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The Future of E-Bikes on Public Lands: A Human Factors Field Study at Minute Man National Historical Park

Final Report

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<tr><td colspan="4">16. Abstract
Electric-assist bicycles (e-bikes) are growing in popularity, and their use has increased on public lands managed by federal, state, and local agencies. Evaluation of e-bike use on public lands is hindered by a dearth of scientific research. This paper presents the results of a human factors field study that evaluated participant speed and behavior on an unpaved, multiuse trail to answer research questions about trail user safety and social interaction. The study concludes that e-bike riders travel approximately one to two mph faster than conventional bike riders on average, but that individual speeds among conventional and e-bike riders are largely distributed and overwhelmingly overlap. The study also found conventional and e-bike riders generally reduce speed in areas of potential conflict and exhibit similar precautionary behaviors when passing other trail users and crossing trail junctions and vehicle paths.</td></tr>
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INTRODUCTION

Electric-assist bicycles (e-bikes) are growing in popularity, and their use has increased on public lands managed by federal, state, and local agencies. Agencies seek to manage different uses on public lands by evaluating their potential for positive benefit or negative impact. There is a growing body of literature on e-bike trends, impacts, and opportunities, particularly in the urban context and considering their use as a transportation mode (*1*). However, agency evaluations of e-bike use are hindered by a dearth of scientific research into the opportunities and challenges focused on e-bike use on public lands.

In 2020, the Federal Highway Administration (FHWA) Innovation Research Council (IRC) sponsored research into the use of e-bikes in public lands to help address this need. Western Federal Lands Highway Division (WFL) provided funding to the U.S. DOT Volpe Center (Volpe) and oversaw the research project. FHWA and Volpe published a report documenting the state of research in November 2022 (*2*). The report is organized into four categories of consideration: Ecological/Cultural/Historical, Social, Safety, and Management Processes. The team collaborated with land managers and stakeholders to develop 60 research questions that aim to capture the universe of information needed to make informed decisions about e-bike policies on public lands. The literature includes partial answers to many of these questions, but numerous research gaps remain.

To begin addressing gaps in the literature, Volpe conducted a human factors field study to develop a novel, replicable study protocol and apply it to a local public land to collect primary data that addresses two key research questions:

1. Safety Considerations: Does rider behavior (average speed, passing other trail users, yielding to other trail users, etc.) in a public lands setting differ between e-bike and conventional bike riders?

2. Social Considerations: Does average speed, passing behavior around other trail users, yielding behavior related to other trail users, etc., create problems or provide benefits to others traveling by different modes?

This report documents the protocol, analysis methods, results interpretation, and conclusions of this human factors study.

FIELD STUDY DESIGN

Study Setting

Volpe conducted the field study on the Battle Road Trail between Meriam's Corner and Fiske Hill Loop at Minute Man National Historical Park in Concord, MA. Figure 1 shows a photograph of the setting of the trail, and the route is mapped in Figure 2. This segment of the Battle Road Trail is an unpaved, multiuse path that caters to park visitors of all ages for walking, running, and bicycling. The trail is not an accessible route of travel for people with limited mobility and recreational horseback riding is prohibited throughout the park. The National Park Service allows park superintendents to manage the use of bicycles and e-bikes (*4*). Park rules at Minute Man permit bicycles, including pedal-assist e-bikes, on all park roads and trails (*5*).

Figure 1: Battle Road Trail at Minute Man National Historical Park (*3*).

This segment of the Battle Road Trail exhibits varied conditions, including a number of winding turns, narrow and wide sections, elevation changes, and a mix of crushed stone, dirt, and gravel surfaces. The total length of the trail segment that participants rode is approximately 4 miles in each direction, has 380-feet net elevation gain, and has a maximum slope of six percent. Portions of the Battle Road Trail cross roadways and driveways and intersect with other trail segments; these locations required participants to negotiate interactions with other trail and road users, including people driving vehicles. These conditions allowed the study team to investigate context-specific behavior among participants.

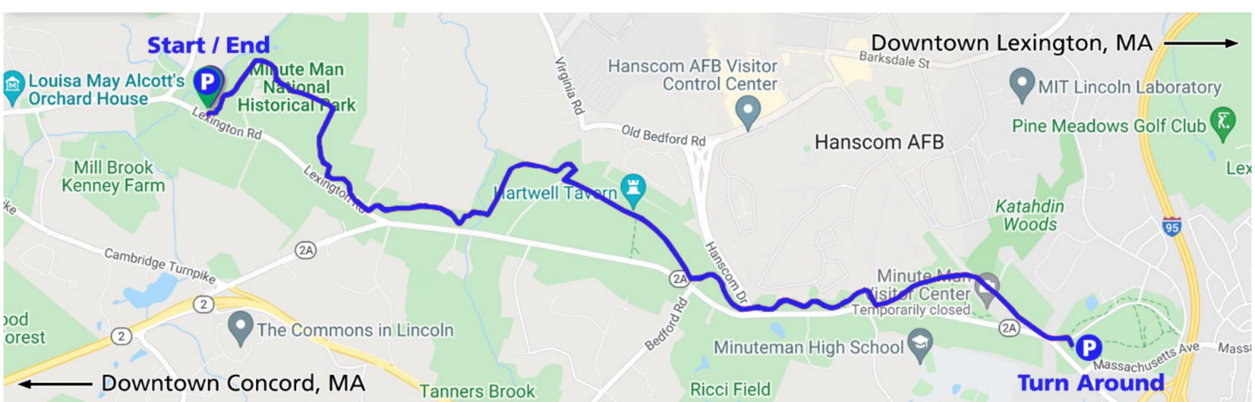

Figure 2: Battle Road Trail field study route.

Participant Recruitment

The study team recruited participants between April and September 2022, with participants completing their rides on a rolling basis. The study team placed posters in bike shops throughout the greater Boston area and distributed a weblink via bicycling-related social media and newsletters.

The study team vetted adult cyclists between 18 and 65 years of age, aiming to recruit roughly equal sized groups of conventional bike and e-bike riders. Participants needed to use their own bicycles and be capable of riding on an unpaved, multiuse trail with grade changes, obstacles, and other trail users. The study team implemented these participant requirements to attract riders that would exhibit behavior typical of local trail users who are comfortable with riding on this kind of facility. The study team avoided novice riders and riders without their own bicycle, as they would likely not represent the typical behavior of experienced riders – the type of riders who generally frequent this trail.

This study recruited a total of 37 riders, including 19 conventional bike riders and 18 e-bike riders. See Table 1 for a matrix of all participants. Some of the 37 riders were ultimately excluded from the analysis. Three of the recruited participants did not complete the study within the allotted time. Eight other participants did not record suitable GPS tracks due to equipment issues and/or user error. In total, the study team included 26 participants' data in the analysis. See Figure **3** for a summary of these 26 participants by sex and bicycle type.

Human factors studies rely on relatively small numbers of voluntary participants. The study team acknowledges that the 26 participants whose data were analyzed for this study do not necessarily constitute a statistically representative sample of all bike riders. Indeed, different contexts would likely attract different "typical" trail users. The limited number of participants in this study, the requirements for participating, and recruitment methods likely influenced group composition and may have introduced some unknown biases.

