, focusing on whether e-bike vouchers would:

1. Increase e-bike purchases and trips
2. Reduce car trips and VMT
3. Reduce transportation insecurity

Key Findings

1. Strong Demand Among Lower-Income and Transportation-Insecure Residents

The applicant pool skewed toward lower-income households, residents without cars, and people reporting higher transportation insecurity. Notably:

- 25% of applicants did not own a car, compared to 2.5% citywide
- Most applicants anticipated using e-bikes for leisure trips, but over half also planned to use them for shopping or commuting

2. High Voucher Redemption and Bike Acquisition Rates

Among voucher winners, over 82% purchased an e-bike, compared to fewer than 8% in the control group—a statistically significant effect demonstrating the program's success in overcoming affordability barriers.

3. Substantial Increase in Cycling

Survey and OpenPATH data converged to show a large and statistically significant rise in cycling:

- In follow-up surveys, voucher recipients reported higher biking frequency in about two-thirds of randomly selected treatment-control comparisons
- OpenPATH data confirmed a **174% increase in daily bike/e-bike trips** among voucher recipients versus non-recipients

4. No Significant Change in Car or Transit Use or Total Tripmaking

Despite the surge in cycling, the study did not find statistically significant reductions in car use or VMT overall. Patterns suggest new e-bike trips partly replaced other modes and partly represented induced travel or unlocked suppressed travel.

5. Meaningful Reduction in Transportation Insecurity

Voucher recipients reported significantly lower transportation insecurity scores compared to non-recipients (average scores 1.18 vs. 2.24), with a significantly greater decline over time. This suggests e-bikes enhanced participants' confidence and ability to get around reliably.

6. Positive but Uneven User Experiences

Interviews revealed that most voucher recipients found the redemption process smooth and appreciated the opportunity. However, common challenges included:

- Delays due to limited bike inventories
- Unanticipated out-of-pocket costs (helmets, locks, etc.)
- A limited selection of bike types and retailers

Many recipients emphasized that e-bikes had transformed their daily lives by:

- Reducing reliance on cars
- Saving money on fuel and parking
- Improving health and recreation
- Enhancing independence and well-being

At the same time, barriers to greater e-bike use persisted, including a lack of safe infrastructure, time constraints, weather, and ingrained driving habits.

Recommendations

For Program Improvements:

- Provide clearer upfront guidance about eligible retailers, bike models, and costs
- Expand retailer and bike options, including cargo and adaptive bikes
- Improve communication about approval and redemption timelines

For Other Cities Considering E-Bike Incentives:

- Pair subsidies with investments in safe cycling infrastructure
- Prioritize outreach to households without cars, older adults, and individuals with disabilities, groups that may benefit more from the program
- Partner with NGOs that can offer training to build rider confidence and skills
- Highlight success stories to build community momentum

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Introduction

E-bikes, or electric bicycles, offer a sustainable mode of active transportation that overcomes several key limitations of traditional bicycles. Many Americans live too far from activity centers to bicycle for transportation, even where infrastructure exists. Others find climbing hills or escorting children cumbersome on a bike. E-bikes help remedy these challenges by providing riders with additional speed and power, offering the potential to help cities meet public health and sustainability goals. Multiple cities across North Carolina are experimenting with e-bicycle incentives to promote uptake of the mode.

The price of e-bikes remains a significant barrier to broader adoption. North Carolina cities are piloting financial incentives such as cash rebates or vouchers to ameliorate this barrier. Recent research on similar programs in British Columbia, Canada, and Sacramento, California, suggests these incentives may have major effects on recipients' driving rates (vehicle miles of travel) and quality of life (Bigazzi et al. 2024; Johnson et al. 2023). However, these contexts differ from North Carolina in terms of climate, demographics, transportation system configurations, and built form. Local data are needed to document the extent to which e-bike vouchers can help North Carolinians.

This report documents the results of a natural experiment that jointly measures the impacts of the City of Raleigh's e-bike voucher program on vehicle miles traveled (VMT) and transportation insecurity. The city invited residents to enter a lottery to win one of 150 e-bike vouchers. The lottery created a unique opportunity to conduct a natural experiment that allows us to evaluate the causal effects of e-bike incentives, and e-bikes themselves, on travel behavior and quality of life.

We collected data through a panel survey of lottery participants before and after vouchers were awarded, with those who did not receive vouchers serving as a control group. Randomness in lottery awards allows for causal inference. The survey drew on existing, peer-reviewed instruments for documenting the impacts of transportation investments, allowing us to assess changes in travel behavior, transportation insecurity, and well-being. We additionally provided study participants with access to OpenPATH, a real-time smartphone app developed by the National Renewable Energy Laboratory (NREL) to track travel behavior. OpenPATH provided an objective measure of changes in driving levels. Finally, we interviewed voucher recipients to uncover the unanticipated benefits of, and barriers to, e-bike use. The research team pre-registered our key hypotheses before data collection.

Background

A recent global scoping review found only four studies offering rigorous evaluations of e-bike incentive programs, despite governments funding these programs to meet readily quantifiable goals like reducing emissions and promoting well-being (Nosratzadeh, Bhowmick, Ríos Carmona, et al., 2025). A similar review argues that there is "a critical need for more rigorous studies, preferably employing experimental or quasi-experimental longitudinal designs" that evaluate the effects of e-bike incentives on policy outcomes (Nosratzadeh, Bhowmick, Carmona, et al., 2025, p. 1). This report helps fill this gap in knowledge by testing for the impacts of Raleigh's E-Bike voucher program on both vehicle miles traveled and transportation insecurity using a natural experiment design. The following background section summarizes existing knowledge on the impact of e-bikes on each of these outcomes in turn before describing the Raleigh E-Bike Program in detail.

E-bikes and vehicle miles traveled

Methods for assessing whether e-bikes reduce VMT have evolved as the technology has grown in popularity. Early U.S. research developed mode replacement models to estimate VMT and emissions reductions from surveys of e-bike owners, finding that e-bikes could reduce carbon emissions from personal transportation by up to 12% (McQueen et al., 2020). More representative household travel surveys from countries with greater e-bike penetration show similarly promising results. A structural equation model on Dutch data found e-bike ownership reduces driving rates, but also reduces conventional bicycling by twice as much (Kroesen, 2017). A Shanghai household travel survey revealed that e-bike ownership is associated with a 19% decrease in driving mode share within households that owned both e-bikes and automobiles (Yin et al., 2024). The relevance of these studies to the U.S. context might be limited, however, given national differences in built form and cultural acceptance of utilitarian cycling. Further, these studies look cross-sectionally at the entire population, and only show effects among households that self-selected into e-bike ownership without any policy inducement.

Fewer studies look at the potential for e-bike incentive programs to reduce VMT, but their results suggest incentives do shift behavior. A survey of participants of three rebate programs in Northern California estimated carbon emissions reductions of 12–44 kg of CO_2 per rebate (Johnson et al., 2023). Specifically, the percentage of program participants who reported that they drove a car daily dropped from 60% in the pre-treatment period to just 40% eighteen months after receiving the rebate. A similar evaluation of British Columbia's income-conditioned rebates revealed similar benefits of 16 kg of CO_2 per rebate per week (Bigazzi et al., 2025). That study finds that lower-income individuals who receive more generous, income-targeted incentives yield greater emissions reductions (Bigazzi et al., 2025).

Transportation insecurity and e-bikes

At a basic level, transportation insecurity describes the inability to regularly get from place to place in a safe and timely manner (Murphy et al., 2022). Analogous to food insecurity, transportation insecurity results from a lack of resources, like owning a car or affording transit fare. Unlike food insecurity, it can be shaped by specific elements of the transportation system, such as transit service provision and reliability or the presence of safe pedestrian infrastructure. Transportation insecurity is measured through the transportation security index (TIS), which measures the frequency at which individuals experience different symptoms of transportation insecurity, such as missing an appointment or giving up on trying to go somewhere (Gould-Werth et al., 2018). The TIS also measures the emotional and psychological impacts of a lack of transportation. For example, one item asks the respondent how often they felt left out because they did not have adequate transportation, while another asks how often they worried they were a burden to family or friends who they relied on for transportation (Murphy et al., 2022).

Theoretically, e-bikes offer a means of ameliorating transportation insecurity by providing a means of travel that can reduce the gap between motorized and non-motorized travel speeds at a cost much lower than an automobile. In “The E-Bike City,” Ballo et al. speculate that e-bikes may “reduce the accessibility disadvantage typically experienced by people who don't have access to cars” (Ballo et al., 2023, p. 5). A recent review argues that e-bikes may improve independent mobility for some older adults and people with disabilities by requiring less physical exertion (Lee & Sener, 2023). The possible benefits of e-bikes include family dimensions, as parents may find e-bikes more suitable for schlepping small children or carrying groceries compared to a conventional bicycle (Thomas, 2022). E-bikes may help ameliorate transportation insecurity by providing these benefits to riders, yet barriers to their adoption remain.

Populations at risk of transportation insecurity may be less likely to adopt e-bikes, limiting the potential benefits of the technology. Barriers include a lack of education and support for organizations that promote local biking culture, as well as financial barriers (Witten et al., 2024). Financial costs may significantly prohibit uptake, as prices can range from $1,000 to $5,500 USD, tantamount to a down payment on an automobile (Lee & Sener, 2023). Financial incentive programs can help transportation-insecure households overcome this barrier. For this reason, about 21% of incentive programs included in a recent global review tiered incentives by income group (Nosratzadeh, Bhowmick, Ríos

Carmona, et al., 2025). However, no prior studies have examined whether e-bikes or e-bike vouchers actually reduce transportation insecurity. This study fills this gap.

The Raleigh E-Bike Program

The City of Raleigh launched its e-bike incentive program in October 2024. The program initially offered 75 vouchers worth $500 USD to individuals in households with incomes at or above 80% of the city's Area Median Income (AMI). Another 75 vouchers worth $1,500 USD were made available to individuals in households below the 80% AMI threshold. Area Median Incomes vary by household size, and are set by the U.S. Department of Housing and Urban Development for affordable housing programs (City of Raleigh, 2025).

The city anticipated oversubscription and opted to distribute vouchers via a lottery system. Residents of the city could sign up for the program through an online portal on the city's website between October 24th and November 10th, 2024. After this application period ended, the city randomly selected winners from the applicant pool. Winning individuals had 90 days from notice of receipt to redeem a voucher at one of six participating bike shops located within city limits. If an individual did not redeem a voucher within this time period, it was cancelled and re-allocated to a newly selected winner.

Eligibility was limited to city residents aged 18 years of older. All applicants had to provide proof of income and were automatically entered into lotteries for either the $500 or $1500 vouchers based on their verified household income. The sign-up form also included several demographic variables to help the city track interest in the program and identify any communities that may require further engagement in future programs.

Data and methods

We achieve a natural experiment design by collecting baseline data after participants signed up for the voucher program, but before anyone received notification that they won a voucher. To do this, we asked the City of Raleigh to include a question on their intake form asking whether the participant would opt in to a survey from UNC. Nine hundred and eighty-three did so. Additionally, the city provided voucher winners who did not opt in to receiving survey invites another opportunity to opt in when they received notification that they won a voucher. This was not included in the preregistration as we were unaware such an opportunity would come available. This yielded an additional 19 individuals, bringing the final total of opt-ins to 1,002.

We contacted these individuals via protocols outlined in our pre-registration below, with noted minor deviations. This included invitations to both an online survey and use of a trip-logging app, OpenPATH, developed by the National Renewable Energy Laboratory (NREL). We conducted a second survey wave in April 2025, however, many individuals had not redeemed their vouchers by this time, as the first wave of voucher approvals were disbursed in late January of that year. To ensure the study measured post-treatment effects, we collected a third survey wave in June 2025. The third survey wave included the use of the OpenPATH app. In between waves two and three, the research team conducted 30 interviews with voucher winners. In sum, we employed three data collection techniques for this study: a survey, an app-based travel diary, and participant interviews. Each of these methods, along with our pre-registered data collection protocols, is below.

Preregistration

The randomized nature of this study allows us to identify causal effects—that is, not only what outcomes are associated with e-bike voucher receipt, but what outcomes were directly *caused* by the program. A key concern with randomized control trials is that the causal nature of the results may be undermined by bias coming from which results the researchers—often unconsciously—choose to present (Ioannidis, 2005). To help avoid these types of bias, researchers often *preregister* their studies. In a preregistration, you describe what data you will collect, how you will collect it, and how you will analyze, *before* beginning data collection. This way, there is no possibility that the results of the analysis will unconsciously affect decisions about what to present.

We preregistered key hypotheses and data collection procedures prior to collecting our Wave 1 sample (Bhagat-Conway & Palm, 2024). Since our data collection proceeded in waves, we submitted addenda to this preregistration before each wave, detailing any changes in data collection in that wave (Bhagat-Conway & Palm, 2026; Palm & Bhagat-Conway, 2025). Specifically, we preregistered the following hypotheses:

- H1: Voucher recipients will be more likely than non-recipients to purchase e-bikes
- H2: E-bike owners will make more trips overall
- H3.1: E-bike owners will make more trips by bike (electric or non-electric) than non-e-bike owners
- H3.2: E-bike owners will make fewer trips by car than non-e-bike owners
- H3.3: E-bike owners will make fewer trips by transit than non-e-bike owners
- H3.4: E-bike owners will travel fewer miles by car than non-e-bike owners
- H3.5: The effects in H3.1–H3.4 will be stronger for people who report often traveling to locations within four miles of their home
- H4: E-bike owners will report lower levels of transportation insecurity We expect that voucher recipients will score lower on the transportation insecurity index included in the survey.

- H5: E-bike owners who do not have access to an automobile will report a greater number of e-bike trips as “would not have made trip” without e-bike, compared to those with access to an automobile.

For most of these, we preregistered several different analysis methods to test the hypothesis. Most use t-tests or non-parametric tests to test how voucher recipients respond to vouchers.

Voucher receipt is not perfectly predictive of e-bike purchase—some people may get vouchers and not purchase bikes, while others may not get a voucher but decide to purchase a bike anyway. Thus, the effect of voucher receipt on travel is not necessarily exactly the same as the effect of having an e-bike. To test the latter, we proposed instrumental-variables regressions (Huntington-Klein, 2022) and conditional mixed process models (Roodman, 2011). These regressions are beyond the scope of this report, but consistent with the requirements of the preregistration, we will present them in future publications.

Survey data

We surveyed program participants three times. Our Wave 1 survey was between November 2024 and January 2025, before participants got their vouchers (with a few exceptions). We initially planned to do only one follow-up, in Spring 2025, but due to a slower-than-expected rollout of the vouchers, we opted to undertake a short interim Wave 2 survey in April 2025, with a full Wave 3 survey in June 2025.

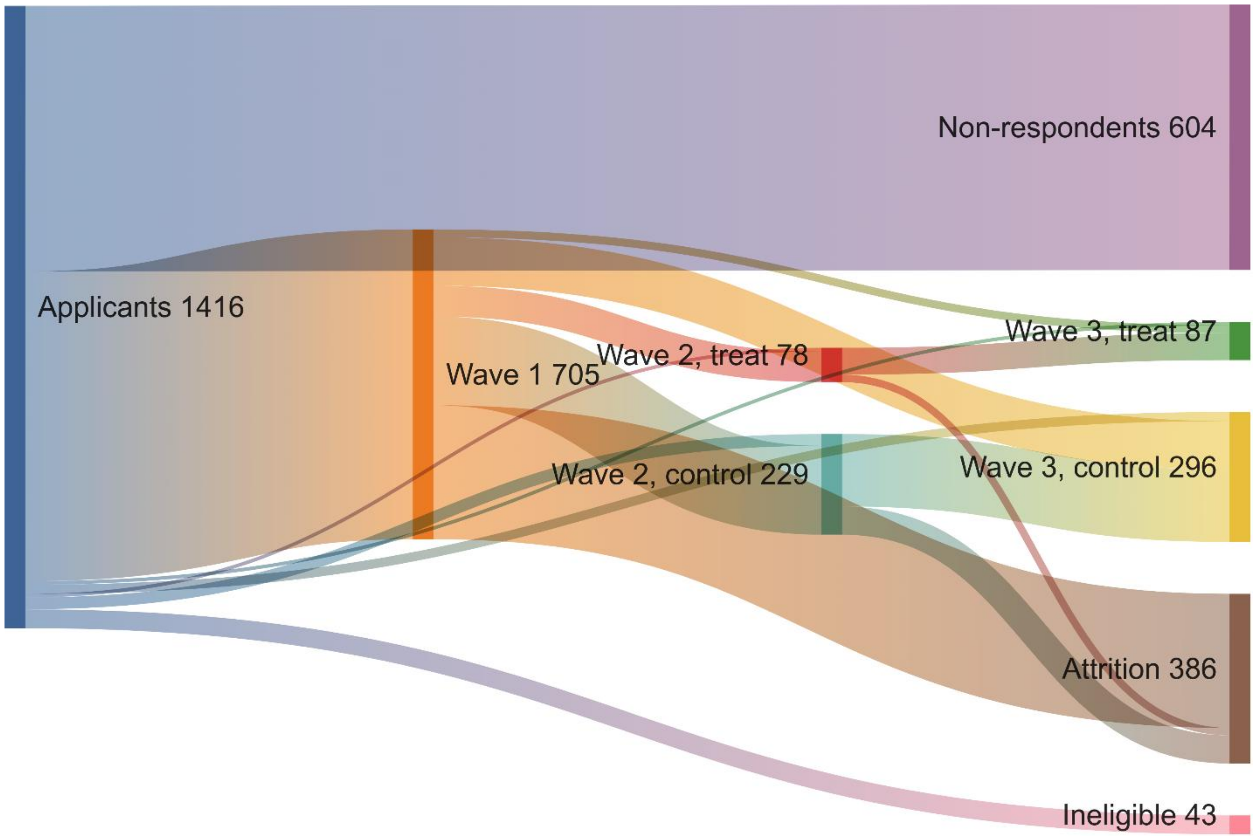
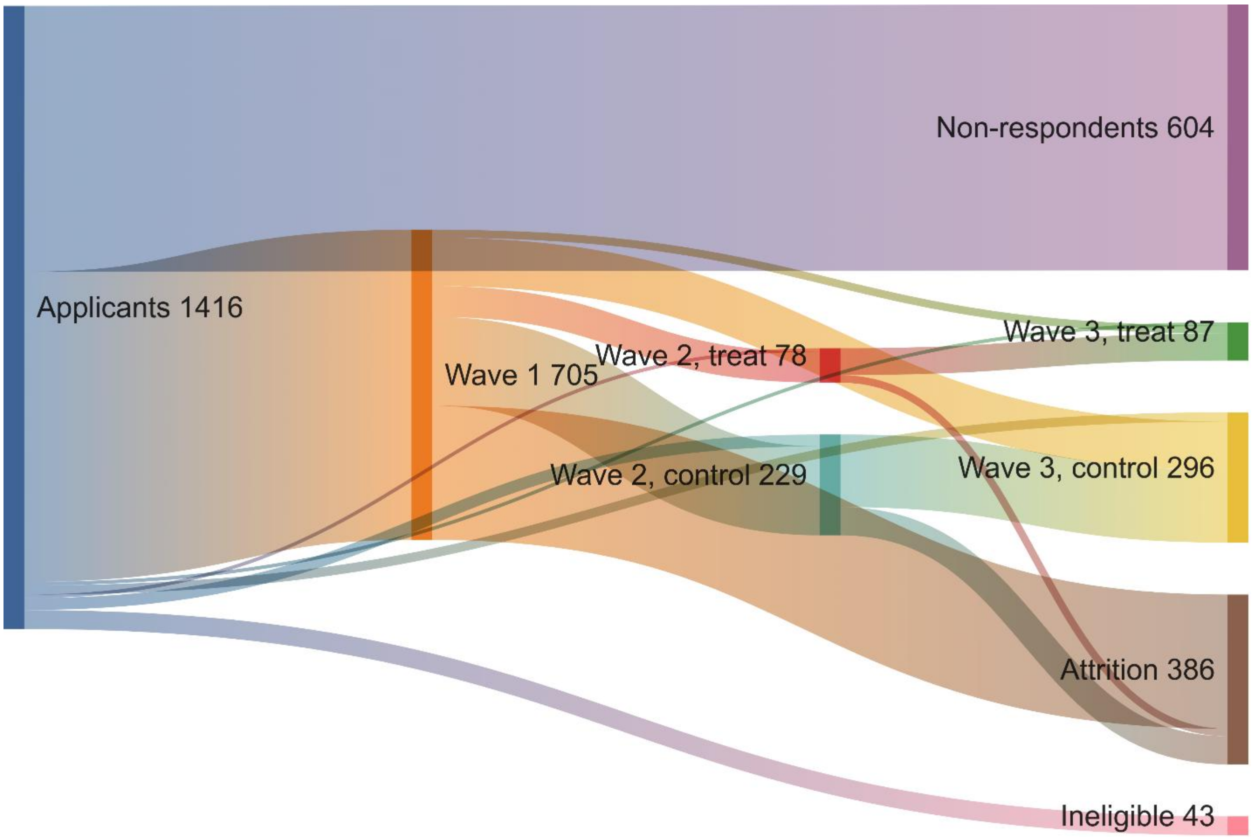


Figure 1: Sample sizes and attrition between survey waves

The Ral-E-Bike program garnered 1,416 applicants. Of these, 705 completed our Wave 1 survey, while 604 either opted out of being contacted or did not respond to our survey invitations and/or complete the survey.

Seventy-eight voucher recipients and 229 control group members took the Wave 2 survey, while 87 voucher recipients and 296 control group members took the Wave 3 survey. 43 respondents were determined to be ineligible for the program by the City of Raleigh and are excluded from all analyses below. Many respondents did not take all three waves, but rather some subset; response patterns between waves are shown in Figure 1.



Recruitment

We recruited participants via email and text message. We also recruited some voucher recipients through flyers placed at bike shops when they picked up their bikes. Our initial recruitment plan in the preregistration for Wave 1 proved to be overly optimistic, and we ultimately sent two more reminders than we initially planned to: one additional email and one text message. By the time we conducted Wave 3, we had a better handle on the responsiveness of our study population and followed the plan in our preregistration of up to 4 email reminders and three text messages for the main survey.

Data analysis—travel behavior data

Travel outcomes in the survey were measured by a set of ordinal questions asking about the frequency of using walking/running, biking/e-biking, e-scooters/mopeds, cars, transit, and for-hire vehicles. Response options for these questions were never, less than once a week, 1-2 days a week, 3-5 days a week, and 6-7 days a week. We asked these questions for all destinations, and also specifically for destinations within 4 miles of home, which is a reasonable distance to travel by e-bike. To evaluate our hypotheses using these variables, we used a nonparametric permutation test for stochastic dominance.

Specifically, we want to evaluate the probability that a randomly-selected individual from the treatment group has a higher (or, for some hypotheses, lower) frequency of use for a particular mode. For example, for bicycling, we would like to know what the probability is that a randomly-selected voucher recipient bicycles more frequently than a randomly-selected control group member. We compute this by randomly sampling a large number of randomly-chosen pairs from the treatment and control group, and calculating the percentage where the treatment group cycles more.

Figure 2: Example of stochastic domination calculation

We would of course like to know if the value calculated indicates that one group has a higher propensity to use the mode than the other. This is not as simple as comparing the estimated value to 50%, because of ties. For instance, consider the hypothetical situation shown in Figure 2. Here, when comparing randomly-selected individuals from the treatment group with randomly selected individuals from the control group, we find that 20% of the time the treatment group individual uses a mode less frequently than the control group individual, 40% of the time they use it more, and 40% of the time it is a tie. In this case, it is clear that the treatment group has a higher propensity to use the mode, even though they use it more often in less than 50% of cases.

Knowing whether a particular percentage indicates more or less frequent use of a mode depends on the data distribution and in particular, the frequency of ties. In addition, we would like to be able to assign statistical significance to a particular estimate.

We address both of these questions using a technique known as a permutation test, which is an oft-used technique for situations where parametric statistics falter. We first construct a null hypothesis, which is that the treatment and control groups do not, on average, differ. The key insight of a permutation test is that this null hypothesis, if true, implies that observations from the treatment group are interchangeable with observations from the control group (Efron & Tibshirani, 1993). Therefore, you can sample from the sampling distribution under the null hypothesis by randomly "permuting" observations between the treatment and control groups.

To operationalize this, we calculate the probability that a random treatment group member bikes more than a random control group member by sampling with replacement pairs of random individuals from the treatment and control groups, and determining the frequency with which the treatment group member bikes more often. We then randomly permute the treatment and control group, calculate a sample under the null hypothesis, and compare the two samples. We repeat this process many times. If the estimate from the actual data is larger than the permuted value more than 97.5% of the time, or less than 2.5% of the time, we reject the null hypothesis that the two groups are equal, and accept the alternative hypothesis that they are not. We calculate an estimate for the percentage of randomly-selected treatment-control pairs where the treatment group member cycles more by taking a mean of the frequencies from the randomly-selected treatment-control pairs, and an expected value under the null hypothesis by taking a mean of the permuted values.

In order to produce a stable estimate, we sample with replacement 10,000 pairs of respondents for both the point estimate and the permutation test. We then repeat the process 10,000 times. In the preregistration, we proposed 1,000 rather than 10,000 replications, and proposed sampling the estimate from the actual treatment/control groups only once. We found that these led to estimates with high variance, so we increased the sample size and sampled the treatment-control group difference many more times.

Data analysis—transportation insecurity

In line with our pre-registration (H4), we conducted standard t-tests of differences in transportation insecurity levels between voucher winners and non-winners. Responses to the six-item TIS index were converted into a score following the procedures established by the index's authors (Poverty Solutions, 2024).

OpenPATH data

At the end of the Wave 1 and 3 surveys, we invited respondents to download the OpenPATH app, which would automatically record their trips. OpenPATH is an app provided free to researchers by the National Renewable Energy Laboratory (Shankari, 2019). Data collected by OpenPATH is made available to the research team, but also to other researchers (with appropriate approval and security requirements) through the Transportation Secure Data Center (Gonder et al., 2015).

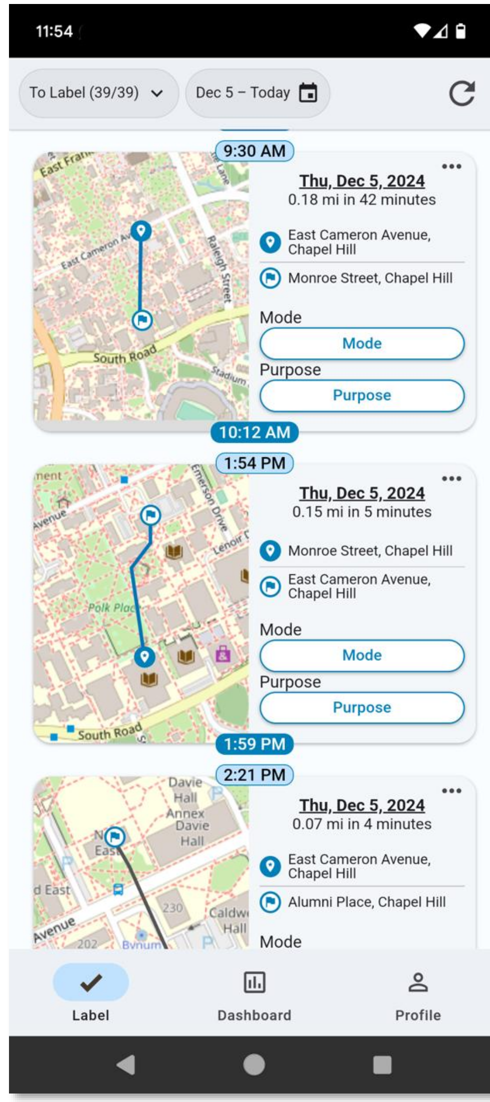


Figure 3: The OpenPATH app interface

We sent reminders to respondents who opted in to using the OpenPATH app if they did not set the app up within a few days of opting in. While we initially planned (and preregistered) to only send reminders to respondents to download the OpenPATH app via email, we found that many participants had not downloaded the app, and opted to send text messages as well during Wave 3.

Periodically, OpenPATH users are asked to “label” their trips with the mode and trip purpose. For e-bike trips, they were also asked to specify how they would have made the trip had the e-bike not been available. During the Wave 1 survey, participants were asked to use the app for a month and received a $20 gift card (initially $10, but we raised the gift card amount for all respondents to improve response rates). During the Wave 3 survey, we only asked participants to use the app for a week, for a $40 gift card, to improve response rates. In both waves, participants needed to “label” 80% of their trips during that time period in order to receive a gift card.