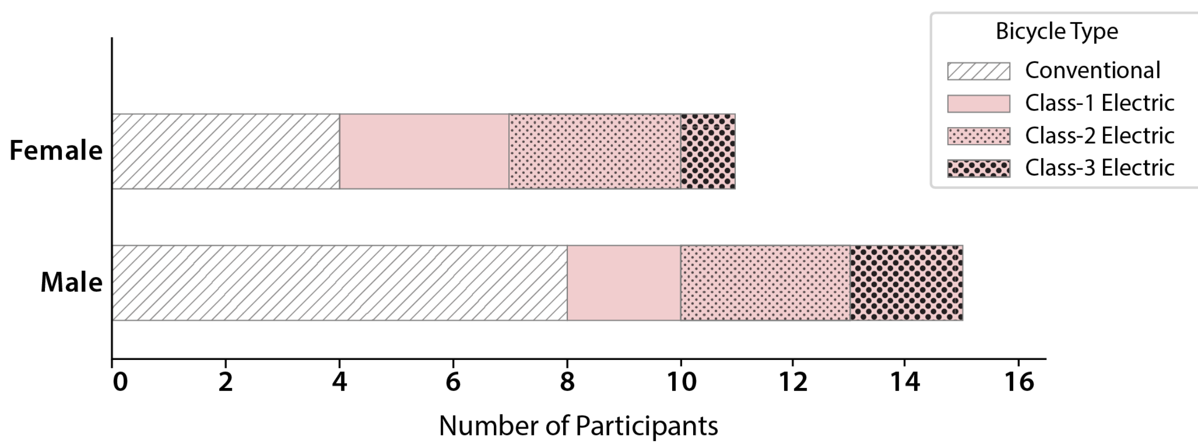

Figure 3: Distribution of 26 study participants with suitable data for analysis, grouped by self-reported sex and bicycle type.

Table 1. Participant Characteristics.

#	Age (yrs)	Sex	Bicycle Type	Class (E-Bikes Only)	Number of GPS Pings (Raw)	Number of GPS Pings (After Filtering)	Notes
1	65	Male	Conventional	n/a	37,465	36,861	
2	33	Female	Conventional	n/a	25,652	24,581	
3	34	Male	Conventional	n/a	20,929	392	
4	61	Male	Electric	Class 3	660	502	
5	36	Female	Electric	Class 1	38,019	36,535	
6	37	Female	Conventional	n/a	426	224	
7	42	Male	Conventional	n/a	22,156	19,680	
8	27	Female	Conventional	n/a	16,372	13,562	
9	37	Male	Conventional	n/a	1,858	0	GPS recording error
10	56	Male	Electric	Class 3	71	0	GPS recording error
11	25	Male	Electric	Class 3	0	0	Study not completed
12	33	Female	Electric	Class 2	34,116	29,918	
13	37	Male	Electric	Class 2	0	0	Study not completed
14	37	Male	Electric	Class 1	39,085	18,864	
15	33	Male	Electric	Class 2	18,215	17,942	
16	36	Male	Electric	Class 1	4,217	3,287	
17	52	Female	Conventional	n/a	0	0	GPS recording error
18	56	Male	Conventional	n/a	0	0	GPS recording error
19	35	Female	Electric	Class 2	17,670	17,254	
20	57	Male	Conventional	n/a	0	0	GPS recording error
21	38	Female	Electric	Class 1	16,716	15,898	
22	35	Female	Conventional	n/a	0	0	GPS recording error
23	34	Male	Conventional	n/a	22,422	21,734	
24	65	Male	Conventional	n/a	50,742	30,251	
25	51	Female	Electric	Class 3	20,240	19,788	
26	40	Male	Conventional	n/a	29,900	29,254	
27	41	Female	Conventional	n/a	0	0	GPS recording error
28	27	Male	Conventional	n/a	4,564	3,521	
29	35	Male	Conventional	n/a	0	0	Study not completed
30	47	Male	Electric	Class 2	0	0	GPS recording error
31	65	Male	Electric	Class 3	1,780	1,064	
32	63	Female	Conventional	n/a	36,242	34,977	
33	31	Male	Conventional	n/a	16,393	16,209	
34	59	Female	Electric	Class 1	7,358	7,211	
35	29	Male	Electric	Class 2	3,426	2,286	
36	40	Male	Electric	Class 2	4,901	3,532	
37	42	Female	Electric	Class 2	5,543	3,036	

Instructions to Participants

Participants received a GoPro Max 360-degree video camera and bicycle handlebar mount, completed an informed consent form, and provided voluntary demographic, bicycle type, and riding history information. The study team trained participants to install and operate the camera themselves. Each participant was guided through a practice ride using the camera with video and audio recording enabled and was given nine days to complete the route on their own. The study team then reviewed the route with the participant and answered any clarifying questions.

The study team did not provide details about the study's research questions to avoid influencing participant behavior during their ride. Participants were asked to ride the trail as they would under normal circumstances.

Figure 4 shows two still views from the GoPro 360-degree video, illustrating the capabilities of the video to reveal a forward view that simulates the rider's vantage point (top), or to reveal a wider view of the rider and their surrounding area (bottom). A presentation video (https://vimeo.com/741907069) illustrates how the 360-degree video affords observation of different aspects of the scene around the rider, which was important for the study team's analysis.

Figure 4: Still images from a demonstration 360-degree video recording.

GEOLOCATION ANALYSIS

The primary goal of this study was to identify whether speed and behavioral differences exist between conventional and e-bike riders on unpaved, multiuse trails of this type. Rather than evaluate average speed and behavior across the entire study corridor, Volpe designed this field study to conduct specific analyses within key contexts that repeated along the trail. This method sought to increase the precision of the findings and the value for land managers seeking to apply the findings to their own trail networks. The study team identified five different contexts – *designated segment types* – where increased rider speed and certain rider behaviors would increase the risk of conflicts or crashes, and/or be considered impolite or disrespectful to other trail users.

These categories are:

- *Blind Turns*: Changes in trail direction where vegetation or other obstacles visually obscure on-coming trail users.
- *Narrow*: Areas where vegetation, trees, rocks, and other natural or manufactured obstacles like boardwalks constrict the trail width.
- *Trail Hazards*: Locations where vegetation, trees, rocks, and other natural or manufactured obstacles appear erratically within the trail, requiring trail users to navigate around or over them.
- *Trail Junctions*: Locations where the trail branches or intersects to connect with other trail spurs.
- *Vehicle Conflict Points*: Locations where the trail crosses designated vehicle paths, such as roadways and driveways.

Trail obstacles and narrowed segments reduce space for maneuvering, visual obstructions shorten reaction time, and merge/crossing locations are more likely than other segments to introduce conflicts. Focusing data collection and analysis on this subset of designated segments means the conclusions of this study should better reflect conditions where safety risks are higher and where riders would ideally exhibit more cautious and courteous behavior. If, for example, these data were to reveal a predominant trend among riders of one bicycle type that did not appear among riders of another bicycle type, then it would be more useful for land managers making decisions about trails with similar, higher-risk segments than data showing only average speeds across the entire corridor. Inversely, if all riders exhibit similar speeds and behaviors, that suggests it is acceptable to manage both bike types similarly.

Data Preparation

The study team analyzed rider speed using a dataset of GoPro-recorded GPS pings. The full dataset included approximately ten GPS pings per second for each participant's recording, for a total of 408,363 pings across the 26 included participants. Each ping provided information on a rider's location coordinates and speed. The data from the 360-degree video files included sensor data encoded using the GoPro Metadata Format (*6*). The research team used open-source tools to extract the GPS track into data tables for analysis (*7*).

Some of the extracted GPS pings were located outside of the study area. Figure 5 illustrates the variability in GPS data quality. Different colors represent distinct participants. While some of this can be explained by participants using the equipment beyond the Battle Road Trail corridor (black line), other erroneous data appeared due to poor-quality GPS reception. Erroneous pings often occurred during the first several minutes after the device was turned on, potentially due to the GPS device not yet having acquired a signal from enough satellites to accurately determine its position or time.

The study team conducted initial data cleaning by filtering out pings with timestamps outside of the data collection period, often occurring at the beginning of recording, and removing pings located further than 15 meters from the trail. The resulting dataset retained 82% of all pings.

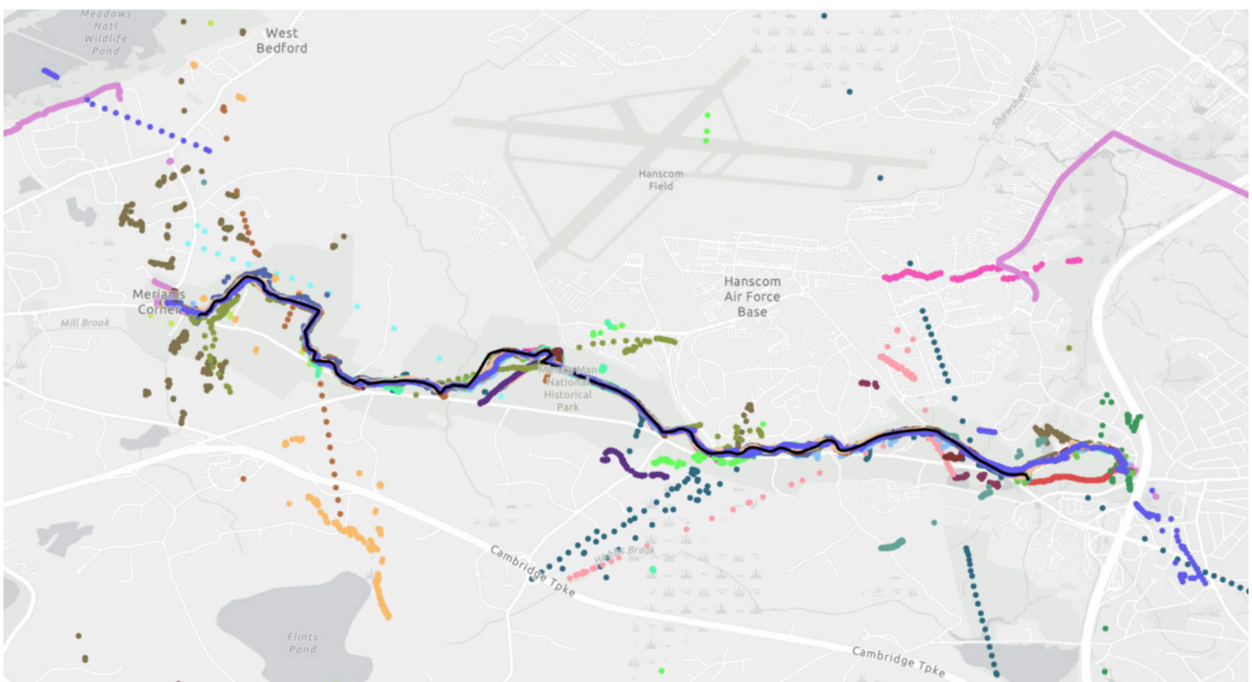

Figure 5: Variability in GPS ping quality, with different colored points representing pings from distinct participants.

Designated Segment Definition

To extract pings within designated segment types, the study team created a set of spatial polygons representing each segment of interest and identified all GPS pings that fell within each polygon's area. Polygons were created programmatically from an annotated list of video time stamps based on a reference rider's video and GPS pings. To develop this list, a study team member rode the route and documented when designated segments occurred. The final input dataset contained columns for the segment type, video file name, the video time stamp at which the individual entered the segment, and the time stamp at which the individual exited the segment; this data was cross referenced with the individual's GPS pings to extract just the pings corresponding to a segment of interest along the trail ("target pings"). The study team produced spatial polygons from the target pings in the following steps, illustrated in Figure 6:

1. Snap the target pings to the nearest point on a line feature class representing the trail
2. Generate a buffer (radius of 40 feet) around the route line
3. Generate a buffer (radius of 50 feet) around the snapped target pings
4. Dissolve the boundaries between the buffers to create a single polygon
5. Use the dissolved polygon to clip the intersecting portion of the buffered route line

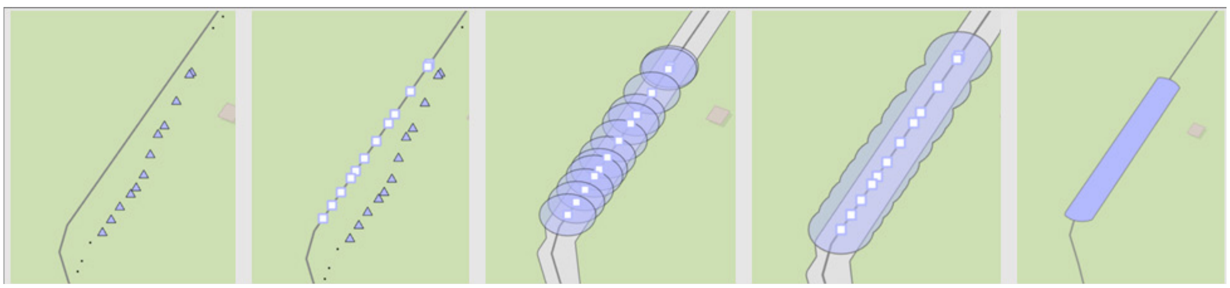

Figure 6: Five-step process for creating spatial polygons from target pings for designated segments.

This process yields smooth polygons that cleanly illustrate segment locations and limit opportunities for pings to land outside of the polygon perimeter before the participant exits the segment. The script that uses polygons to extract pings detects each time a participant enters or exits a polygon. The buffer radii were selected through experimentation to yield smooth polygons large enough to extract GPS pings falling on either side of the route linear feature while minimizing overlap between polygons of the same segment type. Figure 7 presents a snapshot of some of the resulting polygons along a short segment of the trail.

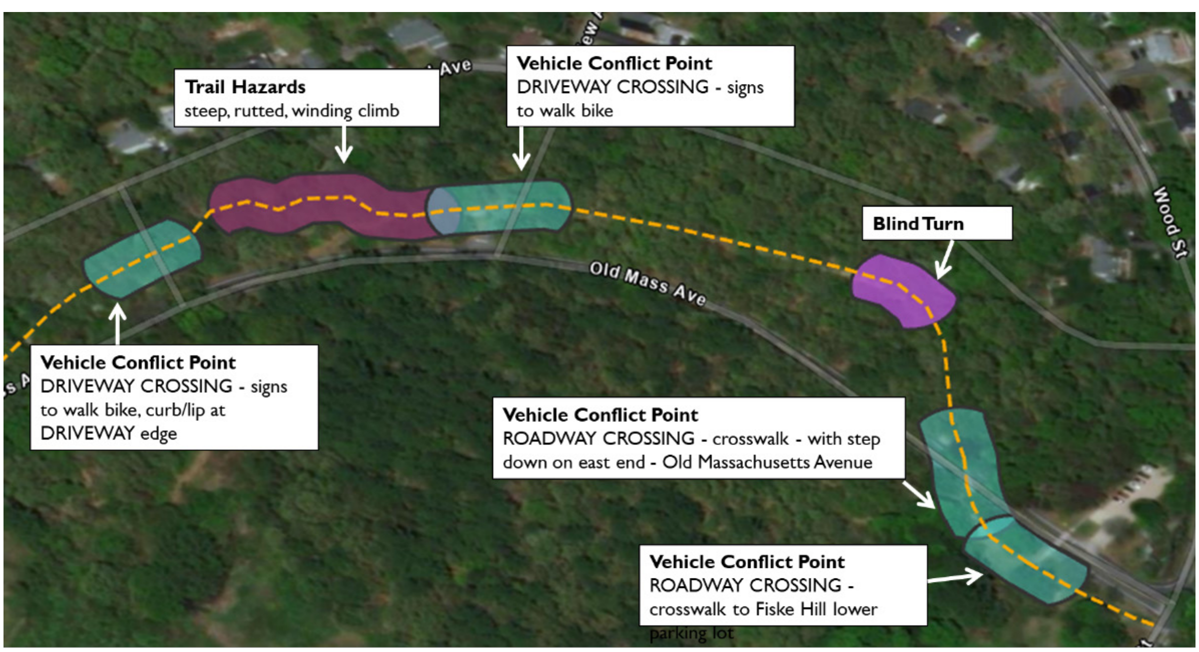

Figure 7: Snapshot of resulting polygons from the reference participant.