As with any data collected from mobile sensors, some data cleaning is required. We used the same data cleaning rules for Wave 1 and Wave 3, even though the samples were not collected in a completely identical way. We described these data cleaning rules in our preregistration to help ensure the data cleaning would not inadvertently bias the results.

We excluded any respondent who did not have the app on their phone for at least a week. We also excluded anyone who did not have at least one seven-day period where they labeled 80% of their trips.[1] We excluded trips that were less than three minutes long or with a GPS-reported average speed of less than 1 or greater than 90 mph, as we believe these to be data errors.

When respondents do not label a trip with a mode, OpenPATH "imputes" a mode based on speed and sensor data. In analysis by mode, we use the mode the respondent labeled if it is available, and otherwise use the imputed mode. Occasionally, there is not enough data for OpenPATH to impute a mode. We exclude any day where more than 5% of the respondents' trips had no labeled or imputed mode.

We initially planned to also exclude respondents where 20% of the days when they had the app on their phone were missing more than 5% of the mode information. However, we ultimately did not do this as it excluded a large portion of the sample. We believe that many recipients did not turn off tracking or delete the app after labeling the requested number of days, so they have many days where trips were recorded but no mode information was available. We do not think this indicates a data quality issue with the days where they do have imputed or manually labeled modes.

In addition to the above exclusion rules defined in the preregistration, we exclude individuals who reported no trips at all during the time they had the app, as we believe these are more likely to reflect technical issues with the app than actual long-term non-travel. We also exclude individuals who were determined ineligible for the Ral-E-Bike program.

Many of the results presented below are based on daily averages. This requires a clear estimate of the number of days each person used the OpenPATH app. Unfortunately, there is no accurate way to differentiate a day where the respondent made no trips from a day where they were not using the app. To calculate the denominator for these averages, we calculated the number of days between their first and last recorded trips, inclusive, assuming any zero-travel days in the interim are truly zero-travel days and not days when they are not using the app. We calculate the first and last trip date before doing any data filtering to remove invalid trips (e.g., too short), even if the app recorded an invalid trip on a day that indicates that it was recording. We subtract from this number of days that we remove due to our exclusion criteria above.

We expect any violations of this assumption to be exogenous with respect to voucher receipt, as they would likely represent an unpredictable technical issue. The only

[1] In the preregistration, we said we would base this criterion on a calendar week (Monday-Sunday), rather than any consecutive seven day period. Since Wave 3 data collection only required a week of OpenPATH use, the calendar-week criterion would exclude people who started recording trips midweek.

mechanism we can imagine where this would not be the case is if voucher recipients interact with the app more, and therefore, opening it, cause it to restart if it is not working at any point.

This does mean that if the respondent started or ended their data collection period with a zero-travel day, we will exclude that day, slightly inflating average daily travel. We do not expect this to significantly bias results. If anything, they would likely be biased in a conservative direction; if our hypothesis that voucher recipients take more trips is true, then we would be less likely to have a zero-travel day at the start or end of the period, and the control group's estimate would be biased higher than the voucher recipient group's.

In order to avoid any potential for bias, consistent with our preregistration, we did not begin any analysis of Wave 3 OpenPATH data until after the data collection period ended on June 26, 2025. However, due to the asynchronous nature of the app, some trips that took place on or before June 26th were not "synced" to the server with their labels until several days later. We include these trips in the analysis, but do not include any trips after June 26, 2025.

Interview data

The research team invited all voucher winners who took the second survey wave to participate in follow-up interviews. The research team prioritized respondents with high levels of transportation insecurity, as well as those eligible for the deeper incentive, with two-thirds of interviews coming from these groups. Interviews took place over Zoom or the telephone and took on a semi-structured format. Interview questions covered respondents' motivation for applying, how they heard about the program, their mobility barriers and travel patterns before receiving the voucher, their experiences redeeming the voucher and selecting an e-bike, and their experiences riding. We also asked respondents what advice they would give the city, other cities pursuing similar programs, and a hypothetical friend

We conducted 30 interviews in total. Interviews were recorded for transcription purposes. The average interview lasted 19 minutes and 40 seconds, and the total time across all interviews exceeded nine hours and 50 minutes. Two research team members conducted deductive coding of interviews using topics generated from the interview guide. Ties were broken by the PI. The PI then identified the key themes and findings within each topic using an inductive, grounded approach.

Results

Survey results

The city's application form and our first survey wave collected detailed demographic data on applicant demographics. To contextualize our results, we first summarize how the applicant pool varied from the general population of the City of Raleigh before turning to more detailed findings from the survey, OpenPATH app, and interviews.

Analysis of application data: who expressed interest?

The program's income tiering necessitated data collection on participants' incomes. Figure 4 below compares the distribution of verified incomes of program applicants to the city's overall demographics. Lower- and middle-income households were overrepresented in the applicant pool compared while higher-income households were underrepresented. The following household income bands were significantly larger in the applicant pool: those making less than $10,000 a year, $25,000 to $34,999, and $50,000 to $74,999. In contrast, households making $50,000 to $99,999, $100,000 to $149,999, and $150,000 to $199,999 were significantly underrepresented. The program attracted more lower-income segments of the city.

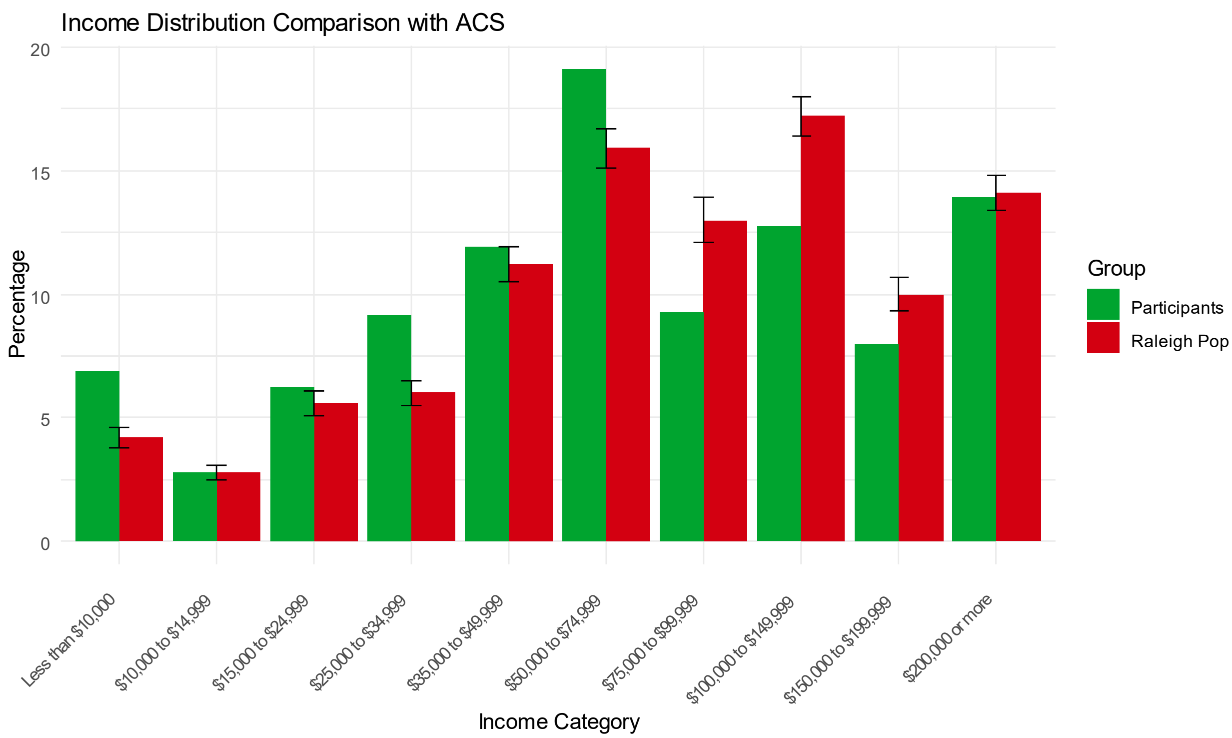


Figure 4: Income distribution of voucher applicants compared to City of Raleigh

By age, the program attracted more middle-aged people and fewer younger or older adults. These differences are presented in Figure 5, which includes mandatory demographic data from the program sign-up form. Specifically, people ages 25 to 35, and those ages 35-60, were significantly over-represented in the applicant pool. In contrast, people under 25 or over 60 were underrepresented. All differences were statistically significant at $p < .05$.

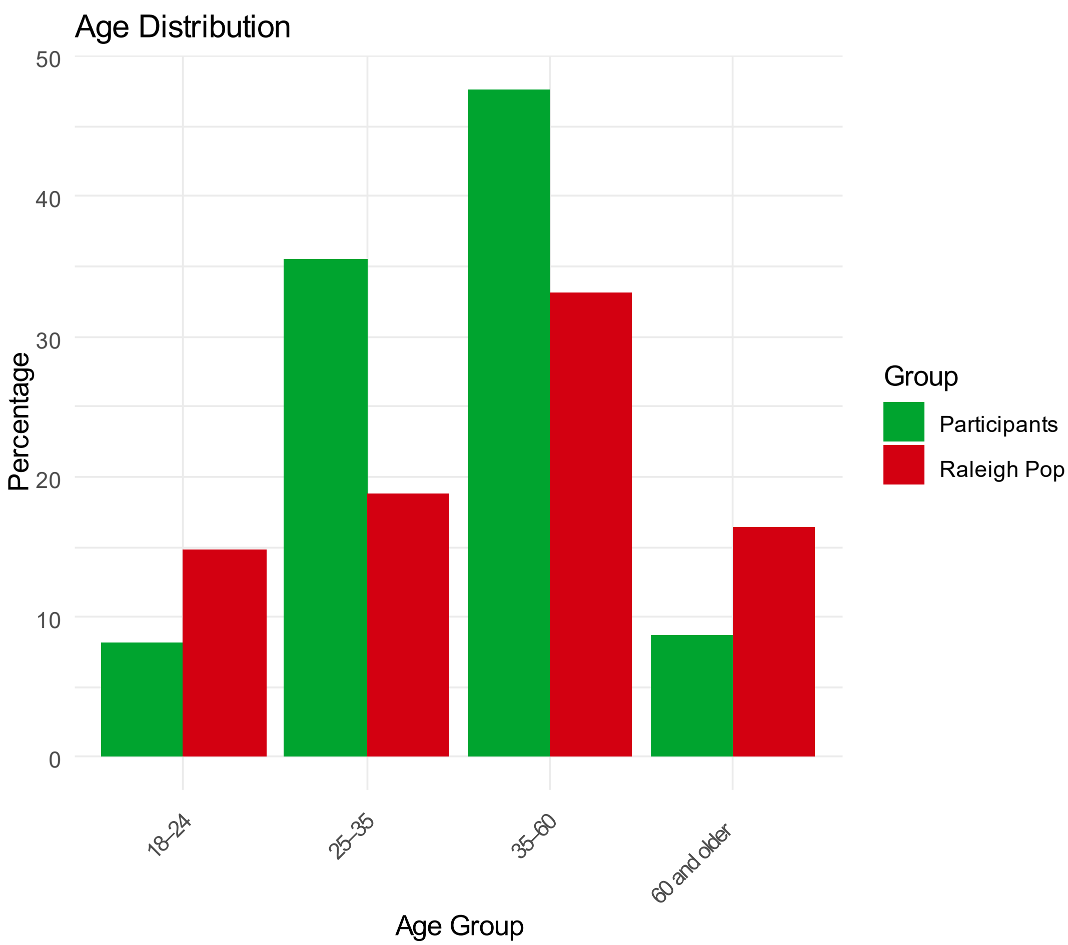


Figure 5: Age differences between voucher applicants and the general population of Raleigh

The sign-up form also required individuals to list their racial identities to help the city track whether it was reaching every community through program outreach. Racial differences between applicants and the city population are presented in Figure 6. Applicants were significantly more likely to identify as White or having two or more races, while Black and Hispanic residents were significantly underrepresented.

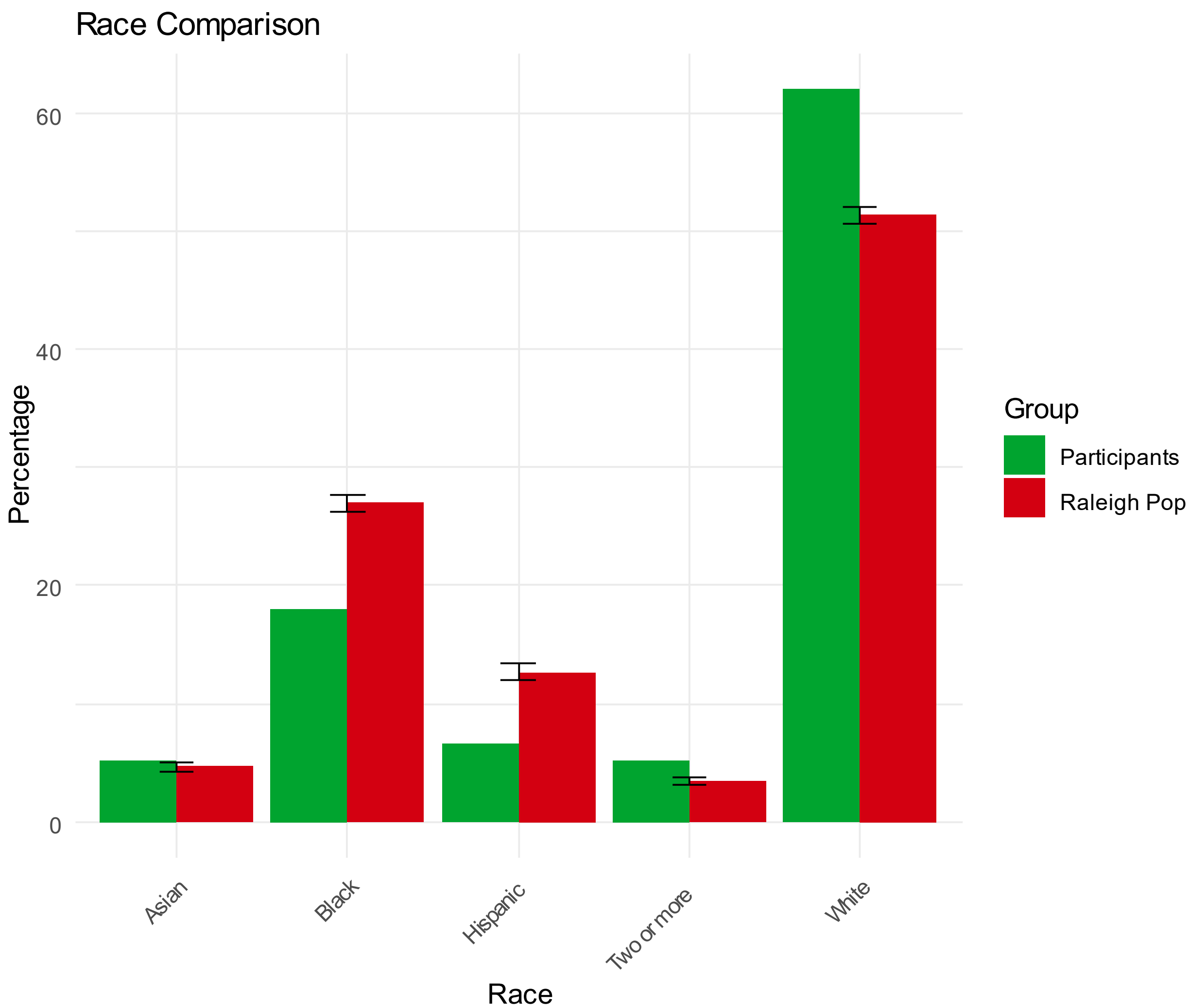


Figure 6: Racial differences between voucher applicants and the general population of Raleigh

Overall, the applicant pool was systematically different from the City of Raleigh's population along lines of age, race, and income. We also found the applicant pool skewed more male—53% than the city's 47.7%.