Separately, the study team generated polygons for the primary uphill and downhill segments of the trail based on terrain data. The team obtained a digital elevation model with one-meter grid cell size from the Massachusetts Bureau of Geographic Information (*8*). Figure 8 shows the elevation along the route along with the six numbered areas designated "uphill" and "downhill" depending on participant direction of travel.

The study team anticipated that uphill and downhill segment analysis would reveal potential errors in the speed analyses or source data, as e-bike riders were generally expected to travel uphill at a higher speed than conventional bike riders. As shown in the results section below, the data confirm this hypothesis and support the validity of the study methods and underlying data.

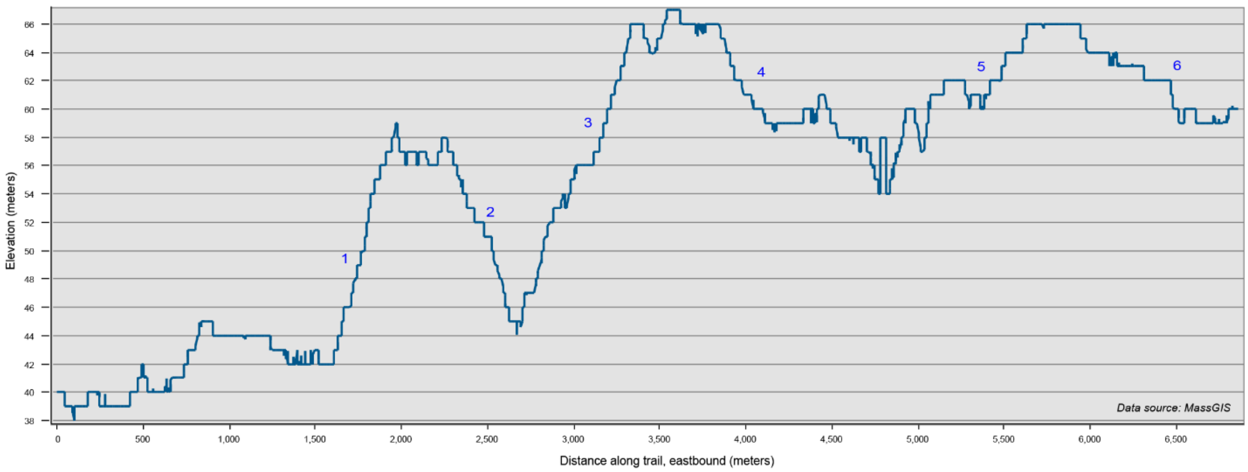

Figure 8: Elevation along the field study route from west to east (Meriam's Corner to Fiske Hill Loop).

The study team recorded each time a participant entered or exited a polygon of interest. This created a list of "events" with each event representing a participant's traversal of a polygon. More than one event could exist per participant, per polygon (for example, a participant traversed it traveling eastbound, then turned around and traversed it again westbound). The direction of travel was also captured, as some polygons were only designated for a particular direction of travel (e.g., elevation segments that change from uphill to downhill or vice versa). The study team completed a spatial join between the polygons and GPS pings and used the pings' speed attribute to calculate an average speed for each event. Participant characteristics – such as bike type – were merged into the dataset to facilitate further analysis.

Methodology

The study team sought to identify any statistical significance in differences in average speeds between electric and conventional bike riders within designated segment types. For an initial analysis, the team performed a series of Student's t-tests. Equal variance t-tests were conducted for individual segment types to compare average speeds of conventional and e-bike riders, with the null hypothesis that there was no difference in average speed between the two groups. E-bike and conventional bike rider average speeds were treated as independent samples of different sizes but with identical variances, based on initial data exploration.

Results

Figure 9 presents a box and whisker plot of average e-bike and conventional bike speeds, by segment category. Each point in the plot represents the average speed for each "event" (a single traversal of a polygon by a participant). For each category presented, the median of the events' average speeds for e-bikes is higher than the median for conventional bikes; however, there is substantial overlap and variability in speeds between e-bike and conventional bike riders in almost every category. The exception to this overlap is the "uphill" category. For uphill segments, e-bike riders exhibited consistently higher speeds than conventional bike riders with less overlap in speeds, as expected by the study team.