Analysis of survey data: the types of riders who expressed interest

We compared our wave one survey responses against city demographics with respect to vehicle availability in the household. These differences are presented in Figure 7.

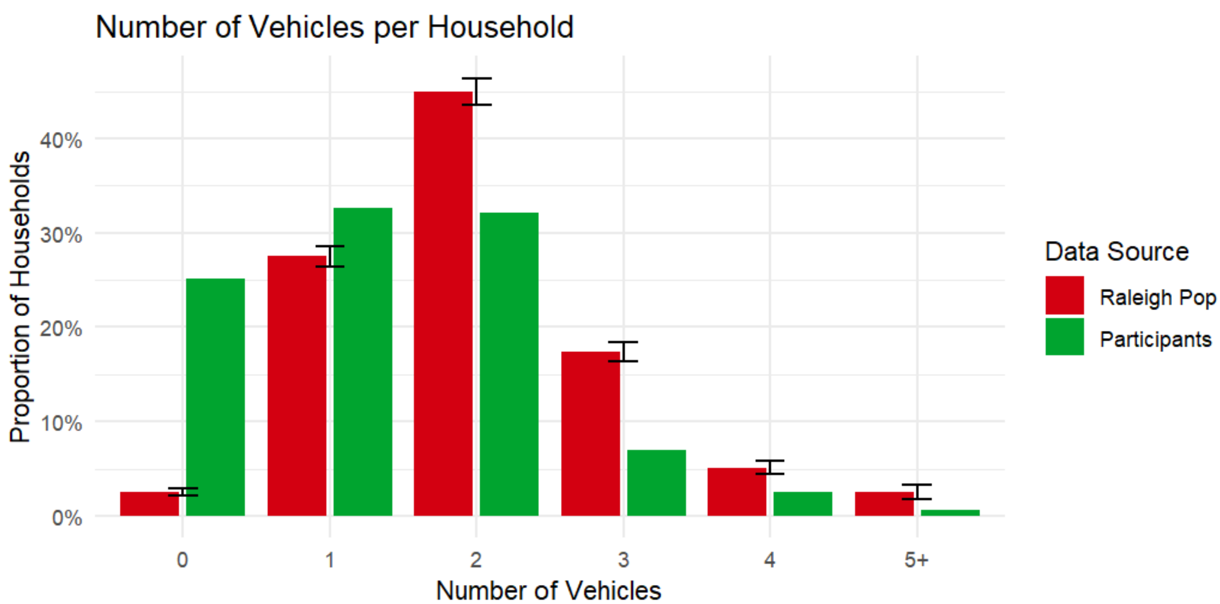


Figure 7: Differences in household vehicle availability between voucher applicants and the general population of Raleigh

Residents without a vehicle were 10 times more likely to apply for an e-bike voucher, constituting 25% of the applicant pool compared to 2.5% of the city population. Residents in households with a single car were also overrepresented, but to a smaller degree (33% vs 28%). Households with two, three, four, or five or more vehicles were all underrepresented among participants. These results demonstrate the strong interest in e-bike voucher programs among households without automobile access.

Analysis of application data: who expressed interest?

It is possible that e-bike programs might attract cycling enthusiasts who may already have lower vehicle miles of travel. To assess this, we asked respondents to answer a set of questions about the types of cycling infrastructure they would feel comfortable riding on. Using this information, we scored all respondents using the Four Types of Cyclists typology developed by Portland State University (Dill & McNeil, 2016). We compare the distribution of applicants against national estimates from Dill and McNeil (2016) in Figure 8.

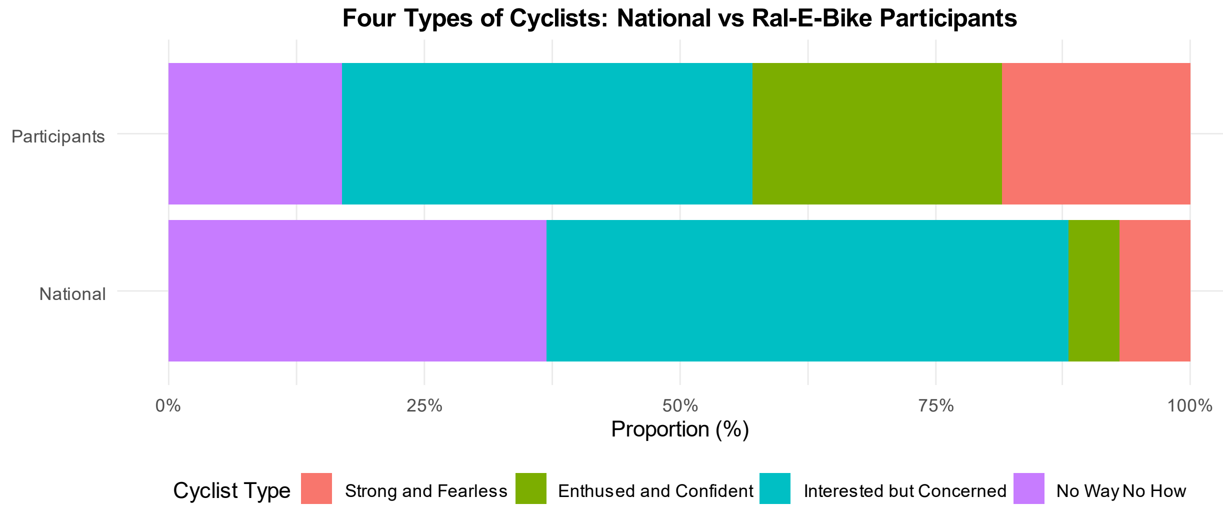


Figure 8: A comparison of cycling types between program applicants and the U.S. population

The applicant pool does overrepresent the "strong and fearless." This is a small set of the population that feels confident cycling almost everywhere and anywhere it is legal to do so. Their share of the applicant pool is almost three times larger than their share of the population. In contrast, the second most pro-cycling group, the "enthused and confident," is more than five times greater as a share of program participants compared to their share of the U.S. adult population. This group will ride on major arterials if bike lanes or cycle tracks are provided. The "interested by concerned" type is underrepresented among applicants. This is almost half of the U.S. population—people who are interested in cycling but will only ride if safe infrastructure is provisioned. Finally, the "no way no how" group is dramatically underrepresented, which reflects their hesitancy to cycle. These are people who would generally refuse to bicycle for utilitarian purposes even with safe infrastructure provided. These are individuals who may not feel fully comfortable riding on quiet residential streets, off-street paths, or trails. Despite their hesitation, they make up over one-eighth of all applicants to Raleigh's voucher program. These findings raise the possibility that some voucher winners may not reduce VMT as they only feel comfortable riding in purely recreational environments.

The survey also shed light on the possibility of the voucher program reducing transportation insecurity. Transportation insecurity levels for applicants are compared against the national distribution from Murphy et al. (2022) in Figure 9.

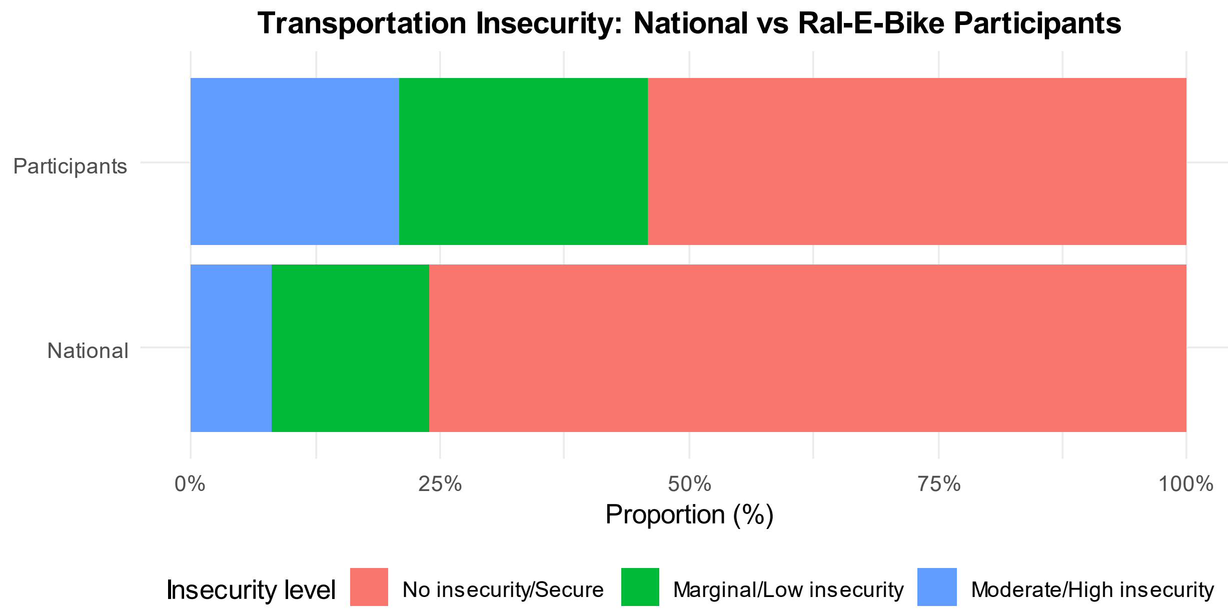


Figure 9: Differences in transportation insecurity levels between program applicants to the U.S. population

People with moderate to high transportation insecurity levels are significantly overrepresented in the applicant pool, as are those with low to moderate insecurity levels. These results complement our findings on vehicle ownership, which is a primary determinant of transportation insecurity. These results suggest there is potential for e-bike voucher programs to serve transportation-insecure individuals. Whether the program actually reduced their insecurity is measured in the next section.

To assess the likelihood of VMT effects, we asked respondents where they hoped to ride an e-bike if they won a voucher. We let respondents select all trip purposes that might apply. These results are presented in Figure 10. The top three most common choices speak to exercise and leisure: 80% selected parks or open space, followed by 70% selecting restaurants or bars, and 68% selecting joyriding or exercise to nowhere in particular. With the exception of trips to bars and restaurants, these results do not suggest the program will yield a significant mode shift, particularly given the high interest in joyriding. While joyriding can improve physical activity and mental health, it is unlikely to replace a car trip. However, over 60% of respondents said they would ride an e-bike to shop, and just under half would ride one to work.

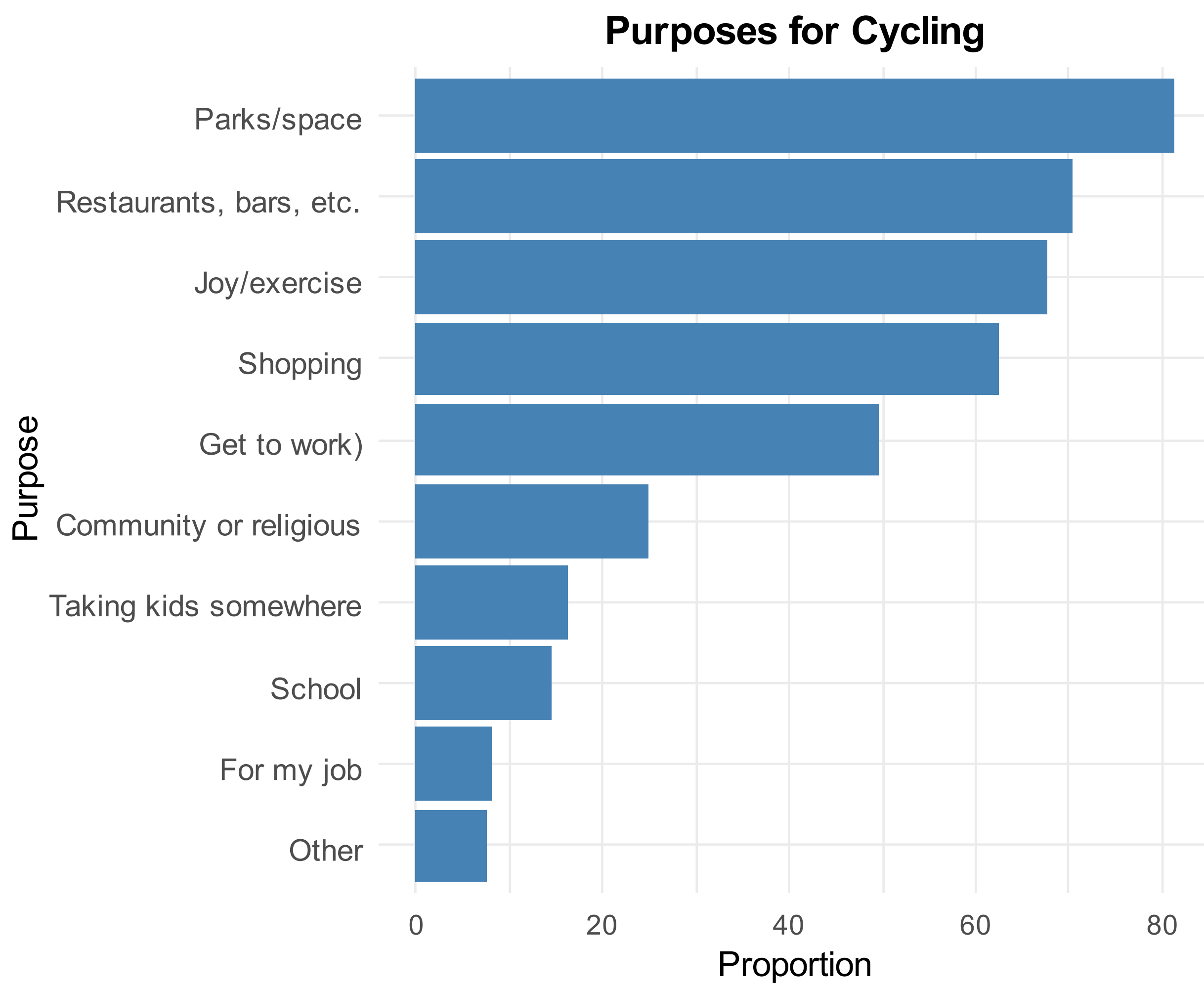


Figure 10: Anticipated e-bike trip purposes among applicants

To support and refine future e-bike voucher programs, we asked respondents about their priorities for selecting an e-bike should they win a voucher. These results are presented in Figure 12. Nearly every respondent highlighted battery quality, while just under 60% selected comfort, and just over half prioritized an e-bike that would be easy to carry. Notably, off-road capability and the aesthetic appeal of an e-bike were not a priority for over 95% of applicants, and safety was a priority for just under a third.

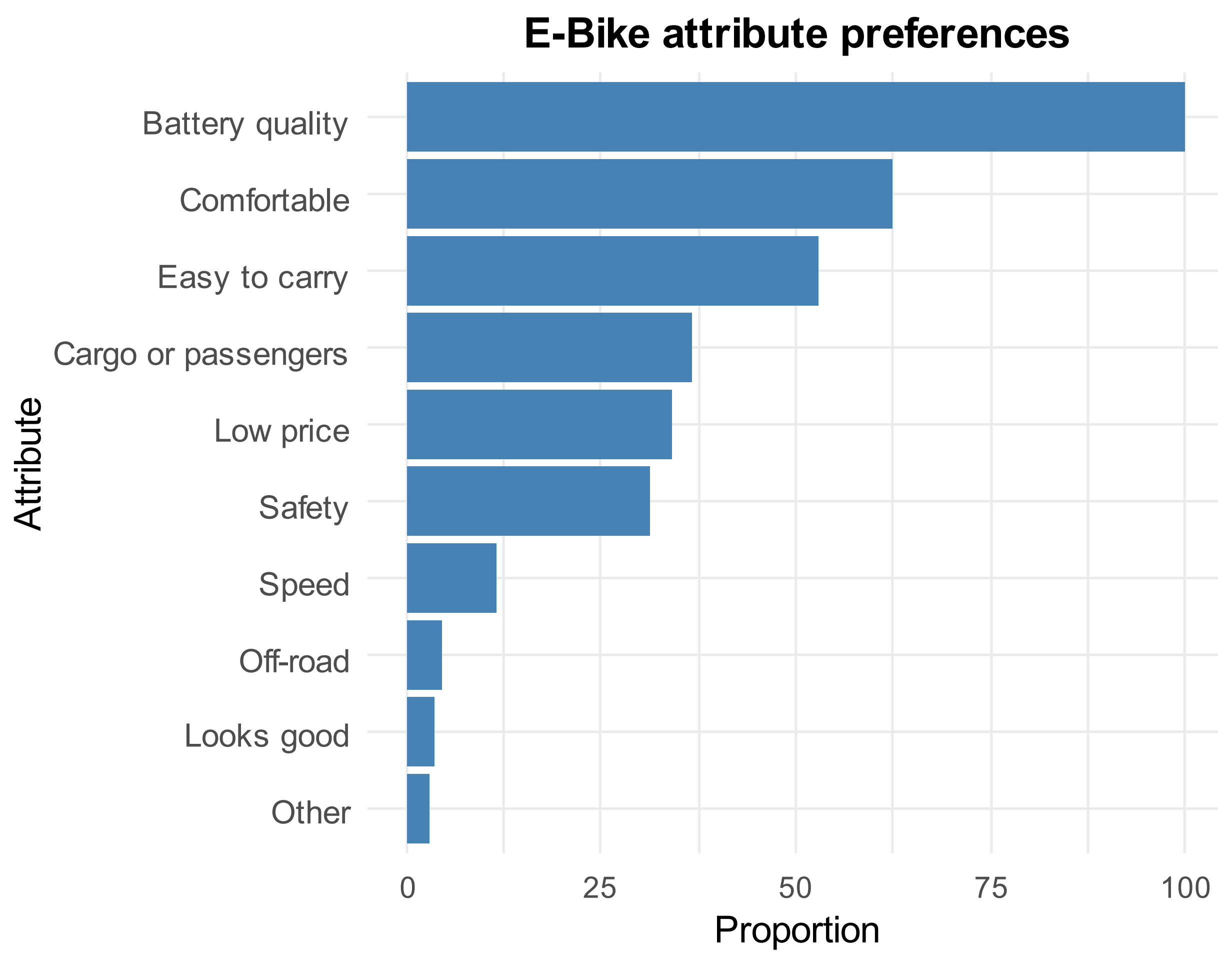


Figure 11: E-bike attribute priorities among applicants

In summary, individuals who signed up for the Raleigh E-Bike program are a blend of enthusiastic and reluctant cyclists interested mostly in riding for recreational and leisure trips. However, a slight majority of respondents planned to ride an e-bike to some recreational trips, such as work and shopping. Respondents prioritized battery quality and comfort in an e-bike, and expressed little concern about safety or off-road capabilities.

The effect of e-bike vouchers on transportation insecurity

Transportation insecurity scores range from 0 to 18, with a fairly low average. Higher scores indicate greater insecurity or more mobility problems. A lower score is better. We started with a two-tailed t-test comparing differences in mean TIS scores between voucher winners and non-winners in Wave 3. Voucher winners average a score of 1.18 versus 2.24 for non-winners, a difference significant at $p < .01$. These results are plotted in Figure 12. In this case, winners who did not actually redeem their voucher still count as treated, given they won a voucher. Despite their inclusion, the results are still significant.

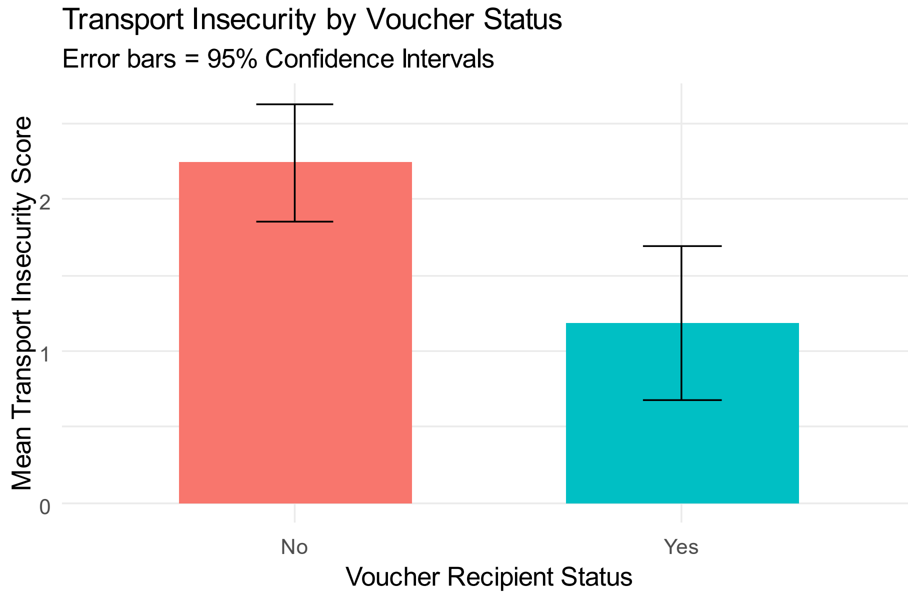


Figure 12: Differences in transportation insecurity between winners and non-winners in wave 3

We then compared changes in self-reported transportation insecurity scores between voucher winners and non-winners between waves 1 and 3. Voucher winners' transportation insecurity scores declined by 1.35, compared to a decline of just .40 in the control group. This difference was significant at the $p < .01$ level, and the changes for both groups are plotted in Figure 13.

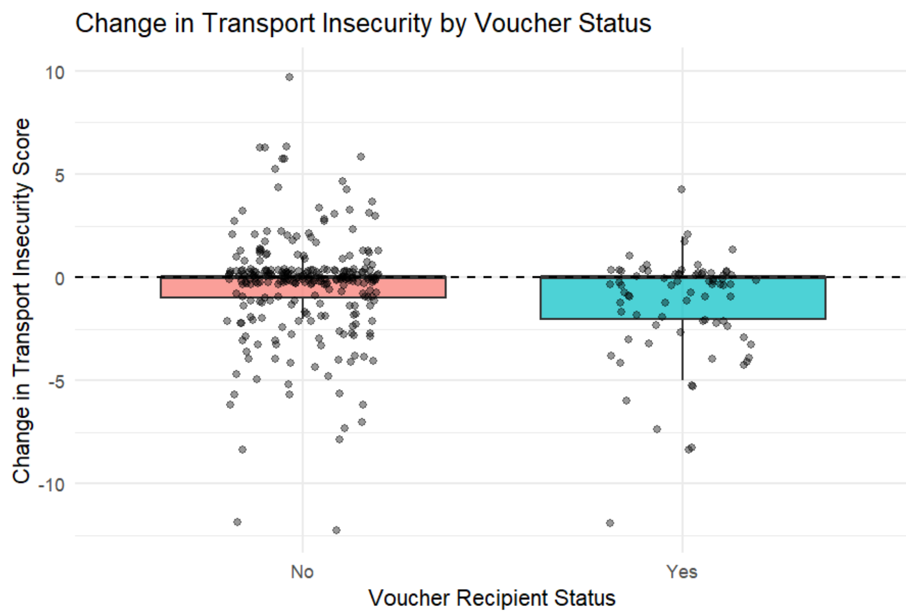


Figure 13: Changes in transportation insecurity levels between waves 1 and 3, by voucher status

These differences are uncontrolled, meaning we do not account for other factors that may affect respondents' score changes. Since the treatment was randomly assigned and we measure intent-to-treat (i.e., voucher awards) instead of actual treatment (i.e., e-bike purchase), this is arguably sufficient evidence to demonstrate that e-bike vouchers successfully reduce transportation insecurity levels among recipients. However, for robustness, we re-computed the analysis with a set of controls using a difference-in-difference regression.

E-bike purchase outcomes

The Ral-E-Bike vouchers were highly successful at getting people to purchase e-bikes. Among people who answered both Wave 1 and Wave 3, and did not own an e-bike during Wave 1, 82.4% of voucher recipients obtained an e-bike (*n*=68), while only 7.6% of non-recipients did (*n*=249). This difference is highly statistically significant ($\mathrm{p} < 10^{-15}$). This is our preregistered hypothesis, H1. This also indicates that the vouchers did not simply go to people who would have purchased e-bikes anyway, but had a meaningful impact on purchasing.

In the preregistration, we did not condition this hypothesis on not owning an e-bike in Wave 1, but our survey does not allow us to identify the purchase of an e-bike unless respondents did not already own an e-bike. A robustness check including those who already own an e-bike yields a similarly large and statistically significant result (82.8% vs. 11.5%, $\mathrm{p} < 10^{-15}$).

Travel outcomes

We evaluated changes in mode use as a result of receiving a voucher using the permutation-test method described above. This method works by computing the probability that a randomly selected voucher recipient would report biking more than a randomly-selected control group member. It then compares this probability with an expected value under the assumption that the voucher respondents are no different from the control group. This expected value will always be less than 50%, because some people reported biking the same amount (recall that biking is divided into a relatively small number of categories). For driving, transit, and walking, the test works the same way, with the direction of the comparison reversed – we evaluate the frequency with which the treatment group has *lower* use of that mode.

Results are shown in Table 1. For each wave and each mode, we present the observed value, the expected value if there were no differences between the treatment and control groups, and the p-value.

We first compared voucher recipients and non-recipients in Wave 1 to test for any pretreatment effects that could bias results. As expected, we see no statistically significant differences and conclude our sample is not significantly biased.

Table 1 Changes in mode use frequency, by wave, survey data

	Wave 1			Wave 2			Wave 3			
	Obs.	Exp.	p	Obs.	Exp.	p	Obs.	Exp.	p	Preregistered hypothesis
Bike	41%	37%	0.129	61%	37%	<0.001***	67%	37%	<0.001***	H3.1
Car	30%	33%	0.239	41%	35%	0.14	39%	34%	0.204	H3.2
Transit	29%	27%	0.167	28%	24%	0.079.	29%	26%	0.144	H3.3
Walk	37%	36%	0.651	43%	37%	0.099.	43%	37%	0.121	-

Post-treatment, however, we see a different story. In both Waves 2 and 3, voucher recipients are likely to report higher cycling frequency than non-recipients, and this difference is highly statistically significant. In both waves, between a randomly-selected voucher recipient and non-recipient, the recipient cycles more frequently in roughly 2/3 of cases. If there were no differences in cycling frequency between the groups, we would expect the voucher recipient to cycle more frequently in only 37% of cases (and to be tied in 26%).