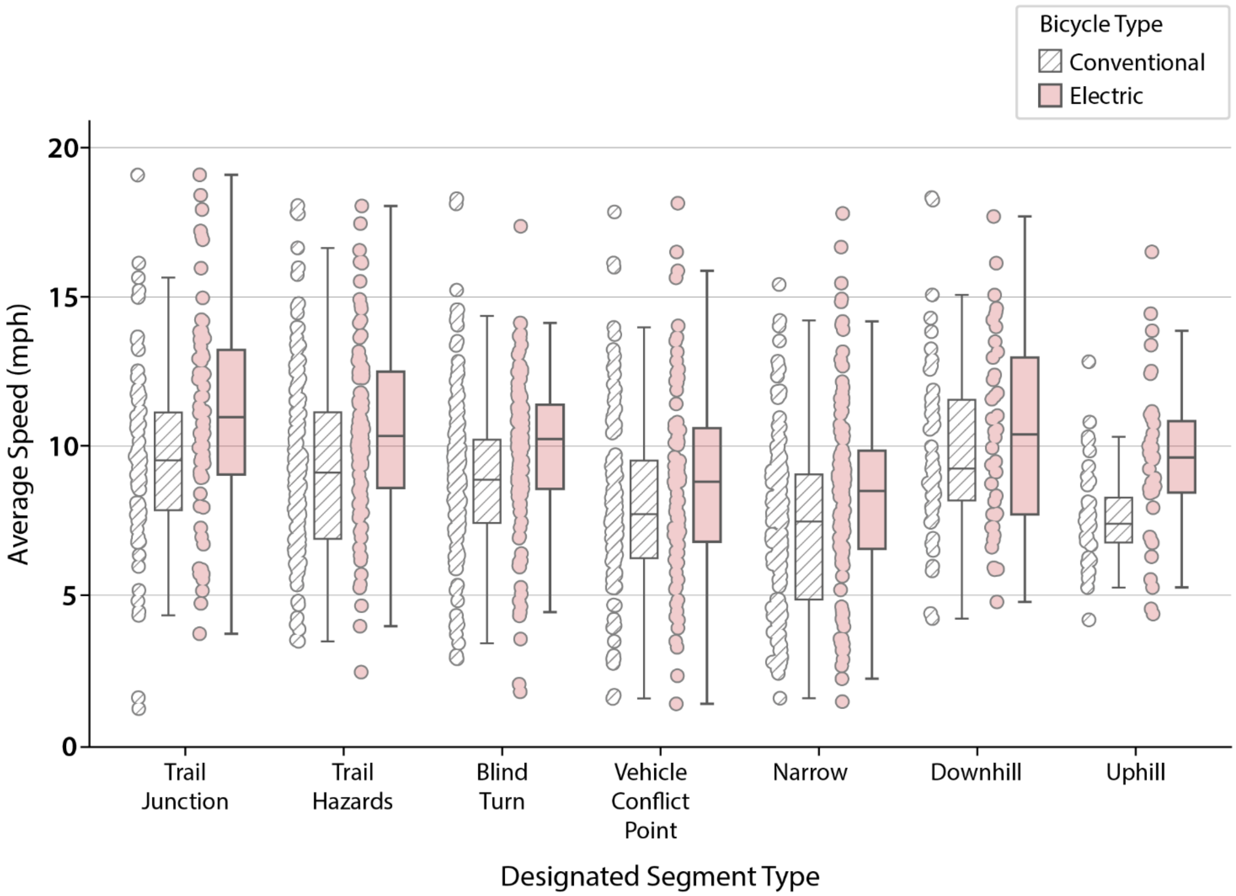

Figure 9: Average speeds (points) and distribution for e-bikes and conventional bikes, by segment type.

Table 2 presents the t-test results by segment category. The difference in mean speeds for e-bikes and conventional bikes is statistically significant at the 5% level for blind turns, narrow segments, trail hazards, trail junctions, and uphill segments.

Table 2: Number of observations and average speed (miles per hour) by segment type and bike type.

Segment Type	Conventional Bike		Electric Bike		P-Value
	n	mean	*n*	mean	
Blind Turn	144	8.94	120	9.82	0.008*
Downhill	48	9.92	42	10.40	0.460
Narrow	138	7.31	119	8.34	0.007*
Trail Hazards	126	9.38	100	10.57	0.004*
Trail Junction	75	9.63	68	11.04	0.011*
Uphill	41	7.65	40	9.49	0.0003*
Vehicle Conflict Point	104	8.07	81	8.83	0.111

* Statistically significant at 5% level

Conclusions from Figure 9 and Table 2 are twofold. First, for most segment types, the median e-bike rider speed is roughly one mile per hour faster than the median conventional bike rider speed. Second, the distributions of conventional and e-bike rider speeds overwhelmingly overlap with one another. Both electric and conventional bike rider speeds have a large distribution across each of the designated segment types, including many similar extremes at the high and low ends of the speed spectrum represented.

Figure 10 further illustrates the second part of this conclusion. This histogram bins the participant speed pings that are located within the designated segments, divided by bike type. Each bin's height represents the fraction of all pings within a bike type that appear in that bin. The chart also shows a distribution curve fit to the data. This curve illustrates the large distribution of speeds, and the high volume of overlap between speeds, for e-bike and conventional bike riders. Conventional bike rider speeds are more highly concentrated, with the modal bin around 8 mph, while e-bike riders speeds are slightly more distributed with a mode around 9 mph.

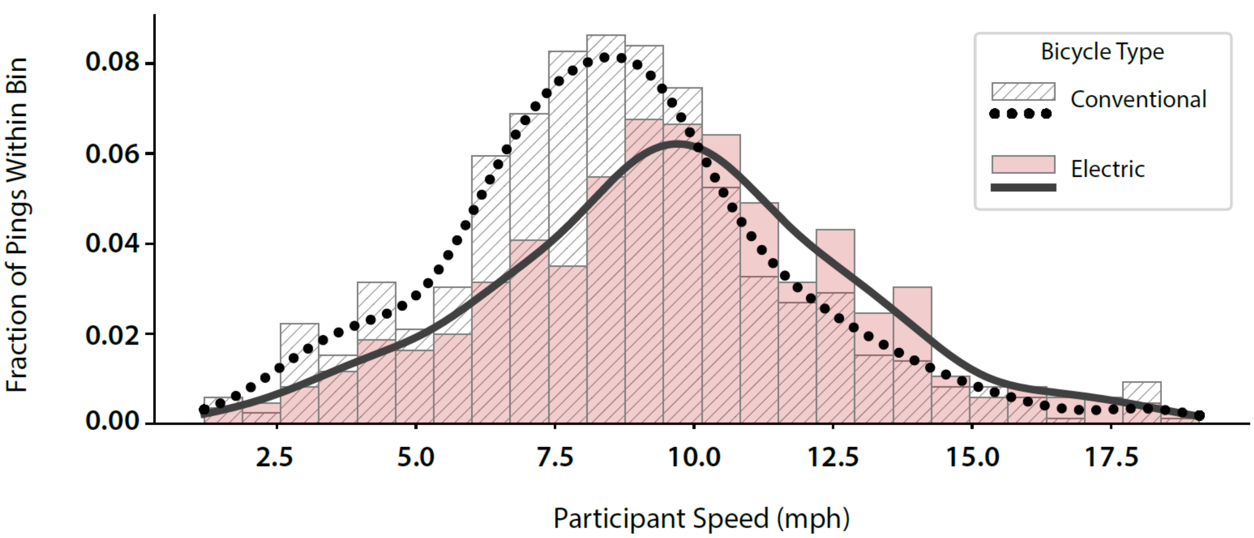

Figure 10: Relative distribution of speeds for all participants across all designated segments.

The uphill and downhill segment data illustrate the least and greatest overlap in speed distribution, respectively. Figure 11 illustrates that uphill conventional bike rider speed density concentrating primarily between 6 mph and 8 mph, while uphill e-bike rider speed density concentrates primarily between 9 mph and 11 mph – representing the greatest distinction between rider speeds by bike type. Figure ***12*** illustrates that downhill conventional and e-bike rider speed densities are far less distinct from one another. The distribution curves peak at similar speeds, around 9 mph, and the shallow curve shapes reflect more even distribution of speeds across the spectrum.

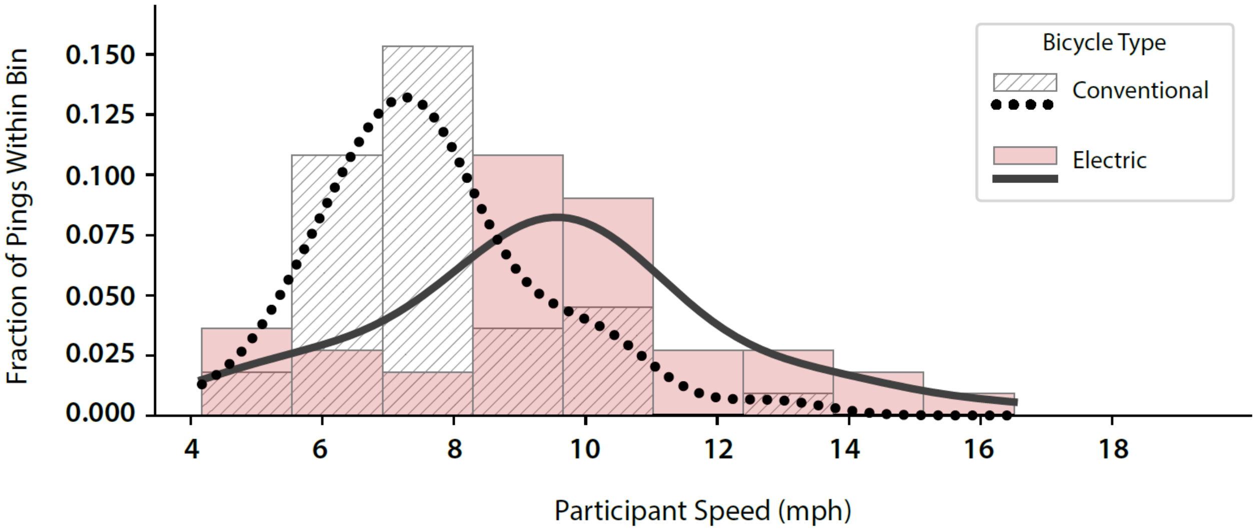

Figure 11: Relative distribution of speed events for all participants across uphill segments.

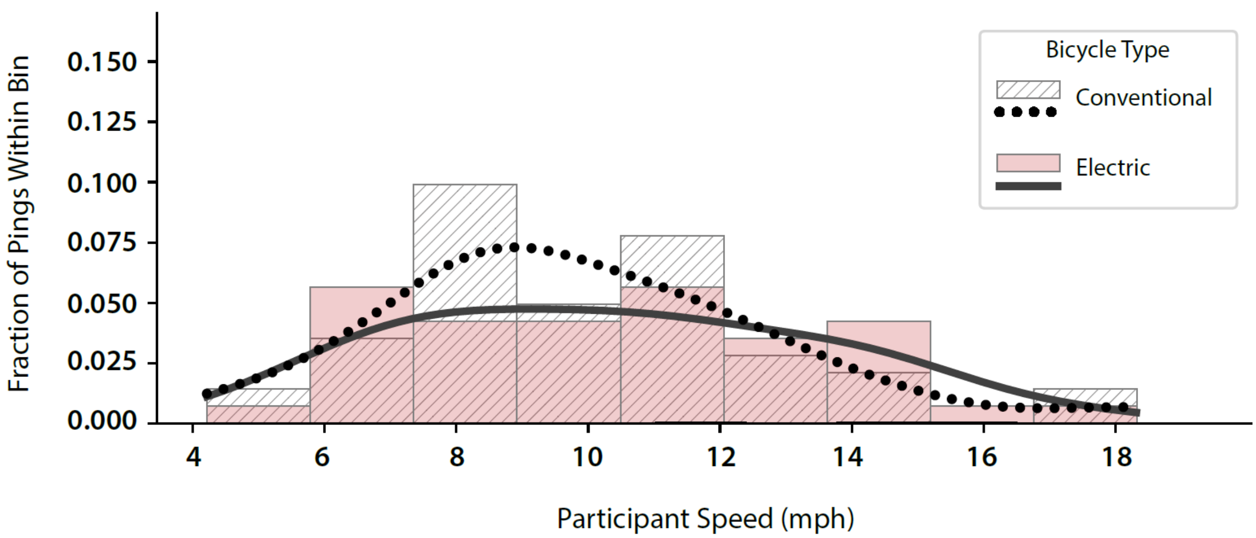

Figure 12: Relative distribution of speed events for all participants across downhill segments.

PASSING EVENT DETECTION

In addition to segments designated by geography and trail characteristics, the study team sought to investigate rider speed when passing other trail users. Mitigating conflicts between users such as near misses, startling encounters, and crashes are of particular importance to land managers and trail users alike. Crashes involving multiple trail users are undoubtedly the events people want most to avoid, but perception of trail users being impolite or disrespectful can be damaging to a visitor's experience and are likely to be much more common than crashes (*9*). Passing speed is a useful proxy for investigating the likelihood of potential conflicts; in the urban context, lower cyclist speeds have been shown to correlate with lower conflict likelihood (*10*).

To isolate passing behavior in the video data, the study team leveraged open-source computer vision libraries. These libraries allowed the study team to use artificial intelligence to detect when passing events occurred in the dataset. This innovation saved hundreds of hours of manual analysis of the over 40 hours of video in the participant dataset. The computer models accurately detected, coded, and output passing event data in a matter of days with minimal human oversight.

Methodology

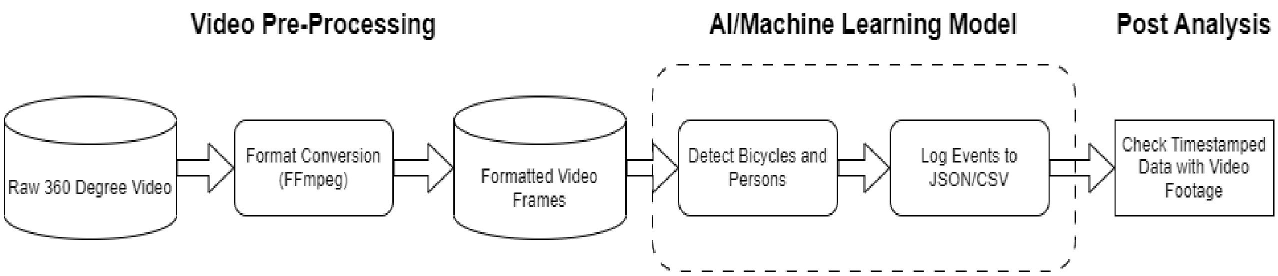

Figure 13. Data processing pipeline for the computer vision model.

The data processing pipeline used to detect these events is depicted in Figure 13. First, for the data gathered from the GoPro Max 360 cameras to be used in an AI-powered passing event detection tool, the 360-degree frames from the footage captured on each participant's ride must be converted into a single stitched image. Conducting this conversion allows for object detection across a single frame of footage at a time. The collection of libraries used to handle the 360-degree camera footage is FFmpeg (*11*).

After the video frames are formatted, a computer vision model is used to detect bicycles and persons present in the video. Pretrained models were selected because the objects being classified are well-represented in existing datasets, and the ability of existing models to detect these objects has already been robustly tested. The selected models required use of a computer equipped with a graphical processing unit (GPU).

The object detection and depth estimation models utilized in this study analysis were Meta AI's DEtection TRansformer (DETR) model, and Intel's Dense Prediction Transformer model (*12*, *13*). The object detection model was set to only detect persons and bicycles. As the program parses through video files, it detects when persons and bicycles are in the field of view of the camera and draws a bounding mask around each object in the video. Figure 14 shows a sample video frame with detected objects labeled. As can be seen in the image, the model detects the rider who is recording data. A filter is applied to remove the subject rider from analysis. When a "bicycle" object is identified, that event is labeled "cyclist" and when only a "person" object is identified, that event is labeled "pedestrian." To reduce potential false positive detections, an "event" is only recorded when an object is detected for five consecutive frames (approximately 1/6 of a second) of video.

Figure 14. Sample video frame depicting object detection results. Note: this frame is from a video recorded outside of the study area by a member of the research team used for evaluation of the computer vision model.

Results

In addition to the detected objects and their locations within each frame, the computer vision pipeline outputs a table of all detected passing events. Across all video footage collected by participants (which includes some footage where the corresponding GPS data was discarded by quality filters), 18,602 events were detected. A significant number of events (6,843 events) lasted less than one second. For events that lasted longer than one second, and where trail-aligned GPS data were available, the corresponding pings between the start and end of the passing event were tagged as “passing”, which was then used in the regression analysis below.

Figure 15 shows passing events by length and rider type for participants passing pedestrians, and Figure 16 shows the length of time and rider type for participants passing other bicycle riders. Overall, e-bike riders and conventional bike riders exhibit similar distribution of passing event duration, and similar shares of passing events longer than 2 seconds (26.3% for e-bike riders, compared to 27.1% for conventional bike riders). This suggests that e-bike riders and conventional bike riders similar maintain awareness of other trail users and adjust their speed in a similar manner when passing both pedestrians and other cyclists.