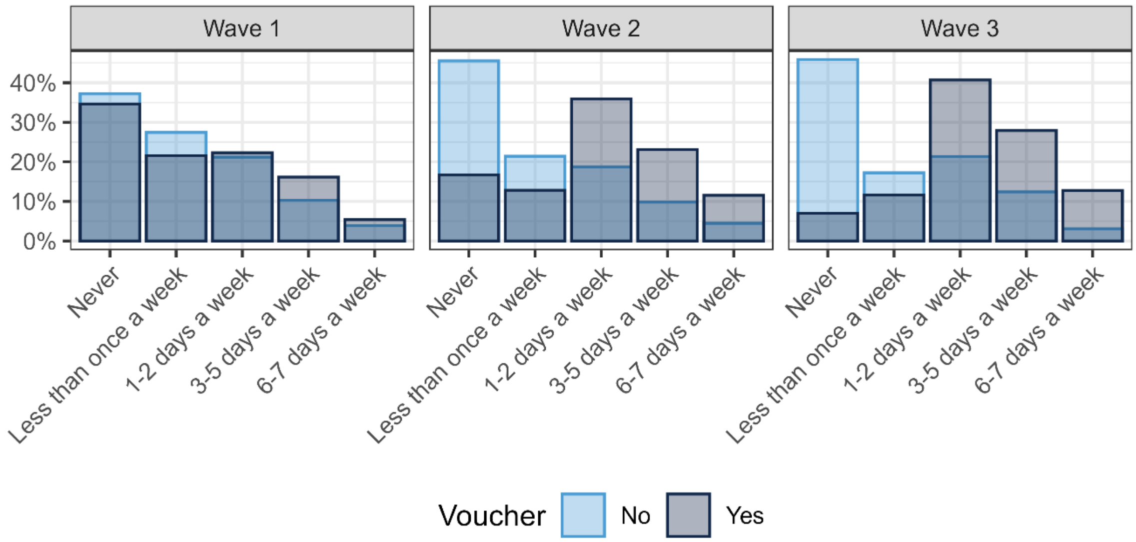


Figure 14: Relative frequency of cycling, voucher recipients vs. non-recipients

Figure 14 shows this graphically. In Wave 1, the distribution of cycling frequency is almost identical among voucher recipients and non-recipients, whereas in Wave 2 and especially Wave 3 is much higher among voucher recipients. In both waves, for non-voucher recipients, the modal frequency of cycling is 0, whereas it is 1-2 days a week for voucher recipients. The distributions do overlap somewhat, but this all-but-guaranteed with a constrained scale such as this and even large differences in mean are often associated with distributions that significantly overlap. Combined with the tests of statistical significance above, this is clear evidence that the program is remarkably effective at increasing cycling.

We see no statistically significant differences in driving, transit, or walking in any wave.

We were also curious if these results would be stronger for individuals who frequently travel to locations within four miles of their homes (H3.5). We repeated the same analysis for only those individuals who reported travel to such locations at least 3-5 days a week by any mode, or at least 1-2 days a week by two or more modes. The results were almost identical to those Table 1, so are not presented here for brevity; they are in the Appendix Table A 1.

Attrition

The key aspect of our research design that allows us to identify causal effects is the random assignment of recipients to vouchers. During Wave 1, respondents did not (with few exceptions) know whether they would be receiving a voucher, so there is no conceivable way the voucher recipients could differ from non-recipients. However, in Waves 2 and 3, they of course did, as these were post-treatment surveys. This does introduce one potential form of endogeneity into the treatment assignment in these waves: non-response. If the determinants of non-response differed for treatment and control group individuals *in a way correlated with our outcome variables, conditional on treatment,* this could lead to biased estimates.

In Wave 1, we measured all of our outcome variables. We also know that assignment to treatment or control is exogenous with respect to any variable measured in Wave 1, since assignment was done randomly after (almost all of) the Wave 1 survey was conducted. To test whether these outcome variables were associated with nonresponse in Wave 3, we estimated two logistic regressions predicting the probability of responding to Wave 3 for all Wave 1 respondents.

The first estimates the probability of response based on voucher receipt and the transport outcome variables tested in Table 1. Significant coefficients in this model are not problematic, as nonresponse being correlated with the outcome is only a problem if it affects the treatment and control groups *differently.* We then estimate a second model where we interact all of these transportation outcomes with voucher receipt.

We perform a likelihood-ratio test to determine if the interaction terms improve the fit of the model. This test finds no statistically significant difference in the effect of our outcome variables on nonresponse between the treatment and control group ($p=0.334$). Model output is shown in the Appendix Table A 2. Furthermore, none of the interaction terms are statistically significant at the $p<0.05$ level, and only one is at the $p<0.1$ level. Thus, we conclude that the results above do not suffer from non-response-induced endogeneity, and we can interpret the results as causal.

OpenPATH results

Tripmaking, overall and by mode

We hypothesized that receiving an e-bike voucher would result in more trips overall (H2) as well as more trips by bike/e-bike (H3.1), while it would result in fewer trips by other modes (H3.2-3.3). The OpenPATH data allows us to test these hypotheses directly by comparing average tripmaking per day by various modes between voucher recipients and nonrecipients.

Results from these tests are shown in Table 2**Error! Reference source not found.**, which shows the mean daily trips overall and by different modes, as well as the difference between the voucher and control group, and the results of a statistical significance test. The final column of the table identifies which of our preregistered hypotheses each row tests. Rows without a preregistered hypothesis are tests that were selected during analysis, and thus should be considered exploratory and tested by further data collection.

We first conducted the tests with Wave 1 data to confirm that there were no differences between voucher recipients and non-recipients pre-treatment. The sample for this is all individuals who used OpenPATH during Wave 1 and also answered the Wave 3 survey, whether or not they used OpenPATH in Wave 3 (n=14 voucher recipients and 65 non-recipients). Due to the timing of recruitment and vouchers, a small percentage of OpenPATH respondents in Wave 1 may have had their e-bikes for at least part of the data collection period. This makes the tests more conservative, as it could bias the results slightly towards the treatment outcome.

As expected, no differences are statistically significant at the p=0.05 level. We thus conclude that there are no pre-treatment effects, and we can interpret the Wave 3 effects as causal.

The second section of the table shows results for all Wave 3 OpenPATH respondents who met the inclusion criteria (n=34 voucher recipients and 76 non-recipients). We find that there is no statistically significant increase in overall tripmaking among voucher recipients.

Table 2 Tripmaking, overall and by various modes, voucher recipients vs non-recipients, OpenPATH data

	Trips per day		Difference				Preregistered
	Voucher	Control	Absolute	%	t-value	p-value	hypothesis
Wave 1							
Overall	3.77	3.68	0.09	2%	0.22	0.829	H2
Bike/e-bike	0.34	0.23	0.11	45%	0.73	0.476	H3.1
Car	2.31	2.38	-0.07	-3%	-0.23	0.818	H3.2
Transit	0.20	0.22	-0.02	-7%	-0.12	0.909	H3.3
Walk	0.91	0.79	0.12	15%	0.58	0.567	-
Transit/walk	1.11	1.01	0.10	10%	0.40	0.693	-
Motorized (transit/car)	2.51	2.60	-0.08	-3%	-0.33	0.746	-
Drive/walk/transit	3.42	3.38	0.03	1%	0.10	0.918	-
Wave 3							
Overall	4.32	4.21	0.11	3%	0.33	0.744	H2
Bike/e-bike	0.77	0.28	0.49	174%	3.16	0.003**	H3.1
Car	2.75	2.96	-0.21	-7%	-0.67	0.504	H3.2
Transit	0.13	0.14	-0.01	-9%	-0.14	0.886	H3.3
Walk	0.64	0.77	-0.13	-17%	-0.86	0.391	-
Transit/walk	0.76	0.91	-0.15	-16%	-0.75	0.457	-
Motorized (transit/car)	2.87	3.10	-0.22	-7%	-0.73	0.466	-
Drive/walk/transit	3.50	3.87	-0.37	-9%	-1.08	0.285	-

The effect of vouchers on bike and e-bikes is large and highly statistically significant; voucher recipients take 0.49 ± 0.31 more bike and e-bike trips per day, 174% higher than the control group. This is clear evidence of the program's efficacy. The program leads to more cycling, which has a slew of benefits for health, access to opportunities, and the local economy.

We do not see any statistically significant impact on walking, biking, or transit use, or on these modes collectively. However, an increase in tripmaking by bike must arithmetically mean either that tripmaking increased overall, or that use of other modes decreased.

Our interpretation of this is that the additional trips taken by e-bike are drawn relatively evenly from other modes and from an increase in tripmaking. This leads to relatively small differences in tripmaking or use of any individual mode-small enough that we are not able to detect a statistically significant effect given the sample size in this study. We see 7-17% drops in car, transit, and walking, as well as a 3% increase in overall tripmaking. We also tested combinations of modes, shown in the last three rows of the table, but did not find any statistically significant effects there either.

These results are consistent with those from the survey; clear evidence of an increase in biking, with no statistically significant results for other modes. However, while most of our tests across both the survey and OpenPATH data do not have statistically significant results, the results are all directionally consistent with our hypotheses. This suggests that the lack of statistical significance may be driven by our relatively small sample size. There is ample opportunity for future research to explore these questions with a larger sample size and more statistical power.

Vehicle kilometers of travel

Turning now to vehicle kilometers of travel (VKT), we hypothesized that voucher recipients would drive fewer kilometers than non-recipients. This hypothesis was not supported by the data; in Wave 3 there were no statistically significant differences in VKT. In wave 1, we see a large pre-treatment effect; it is marginally significant (p=0.07).

Table 3 Differences in VKT by voucher status, OpenPATH data, Wave 1 and 3

	Trips per day		Difference				
	Voucher	Control	Absolute	%	t-value	p-value	Preregistered hypothesis
Wave 1	30.05	42.02	-11.96	-28%	-1.88	0.069.	H3.3
Wave 3	48.63	44.63	3.99	9%	0.49	0.625	H3.3

Since vouchers were randomly assigned, this effect is likely due to chance. The main concern is that if voucher recipients truly did drive much less than nonrecipients pre-treatment, the Wave 3 results would be biased. We do not think this is the case. First of all, the samples are not identical; many of the Wave 3 OpenPATH users did not also use it in Wave 1, so we are not directly comparing the same individuals, but rather representatives of larger groups. Second, the sample sizes for Wave 1 are quite small, with only 14 voucher recipients. Means with small sample sizes are notoriously sensitive to outliers. The distributions of VKT for the voucher and non-voucher samples are presented in Figure 15; visually, the distributions look quite similar, save for outliers.

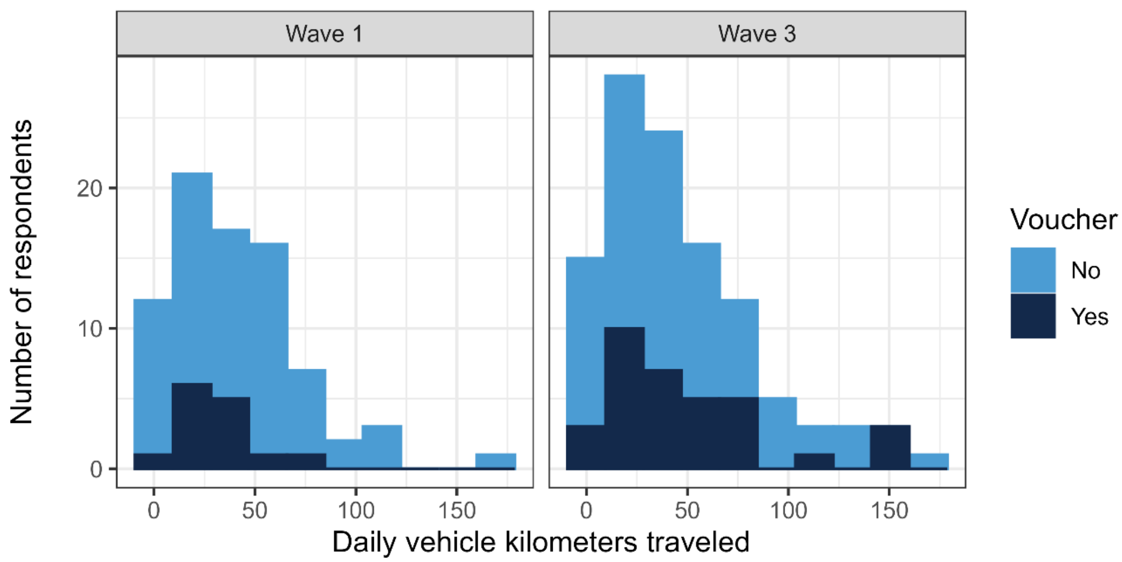


Figure 15: Average daily vehicle kilometers traveled for OpenPATH users, by wave and voucher status

Results for people who frequently visit destinations near their homes

For short trips, e-bike travel times are competitive with car travel times. In some cases, they may even be better than car travel times, as e-bikes are easier to park and can use greenway infrastructure that can be more direct than roads. Thus, we hypothesized that the results above might be stronger for only the subset of individuals who often travel to locations within four miles of home. After filtering to just those individuals who responded to wave 1 and reported travel to destinations within four miles at least a few days a week

(Wave 1 n=13 voucher recipients and 62 non-recipients, Wave 3 n=30 voucher recipients and 62 non-recipients), we repeated the analyses above. Results were effectively identical to those presented above. For this reason, we do not present the results here, but they are in the appendix (Table A 2 and Table A 4). The only remotely notable difference is that the pretreatment effect for VKT is marginally more significant.

Replaced modes

Whenever a respondent made a trip via e-bike and labeled it as such in the OpenPATH app, they were asked to also label how they would have made the trip if they had not had an e-bike. We evaluated this for three groups:

- People who already owned e-bikes when they took the Wave 1 survey (*n*=4 individuals, 246 trips);
- people who owned e-bikes when they took the Wave 3 survey, regardless of whether they received a voucher or purchased the bikes on their own (*n*=30 individuals, 375 trips); and
- people who did not have an e-bike when they took the Wave 1 survey and self-reported acquiring one using the voucher (*n*=19 individuals, 222 trips).

The modes people reported replacing are presented in Figure 16. Across all three groups, cars are the most common mode replaced, further suggesting that e-bikes may have a mode substitution effect. Other modes are reported as alternatives for fewer trips, and some trips would not have been made at all.