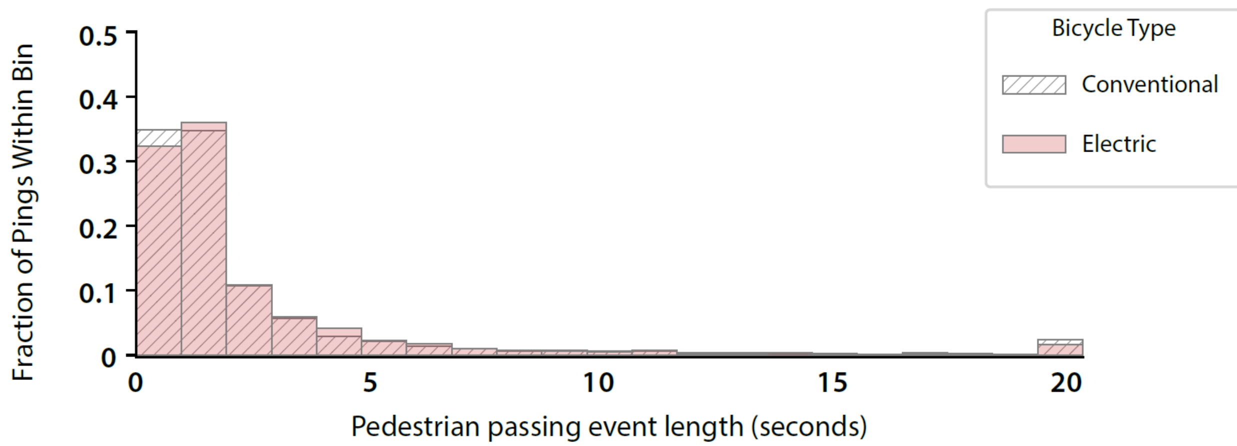

Figure 15: Length of passing events for participants passing pedestrians, by participant bicycle type.

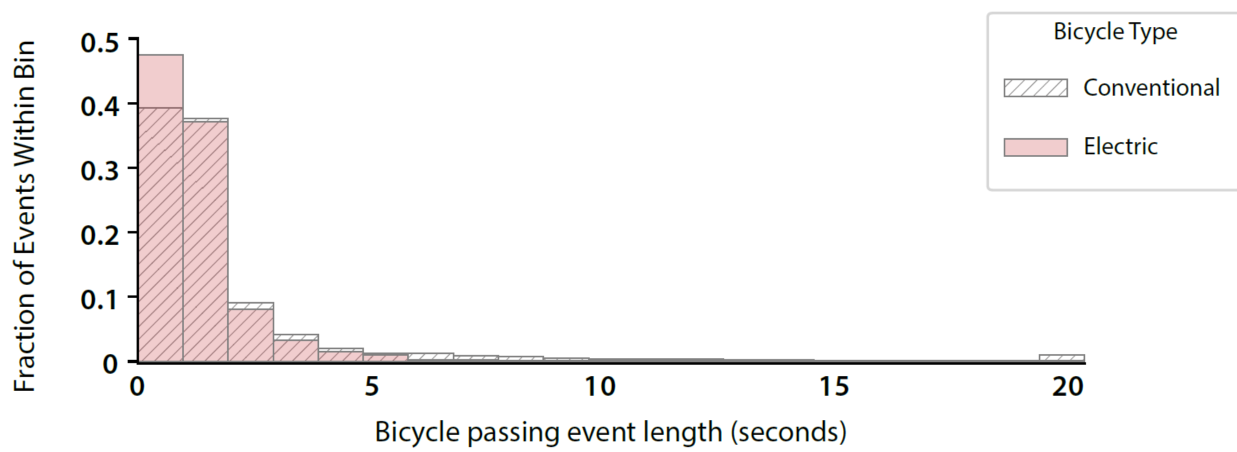

Figure 16: Length of passing events for participants passing other bicyclists, by participant bicycle type.

REGRESSION ANALYSIS

Methodology

The participant speed data collected for this study presented an opportunity to apply regression analysis, which provides a different view of participant speed and behavior to the geolocation analysis described above. The study team fit a linear mixed effects model to the dataset of individual GPS pings, controlling for participant characteristics while accounting for the non-independence of GPS pings collected from the same individual. Several models were considered, including simple linear models with and without variable interactions. Candidate predictors of average speed included bike type, participant age (mean centered), sex, and a set of binary variables indicating whether the GPS ping was located within a particular segment type (e.g., uphill, narrow, vehicle conflict point, etc.,) or occurred during a passing event. The study team calculated the Akaike Information Criterion (AIC) and compared all assessed models to identify the best fit model.

Results

Equation 1 describes the selected linear mixed effects model, which was fit on 407,299 observations across 25 participants. Participant 31 was excluded as none of their cleaned pings fell within a geographic segment of interest.

$$y_i = \beta_0 + \boldsymbol{\beta x}_i + \mathbf{z}_\mathrm{i} + \epsilon_\mathrm{i} \tag{1}$$

In this model, y_i is the speed observed at ping $\boldsymbol{i}$. Then $\boldsymbol{x_i}$ is a vector of information for ping i, specifically the corresponding participant's bike type (1 if electric), sex (1 if male), mean-centered age, and the ping's location within segments of interest (1 if in segment type). Each segment type was included as a separate predictor. The vector $\boldsymbol{z_i}$ contains binary variables for individual participants to account for random effects, where an element in the vector is 1 if ping *i* belongs to that participant and 0 otherwise. This vector captures the variability of individual participants' behavior and focuses the model interpretation on the fixed effects of interest. $\boldsymbol{\beta}$ is the vector of estimated parameters for each predictor in $\boldsymbol{X_i}$. β_0 is an intercept, and ϵ_i is an error term.

Table 3 presents the parameter estimates, confidence intervals and p-values. Controlling for other factors, the average speed for all riders is 7.91 mph. Variables included in the final model are listed under the "predictors" heading. Variables associated with a significant speed increase are *e-bikes* (+2.19 mph), *male sex* (+2.51 mph), *downhill riding* (+0.38 mph), and *trail junctions* (+0.29 mph). Variables associated with a significant speed decrease are *uphill riding* (−1.05 mph), *narrow segments* (−3.33 mph), *vehicle conflict points* (−2.14 mph), *walk bike signs* (−2.92 mph), and *passing maneuvers* (−1.13 mph). These results generally show the speed changes of riders are as expected under specific conditions. Sex, not bike type, predicts the largest increase in speed – an interesting result considering the policy implications of this research (no public land would consider prohibiting riders based on sex). The results show that riders of both bike types reduce speed when passing other trail users. While e-bike riders reduce speed slightly more in absolute terms than conventional cyclists, this may be because they are generally traveling faster in the first place.

Table 3: Regression Results

	Estimates (Speed, in mph)	Confidence Interval	P-Value
Predictors			
(Intercept)	7.91	6.52 – 9.29	<0.001
bike type [electric]	2.19	0.77 – 3.61	0.002
sex [male]	2.51	1.08 – 3.93	0.001
age centered	-0.01	-0.07 – 0.05	0.694
Uphill	-1.05	-1.08 – -1.03	<0.001
Downhill	0.38	0.36 – 0.41	<0.001
Blind Turn	0.02	-0.01 – 0.06	0.174
Narrow	-3.33	-3.36 – -3.30	<0.001
Trail Hazards	-0.33	-0.36 – -0.30	<0.001
Trail Junction	0.29	0.23 – 0.35	<0.001
Vehicle Conflict Point	-2.14	-2.18 – -2.10	<0.001
Walk Bike Sign	-2.92	-3.07 – -2.78	<0.001
Passing [1]	-1.13	-1.17 – -1.10	<0.001
Bike type [electric] *			
Passing [1]	-0.38	-0.43 – -0.33	<0.001
Random Effects			
σ2	9.65		
τ00 ParticipantID	3.11		
ICC	0.24		
Num Participants	25		
Num Observations	407,299		
Marginal R^2 / Conditional R^2	0.242 / 0.427		

VIDEO REVIEW

The study team relied on manual video review to analyze study participants' glance behavior at potential conflict points with motorists or other trail users. Glance behavior refers to the eye movement and/or physical movement of a rider's head and gaze toward the potential source of conflict; for example, glancing to the left and right before crossing a road or driveway, or glancing towards a trail spur that joins the Battle Road Trail. Riders that do not appear to glance toward potential sources of conflict may be more likely to come into conflict with other trail and road users.

Methodology

Glance analysis is common in human factors studies. While it is often conducted with sensitive equipment and/or in a controlled simulation lab setting to track participant eye movements, field studies require a modified approach using equipment that is capable of being used during different weather conditions. Therefore, a dedicated mobile eye tracker could not be used. The videos collected by the handlebar mounted GoPro Max camera required manual video review to observe rider behavior and determine glancing behavior.

This glance analysis task leveraged the output from the geolocation analysis to precisely identify segments of video for manual review. This greatly reduced the volume of footage and amount of time needed for the study team to perform reviews. The geolocation analysis logged the timestamps for each participant as they entered and exited the polygons labeled "trail junction" or "vehicle conflict point." These timestamps were converted into start and stop times that the study team used to scrub through frames to the segments of interest.

Because the GoPro cameras produced 360-degree video, the reviewer was able to set the view to show a scene revealing the participant's head and eyes, the trail in front of the rider, and surrounding trail users. The reviewer confirmed that a trail junction or road crossing appeared at the timestamp, then observed whether the rider glanced to the left or right for opposing traffic.

Results

Results are shown in Table 4 and Figure 17. Within the sample, conventional bike riders glanced toward potential conflict points more frequently than e-bike riders, both at trail junctions (58 percent versus 45 percent) and at road and driveway crossings (69 percent versus 64 percent). The study team speculated that the capacity for more rapid acceleration may contribute to the lower glance rate among e-bike riders but do not have objective conclusions. Data in the analysis demonstrate similar attentiveness between e-bike and conventional bike riders, such as their speed reduction while passing other trail users, so there is no clear explanation from these data for this divergent glance behavior frequency.

Table 4. Glance Behavior Results.

Category	Conventional: Events Observed	Conventional: Glance Occurred	E-Bike: Events Observed	E-Bike: Glance Occurred
Road/Driveway Crossing	70	48 (69%)	47	30 (64%)
Trail Junction	50	29 (58%)	22	10 (45%)

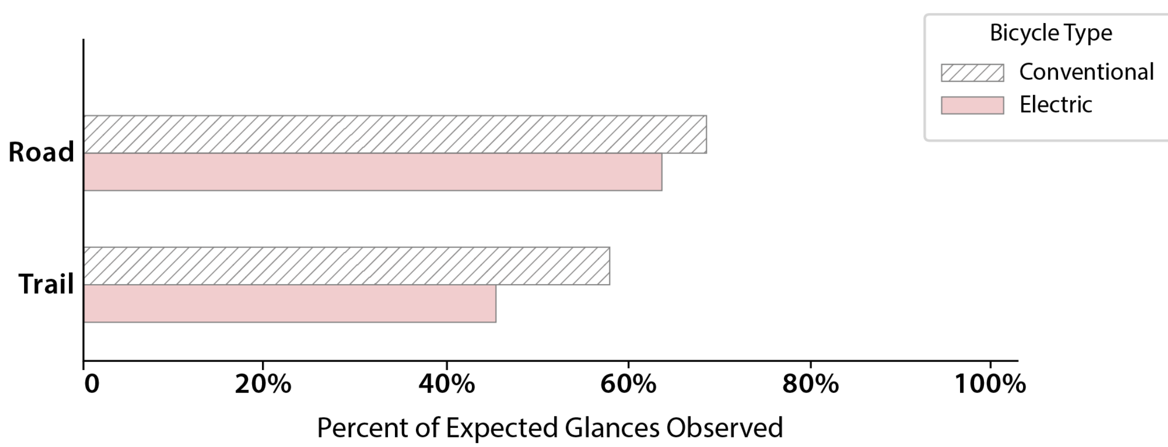

Figure 17. Participant glance behavior frequency at road crossing and trail junction potential conflict points.

Glance behavior analysis is a proxy for evaluating rider intent and risk-taking at conflict points. It is especially useful as a comparative analysis between riders on different types of bikes (e-bikes and conventional bikes). However, it is difficult to ascertain whether riders adequately assessed potential conflicts before proceeding through road crossings and trail junctions, as this is an inherently subjective judgement. Some riders may also have had sufficient peripheral vision and/or used other auditory and visual clues to assess potential conflicts without turning their heads.

OPEN DATA

The study team is committed to sharing the data collected and methods used in this study for reuse. GPS pings used in the regression analysis, which incorporate the geolocation and passing event tags, are available online at https://data.transportation.gov/Bicycles-and-Pedestrians/E-Bike-Field-Study-Data/xdkm-ken4. The raw video files are not posted due to the potential for exposure of study participants' personally identifiable information and file size limitations. Source code developed for the analysis is available online at https://github.com/VolpeUSDOT/E-Bike_PublicAccess. The repository contains code necessary to replicate the results presented in this paper with the data posted online, as well as code used in preparing the data (video extraction, data cleaning, and passing event detection) which may be useful for researchers interested in performing similar analyses using GoPro data.

CONCLUSION AND LESSONS LEARNED

In locations identified as higher risk for potential conflicts along an unpaved, multiuse trail:

1. Analyses show that e-bike riders travel slightly faster on average than conventional bike riders.
    a. T-tests show approximately one mile per hour increase in median speed for e-bike riders.
    b. Regression analysis indicates that e-bike usage predicts an average 2.19 mph increase in rider speed. However, this was not the predictor which had the greatest effect on speed; male sex predicts a greater increase in speed (average 2.51 mph increase).
2. Distributions of e-bike and conventional bike rider speeds overwhelmingly overlap with one another.
    a. Both electric and conventional bike rider speeds have a large distribution across each of the study's designated segment types.
    b. Both electric and conventional bike riders exhibit similar extremes at the high and low ends of the speed spectrum.
3. Conventional and e-bike rider behavior is similar at locations with higher risk of conflict.
    a. Regression analysis shows that both e-bike and conventional bike riders reduce speeds 1) at vehicle conflict points, 2) in narrow sections of trail, and 3) when passing other trail users.
    b. Video data show e-bike and conventional bike riders both exhibit moderate precaution by glancing to the side at trail junctions and vehicle crossing locations, though e-bike riders glance slightly less frequently than conventional bike riders.

Future studies may wish to purposefully recruit novice riders or participants riding unfamiliar bicycles to study their behavior in a public lands context where rental services or tour operators provide bicycles to visitors. Future research may also consider how unpaved trail surfaces are affected by e-bike usage. Also for future studies, modifications to equipment or participant instructions could enable higher GPS and video data quality, and allow usage of additional data (e.g., accelerometer readings). Modifications to consider include mounting instructions for the GoPro device (i.e., the side which should face forward) to ensure directional consistency throughout a ride and across participants, and instructions to participants to turn on their camera a certain number of minutes before beginning their ride to allow the device to obtain an accurate GPS signal.

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