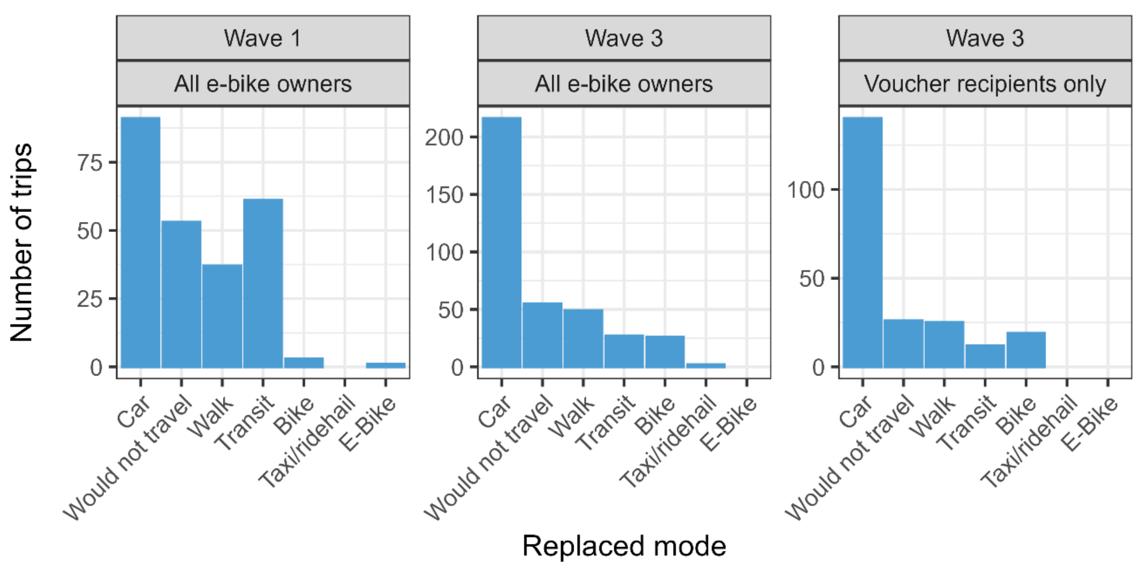


Figure 16: Modes replaced by e-bike trips, in different groups

We preregistered one hypothesis related to replaced modes: that people who do not have regular access to a car would be more likely to report that without the e-bike, they would not have made the trip at all. We divided each of the three samples described above based on whether they said they could drive one of their household vehicles without asking permission (for zero-car households, we inferred they could not). We then conducted a *z*-test for proportions to see if the proportion of trips that would not have been made without the e-bike was the same in the two groups.

Results are shown in Table 4. In the first two samples presented above, about 10% of e-bike trips made by respondents with easy car access would not have been made had the e-bike not been available. In contrast, 25-30% of e-bike trips made by respondents without easy car access would not have been made at all had it not been for the e-bike, suggesting that e-bikes are providing essential mobility for these populations. Both of these results are statistically significant.

Table 4 Replaced travel mode by car access

	Percent of trips where alternative was no travel		Sample size		
	Can drive without permission		Can drive without permission		
	Yes	No	Yes	No	p-value
Wave 1, All e-bike owners	11.11%	29.71%	3 / 108	1 / 138	<0.001***
Wave 3, All e-bike owners	10.83%	25.51%	25 / 277	5 / 98	<0.001***
Wave 3, Voucher recipients only	14.29%	0.00%	15 / 182	4 / 40	0.023*

The results for voucher recipients only, however, are completely the opposite. 14% of e-bike trips made by voucher recipients with car access would not have been made but for the e-bike. Among voucher recipients without car access, however, not a single trip would have been foregone without the e-bike. This difference is likewise statistically significant. This only represented 4 recipients, however. The statistical significance calculation does not account for clustering within individuals, so this may be a spurious finding as it has no theoretical justification. More research and data collection are needed.

Interview results

We begin by summarizing respondents' motivations for applying to the program, before turning to participants' experiences redeeming vouchers. Then we overview the barriers preventing e-bike users from replacing car trips, the mechanisms through which e-bikes address transportation insecurity, and advise the participants have for the city and others looking to implement similar programs.

Motivations for applying

The interviews reveal a range of reasons why participants applied for the e-bike voucher program. These motivations generally cluster into five major themes:

1. Reducing Car Dependence and Avoiding Parking Hassles

Many applicants wanted alternatives to driving, citing the desire to avoid traffic, parking issues, and reliance on a car for short trips. Living in dense or downtown areas made the appeal stronger:

> “I live downtown…people's biggest complaint about being in downtown Raleigh is that there's nowhere to park. And so if I could get to places without having to deal with parking…that was kind of the biggest motivation.” (E14)
>
> “We really don't need to be driving to about half the places…everything that we do is…within a couple of miles from our house.” (E1)

2. Health, Fitness, and Medical Reasons

Several respondents described health-related motivations, from maintaining general fitness to managing serious medical conditions. For some, an e-bike was a way to exercise within their physical limits:

> “The motivation is by biking…I can exercise, which is what is medically recommended for a person of my health issue…I credit the bike with keeping me engaged, keeping me active, and helping me with the health issues…” (E27)
>
> “I always thought that if I had an e-bike, it would be easier to…commute…because it's not as intense as riding a bike.” (E5)

3. Practical Utility and Everyday Errands

Applicants saw e-bikes as useful for errands, grocery trips, and transporting children, especially in hilly areas or where regular bikes felt impractical:

> "I just thought…will that make it even easier to do large grocery trips and things like that?" (E21)
>
> "I used to have a bike…we have a one-year-old son, and I always kind of wanted to get a trailer and take him around." (E28)

4. Affordability and Opportunity

Many people mentioned that they had long wanted an e-bike but could not afford one. The voucher provided a rare chance to obtain something aspirational:

> "I try to be…environmentally friendly…but I never could really afford an EV or an e-bike. So this just seemed like a good opportunity." (E17)
>
> "E-bikes easier and I can get where I'm going quicker…they're rather expensive, and the voucher gave me the ability to have a bike." (E18)
>
> "I really wanted [an e-bike] badly…that voucher situation popped up. I was like, wow." (E26)

5. Environmental and Community Values

A number of applicants were motivated by sustainability and the idea of supporting local programs to reduce car use and improve urban life:

> "I'm excited about this initiative…any initiative to get more people on bikes is exciting to me." (E13)
>
> "I was interested in seeing what kind of voucher I would get, what kind of assistance you would provide." (E30)

Additional Considerations

Several respondents also described practical benefits, such as arriving less sweaty at work (E15) or being able to keep up with family or friends who ride more often (E25, E27). Others applied simply because it was a low-risk opportunity they thought "can't hurt" (E23).

Overall, applicants combined practical, health, environmental, and affordability motivations, reflecting the multiple ways e-bikes can fill gaps in transportation and improve daily life.

Redeeming vouchers: smooth for most

Overall, participants' experiences redeeming vouchers fell into four broad themes: ease of process, delays and supply challenges, unexpected costs or eligibility confusion, and limited retailer options.

1. Generally Simple and Smooth Process

The vast majority of interviewees described the process as straightforward and positive, emphasizing how easy it was to get their bike:

> "Very easy, you know, I went to the store. They were very nice about everything, they explained it, and you know, pretty seamless." (E17)

> "It was pretty easy. They just sent me an email…I took it to the shop…they knew what was going on." (E14)

2. Delays and Inventory Shortages

Some participants reported challenges related to long waits and difficulty finding an in-stock bike. Some had to visit or call multiple stores, or wait months for orders to be fulfilled:

> "I pretty much went to almost all of them, and nobody had any bikes in stock…so you had to wait and wait." (E26)

> "I kept…waiting till I got word that they were in stock, and finally they called me, and they said, Hey, we have this one bike, do you want it?" (E5)

> "From the time I got the voucher or ordered it, it took like four months." (E23)

3. Unexpected Costs and Price Surprises

A couple of respondents were surprised by the required out-of-pocket expenses. They found that the voucher didn't fully cover the bikes they wanted, or learned later about taxes, accessories, or additional fees:

> "They were like, Yeah, you have to pay for the difference plus the tax, and then the accessories, the lock and all that…so it ended up being more than I thought." (E29)

> "If it wasn't on sale…I don't think I would have gotten it because it would have been too much." (E29)

4. Limited Choice of Retailers and Bike Types

Several participants described wishing there were more retailers to choose from or more flexibility in what qualified for redemption. A few expressed disappointment about not being able to apply the voucher to online retailers or other styles of bikes:

> "I had to go to a specific store, and the selection was kind of limited…I wish I could have used it elsewhere." (E18)

> "I was hoping…for more of a cargo bike, but there weren't really options." (E21)

Additional Considerations

A few respondents mentioned uncertainty about the timeline or felt that communication could have been clearer:

> "They sent me an email, but then I didn't hear anything for a long time…I wasn't sure if I was still approved." (E20)

Overall, while the vast majority of voucher winners found the redemption process smooth and appreciated the assistance, supply shortages, unanticipated costs, and limited choices posed challenges that delayed or complicated redemption for a small share of participants.

Why participants couldn't replace car trips

We asked participants if they were riding as much as they would like, and if not, why not. We also asked respondents to consider what trips they had and had not shifted from driving, and why. In response, they shared a nuanced picture of motivation, practicality, and constraint in their efforts to ride frequently and replace car trips. Their comments fell into six key themes.

1. Time Pressures and Competing Responsibilities

Many people described busy work schedules, caregiving duties, or school commitments that made it hard to ride as often as they hoped—even if they liked the bike and wanted to use it for more trips.

> "Um, school and work on top of that." (E4)

> "I think the biggest worry I have about the summer is that my work schedule is going to be crazy." (E14)

Even highly motivated riders said weekdays often defaulted to car trips simply because of time constraints:

> "If I have to be somewhere fast or I'm running late, I just get in the car." (E6)

2. Safety Concerns and Infrastructure Gaps

By far the most frequently cited deterrent to riding—and to replacing car trips—was concern about safety, particularly lack of separated bike lanes, dangerous intersections, and speeding drivers. Participants repeatedly emphasized that infrastructure determined whether they felt comfortable riding instead of driving.

> "Yeah, yeah, for sure, if there were a physical barrier between me and traffic, I would feel a lot better about it." (E17)

> "It's because there is some sort of law that says you can be on the street…but drivers get angry, they pass really close, and it's dangerous." (E27)

> "As far as infrastructure…if there was a dedicated bike lane, I would feel more comfortable riding more." (E25)

Several respondents explicitly said they would replace far more car trips if they felt safer:

> "I think that first we'll have to have bike lanes and make it safer, so you don't feel like you're risking your life." (E27)

3. Trip Characteristics and Practical Suitability

Even when infrastructure was acceptable, respondents noted that some trips were simply more suited to driving, especially those involving heavy loads, multiple stops, or very long distances:

> "I think probably more…the E bike is good for certain trips, but it's not as convenient when I have to carry a lot." (E24)

> "When I go to the supermarket, I never use the bike because there are too many bags." (E27)

Others mentioned that their neighborhood or regional geography made some trips impractical:

> "Where I live, a lot of things are still too far for me to bike every day." (E14)

4. Weather and Seasonal Variation

Several respondents highlighted that rain, heat, and cold significantly constrained usage, limiting both recreation and utilitarian trips:

> "Yeah, I don't know. Maybe because it's summer and it's been so hot." (E23)

> "When it rains, I'm not going to ride it." (E20)

5. Confidence and Personal Adaptation

A few participants shared that getting used to the bike, building confidence, or overcoming fear after falls had shaped their usage patterns:

> "I fell once, so now I'm a little hesitant to ride as much." (E22)

> "I guess part of it is just me getting used to it…it's new, and I haven't figured out how to make it a routine." (E7)

At the same time, some riders said they had become more confident over time, replacing more trips:

> "Yeah, no, for sure, like, I think I could replace almost all my short car trips. I just need to get used to it." (E2)

6. Habitual Car Use and Convenience Defaults

A final group of comments highlighted the inertia of car habits and the ease of defaulting to driving, even when the e-bike was available:

> "I guess from personal experience…because I'm used to driving all the time, sometimes I just automatically take the car." (E20)

> "It's easier to just hop in the car if I'm tired." (E6)

> "I usually walk my bike over to the light, but sometimes if there's no crosswalk, I just end up driving." (E14)

Positive Experiences and Consistent Riders

Importantly, several participants described using the e-bike frequently and successfully replacing many car trips:

> "I'm not going to stop riding my bike. I love it." (E22)

> "I ride it pretty much every day." (E19)

> "Obviously, a lot of trips I would take the car for, now I take the e-bike." (E13)

For these riders, the bike fit their routines well, and they expressed enthusiasm about reducing driving.

Summary

Across all interviews, the most significant factors limiting e-bike use and car trip replacement were:

- Time constraints and busy schedules
- Safety fears related to infrastructure
- Weather conditions
- Practical limitations for some errands
- Confidence and familiarity
- The convenience of ingrained car habits

Conversely, when infrastructure was safe, trips were manageable, and riders felt confident, many described frequent e-bike use and substantial replacement of car trips. This highlights that supportive infrastructure, better trip planning, and ongoing encouragement could help bridge the gap between intention and daily behavior.

Mechanism through which e-bike ameliorate transportation insecurity

Participants described how the e-bike transformed their daily lives by relieving mobility struggles, lowering expenses, enabling a greater sense of independence, and providing unexpected benefits. Their stories highlight how a simple technology can create cascading impacts.

Pre-E-Bike Mobility Challenges

Many respondents faced significant barriers to getting around before receiving the e-bike, including unreliable cars, high transportation costs, limited transit access, and health constraints. For some, driving felt like a financial burden or a logistical hassle:

> "I do, but I just—my insurance just lapsed on my car. So I've been either taking the bus or borrowing a car." (E1)

> "For transportation, I mean…the locations I work are just not walkable, so I would have had to keep paying for Ubers or buying another car." (E17)

Others described how even short trips felt exhausting or impractical without a car:

> "My commute is three miles each way, and then I go to the gym after. So sometimes it just felt like too much to do by regular bike." (E23)

Saving Money Through E-Bike Use

For many, financial relief was one of the most immediate benefits. Respondents emphasized spending far less on gas and parking, and in some cases, avoiding car repairs or insurance:

> "I've maybe only put gas in that car once or twice since I got the bike." (E24)

> "I don't have to fill up the tank every week anymore." (E23)

Some even described the e-bike as pivotal in helping them remain financially stable and depending less on others for rides:

> "And so it actually, like, has replaced a lot of my car rides, which is funny, because obviously that was the intention, but was just not. I wasn't expecting it to, like, do that for me. And then I almost didn't even use the voucher, like I almost sent it back, because I was like, I don't know if I want to spend money on this. And then I'm so glad that I did." (E13)

Greater Sense of Security and Independence

Several participants said they now felt more secure and independent because they had an option other than walking or relying on others:

> "I'd say more secure because sometimes when I was walking, I was worried about time or getting caught out in the dark." (E6)

> "I would say it feels more secure now." (E10)

For some, the e-bike offered a backup plan when other transportation failed:

> "So I do have a car, but I have to put it in the shop sometimes, and I don't feel stuck now." (E29)

Unexpected Benefits and New Routines

Beyond overcoming challenges and saving money, many participants reported unexpected positive impacts: improved health, more recreation, and a stronger connection to their neighborhoods. Some mentioned riding simply because it felt good:

> "I would consider it part of my health routine. I don't even really think of it as just transportation anymore." (E22)

> "I guess recreation a little bit. I've ridden bikes before, but this is the first time I really used one for fun." (E24)

A few people were surprised at how seamlessly the bike integrated into daily life:

> "Not really. I mean, it just kind of fit right in. I didn't expect it to be so easy." (E21)

Others noted that having an e-bike even influenced their mindset:

> "It always encourages me to go a little farther or take a route I wouldn't have tried." (E26)

> "I really didn't expect for it to improve aspect or, like, my quality of life and the ways that it has, and that's been such a pleasant surprise." (E13)

Strengths, Improvements, and Advice for Other Cities

We asked voucher winners what advice they would give the City of Raleigh to promote cycling, to improve the e-bike voucher program. We also asked them what advise they would give other cities considering a similar program. Participants offered detailed feedback spanning three dimensions: what they appreciated, what needed refinement, and their broader recommendations to promote cycling and design effective e-bike voucher programs.

Program Strengths and Positive Experiences

A majority of respondents praised the simplicity and clarity of the program, especially compared to other assistance efforts:

> "No, not really. I thought the whole process was super easy." (E16)

> "Just making transportation easier for me." (E4)

People appreciated the speed of communication and the feeling that the program was designed for real people rather than bureaucratic hurdles:

> "I think that now, especially now that I have the bike, I just appreciate that it didn't feel like a lot of red tape." (E17)

Suggestions to Improve Program Administration

Nonetheless, participants offered constructive feedback on how to make the program smoother and more equitable. Three themes recurred:

1. Clearer Information and Guidance

Several participants said they wished for better upfront information about eligible bike models, participating shops, and expected costs:

> "I did have to do a lot of research on what was qualified, what shops to go to, and I felt like I was guessing." (E6)

> "It was, I thought, more of the people that were doing it were left to figure out a lot on their own." (E22)

2. Improved Communication During the Process

Some respondents described periods of uncertainty after applying:

> "I would maybe just suggest better updates…like I didn't know if I was approved or how long it would take." (E30)

3. Expanded Retailer and Bike Options

Participants wished for more participating retailers, more cargo and adaptive bike choices, and better accommodation for diverse needs:

> "Maybe that they, I would promote that there was more variety…more shops to choose from." (E2)

> "I know for my bike, something that I didn't realize is that it's really hard to get parts or service locally." (E17)

Advice to Other Cities Considering Similar Programs

Respondents emphasized that other cities should think beyond just vouchers and focus on creating a supportive environment for riding. Four insights stood out:

1. Pair Subsidies with Infrastructure Improvements

Many stressed that safe bike lanes and protected routes were critical to make the investment meaningful:

> "If you're going to give people e-bikes, you have to make sure there's infrastructure that makes them feel safe using them." (E23)
>
> "Otherwise, you're going to get people to buy the bikes, but they won't ride them as much." (E17)

2. Make Equity and Inclusion Central

Participants urged that cities prioritize outreach and support for lower-income residents, those without cars, and people with disabilities:

> "I think more outreach to people who don't have any other transportation would be huge." (E22)
>
> "And maybe more adaptive bike options for people who can't ride a standard frame." (E30)

3. Build in Education and Support

Several recommended including training or orientation sessions to help new riders feel comfortable:

> "I would also say maybe classes or workshops on maintenance, because that was the hardest part for me." (E14)
>
> "Make sure people know how to lock it up safely and charge it." (E20)

4. Emphasize Community and Storytelling

A few noted the power of sharing success stories and building a sense of shared mission:

> "Just saying, like, we're basing this off of the success here, we saw how many people got out of cars, how much gas was saved—tell that story." (E30)

General Advice to Promote Cycling in the Community

Beyond program design, participants shared broader thoughts about how cities can encourage cycling culture overall:

- Improve infrastructure: especially protected lanes, better crossings, and bike parking.
- Educate drivers to respect cyclists.
- Create incentives for employers to support bike commuting.
- Ensure long-term support for maintenance and accessories.

Summary

Participants were overwhelmingly positive about the program's goals and impact. However, their advice underscores that vouchers alone are not enough: cities also need safe infrastructure, clear communication, inclusive outreach, and community support to ensure e-bikes become a sustainable, everyday part of people's lives.

Advice to future voucher winners

Finally, we asked respondents what advise they would give to a friend who won an e-bike voucher in a hypothetical future round. When asked, respondents offered practical tips, mindset advice, and reminders about safety and preparation. Their suggestions clustered into four main themes.

1. Choose the Right Bike for Your Needs

The most common advice was to take time to research different bike models and think carefully about how you'll use the e-bike—whether for commuting, errands, or recreation:

> "I would tell them to really look at what they're going to use it for." (E19)
>
> "Well, different bikes have different feels…like the frame is important, how it fits you." (E18)

A few emphasized considering foldable bikes or cargo capacity:

> "Foldable is good. Make sure…it fits your lifestyle." (E23)

2. Prioritize Safety and Visibility

Many respondents underscored the importance of buying good lights, wearing bright clothing, and taking extra precautions when riding in traffic:

> "Yeah, so I would recommend as many visibility things as possible." (E15)

> “UL listed…for safety.” (E22)

A few also encouraged friends to practice in low-traffic areas first to build confidence.

3. Be Patient and Grateful

Some shared encouragement about enjoying the process and appreciating the opportunity:

> “Advice…be thankful for what you have.” (E18)

> “Take your time getting used to it.” (E16)

4. Understand the Redemption Process and Logistics

Finally, respondents recommended preparing for the practical aspects of redeeming the voucher, such as budgeting for accessories, understanding what’s included, and clarifying shop policies:

> “Explain that to the new person that was here…just so they know what to expect.” (E22)

> “I would say figure out where you’re going to buy it and what’s in stock.” (E19)

Summary

Overall, participants encouraged friends to do their homework, think carefully about safety and fit, and approach the experience with openness and gratitude. Their collective advice reflected both the excitement and the learning curve of owning an e-bike.

Conclusions

The Raleigh e-bike voucher program demonstrates the substantial promise—and limits—of financial incentives as a tool to increase e-bike adoption and improve mobility. The program’s randomized design provided rare causal evidence that e-bike vouchers can dramatically accelerate uptake: over 80% of voucher recipients acquired an e-bike compared to less than 10% of non-recipients. These new owners substantially increased their cycling frequency, confirming that financial cost remains a primary barrier to e-bike access.

Importantly, the program measurably reduced transportation insecurity among recipients. The decline in transportation insecurity scores suggests that e-bikes provided many participants with a new sense of control over their daily travel and improved their ability to meet essential needs independently. This benefit was especially significant for applicants without cars or with constrained budgets, aligning with the broader transportation goals motivating such programs.

At the same time, results show that increased e-bike ownership does not automatically translate into consistent car trip replacement or reductions in VMT. While e-bike use surged, the effects on driving and transit were modest and statistically insignificant. Interview data highlight why: many participants still faced barriers—particularly a lack of safe infrastructure, time constraints, and habitual car use—that limited mode shift.

Policy recommendations / Implementation plan

1. Pair or align voucher programs with infrastructure investment

   Cities may find greater benefits from programs if they are implemented alongside or just after investments in new cycling infrastructure or greenways, such as Vision Zero implementation programs. Providing education to program participants on the new infrastructure might increase their utilization and support mode shift.

2. Prioritize zero-vehicle households, older adults, and people with disabilities

   If legally possible, agencies could limit eligibility to individuals who do not have a vehicle registered in their name, or target outreach to communities where individuals are less likely to own vehicles. These participants saw the greatest improvements in quality of life. Older adult recipients also found e-bikes enabled them to ‘keep up’ and participate in cycling with younger family members, and also disproportionately benefited.

3. Explore public health funding sources

   While our results on mode shift are mixed, this natural experiment provides strong evidence that e-bike vouchers increase cycling rates. People who win vouchers use their e-bikes significantly more than pre-intervention and compared to the control group. The public health benefits may justify greater public investment. Government agencies should consider partnering with local health insurance providers and area employers to promote e-bikes among providers’ clients and employees.

4. Consider longer voucher redemption windows

   Some respondents could not save up enough money to purchase a suitable e-bike with their voucher as they received notice shortly after the winter holidays. Individuals for whom price is a barrier will still need time to save up additional funds, even with a voucher, if they are seeking an e-bike that meets particular needs, like carrying cargo. A longer redemption window can help these respondents take advantage of the program. Alternatively, consider partnerships with local credit unions to provide financing for participants with very low incomes.

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Appendix

Table A 1 Changes in mode use, from survey data, for respondents regularly traveling to destinations within 3 miles of home

	Wave 1			Wave 2			Wave 3			
	Obs.	Exp.	p	Obs.	Exp.	p	Obs.	Exp.	p	Preregistered hypothesis
Bike	41%	37%	0.24	60%	38%	<0.001***	67%	37%	<0.001***	H3.1
Car	31%	33%	0.484	42%	35%	0.099.	40%	34%	0.162	H3.2
Transit	30%	27%	0.146	30%	25%	0.071.	28%	26%	0.315	H3.3
Walk	37%	36%	0.791	43%	37%	0.139	45%	37%	0.058.	-

Table A 2 Attrition models

	Model 1			Model 2		
Characteristic	**OR**	**95% CI**	**p-value**	**OR**	**95% CI**	**p-value**
Voucher						
FALSE	—	—		—	—	
TRUE	1.78	1.20, 2.65	0.004	6.55	0.55, 97.8	0.15
Walk/run						
1-2 days a week	—	—		—	—	
3-5 days a week	1.10	0.73, 1.66	0.7	0.98	0.62, 1.53	>0.9
6-7 days a week	1.15	0.75, 1.78	0.5	1.05	0.65, 1.70	0.8
Less than once a week	1.39	0.77, 2.54	0.3	1.46	0.76, 2.82	0.3
Never	1.28	0.50, 3.35	0.6	1.15	0.34, 3.77	0.8
Bike/e-bike						
1-2 days a week	—	—		—	—	
3-5 days a week	0.81	0.46, 1.42	0.5	0.93	0.48, 1.78	0.8
6-7 days a week	1.42	0.60, 3.36	0.4	1.21	0.45, 3.14	0.7
Less than once a week	1.22	0.79, 1.89	0.4	1.37	0.85, 2.22	0.2
Never	1.08	0.72, 1.63	0.7	1.35	0.86, 2.13	0.2
Car						
1-2 days a week	—	—		—	—	
3-5 days a week	1.17	0.68, 2.01	0.6	1.17	0.64, 2.14	0.6
6-7 days a week	0.90	0.53, 1.53	0.7	1.01	0.56, 1.84	>0.9
Less than once a week	0.49	0.19, 1.21	0.13	0.51	0.17, 1.43	0.2
Never	0.82	0.36, 1.82	0.6	0.95	0.40, 2.27	>0.9

Transit						
1-2 days a week	—	—		—	—	
3-5 days a week	1.38	0.55, 3.46	0.5	1.48	0.54, 4.03	0.4
6-7 days a week	1.28	0.47, 3.48	0.6	1.33	0.45, 3.92	0.6
Less than once a week	1.21	0.61, 2.44	0.6	1.34	0.62, 2.95	0.5
Never	1.47	0.79, 2.79	0.2	1.69	0.85, 3.48	0.14
Voucher * Walk/run						
TRUE * 3-5 days a week				2.54	0.77, 8.69	0.13
TRUE * 6-7 days a week				1.92	0.54, 7.02	0.3
TRUE * Less than once a week				1.18	0.22, 6.40	0.8
TRUE * Never				3.18	0.38, 30.7	0.3
Voucher * Bike/e-bike						
TRUE * 3-5 days a week				0.61	0.14, 2.57	0.5
TRUE * 6-7 days a week				21.5	0.75, 2,615	0.12
TRUE * Less than once a week				0.59	0.16, 2.19	0.4
TRUE * Never				0.35	0.10, 1.16	0.090
Voucher * Car						
TRUE * 3-5 days a week				0.75	0.15, 3.48	0.7
TRUE * 6-7 days a week				0.42	0.09, 1.76	0.2
TRUE * Less than once a week				0.11	0.00, 2.81	0.2
TRUE * Never				0.11	0.00, 2.04	0.2
Voucher * Transit						
TRUE * 3-5 days a week				2.64	0.09, 175	0.6
TRUE * 6-7 days a week				1.05	0.02, 91.8	>0.9
TRUE * Less than once a week				0.49	0.05, 3.74	0.5
TRUE * Never				0.42	0.05, 2.64	0.4
Log-likelihood	-483			-474		

Abbreviations: CI = Confidence Interval, OR = Odds Ratio

Table A 3 Tripmaking, overall and by mode, from OpenPATH data, using only respondents who report often traveling within 4 miles of home

	Trips per day		Difference				
	Voucher	Control	Absolute	%	t-value	p-value	Preregistered hypothesis
Wave 1							
Overall	3.86	3.86	0.00	-0%	0.00	0.999	H2
Bike/e-bike	0.37	0.24	0.12	50%	0.78	0.443	H3.1
Car	2.31	2.50	-0.19	-8%	-0.61	0.548	H3.2
Transit	0.22	0.24	-0.02	-9%	-0.14	0.894	H3.3
Walk	0.95	0.82	0.13	16%	0.60	0.555	-
Transit/walk	1.17	1.06	0.11	10%	0.40	0.69	-
Motorized (transit/car)	2.53	2.74	-0.21	-8%	-0.78	0.444	-
Drive/walk/transit	3.48	3.56	-0.08	-2%	-0.23	0.819	-
Wave 3							
Overall	4.36	4.29	0.06	1%	0.17	0.863	H2
Bike/e-bike	0.85	0.31	0.54	174%	3.13	0.003**	H3.1
Car	2.73	2.98	-0.25	-8%	-0.71	0.477	H3.2
Transit	0.14	0.16	-0.02	-15%	-0.23	0.816	H3.3
Walk	0.58	0.78	-0.20	-26%	-1.31	0.194	-
Transit/walk	0.72	0.94	-0.22	-24%	-1.07	0.287	-
Motorized (transit/car)	2.87	3.14	-0.27	-9%	-0.81	0.42	-
Drive/walk/transit	3.45	3.92	-0.47	-12%	-1.25	0.214	-

Table A 4 Vehicle kilometers traveled, for people who report frequently traveling to locations within four miles of home

	Trips per day		Difference				
	Voucher	Control	Absolute	%	t-value	p-value	Preregistered hypothesis
Wave 1	29.39	45.27	-15.88	-35%	-2.33	0.026*	H3.3
Wave 3	45.78	46.13	-0.35	-1%	-0.04	0.968	H3.3