A naturalistic study of child and adult bicycling behaviours and risk exposure

C.J. Hamann[1], M. Pooley[2], D. McGehee[3], C. Peek-Asa[4]

[1] Injury Prevention Research Center
University of Iowa College of Public Health
200 Newton Rd, Iowa City, IA, USA
e-mail: cara-hamann@uiowa.edu

[2] Injury Prevention Research Center
University of Iowa College of Public Health
200 Newton Rd, Iowa City, IA, USA
e-mail: mark-pooley@uiowa.edu

[3] Public Policy Center
University of Iowa
205 SQ, Iowa City, IA, USA
e-mail: daniel-mcgehee@uiowa.edu

[4] Injury Prevention Research Center
University of Iowa College of Public Health
145 N Riverside Dr, Iowa City, IA, USA
e-mail: corinne-peek-asa@uiowa.edu

ABSTRACT

Half a million bicyclists injured in crashes visit emergency departments and even more receive minor injuries that do not require emergent care each year in the United States, but little is known about contributors to the crashes. The purpose of this study is to describe the methods of a naturalistic bicycling study that allows for the examination of bicyclist risk exposure, including factors such as route choice, use of bicycle-specific infrastructure, and rider errors. We enrolled 10 adults (5 male, 5 female) and 10 children (5 male, 5 female) aged 10 to 14 years old between August and October of 2013. Each participant in our Portable Video and Data System for Assessing Rider Locomotion (Pedal PORTAL) study was equipped with a helmet-mounted, GPS-enabled, forward-facing camera. Eligible participants lived in Johnson County, Iowa, and rode their bicycles at least four times per week. Participants completed baseline demographic questionnaires, recorded all their bicycle trips for seven consecutive days, and completed trip diaries, which included trip purpose and descriptions of any near crashes or crashes. Data collection and data processing protocols are described. Characteristics of 261 bicycling trips (57 hours, 670 miles), including rider error, crash, and near crash rates are also presented.

Keywords: naturalistic cycling study, cycling behaviour, cycling safety, children, adults

1 INTRODUCTION

The naturalistic study of bicycling is developing worldwide, with the majority of progress having been made in Europe and Australia [1-9]. As a fairly new field, largely adapted from naturalistic driving methods, naturalistic cycling research contains many gaps. To date, there have been no published naturalistic cycling studies that examine children as subjects or North America as the region of study. This is of concern as riding among children and within North America varies widely from that of adults and other world regions. For example, bicycling only accounts for one percent of the daily trip mode share in the United States compared to 2% in the United Kingdom, 10% in Germany, and 26% in the Netherlands, and ranging from 11-47% in China, and 7-21% throughout India [10-12]. Additionally, the roadway infrastructure in the United States shifted from walkable and compact to sprawling and motor vehicle focused since the mass production and popularity of automobiles beginning in the early 1920s [13]. Since its peak in the 1950s, motor vehicle occupant injuries in the United States have decreased more than 70%, largely due to an evidence-based and comprehensive road safety strategy [14]. Part of the success of this strategy was based on research that described driving exposure, conditions, and behaviour. However, these comprehensive strategies in the US have not focused on vulnerable road users such as bicycles and pedestrians, and very little is known about riding exposure and behaviour.

We do know, however, that the burden of bicyclist injuries is high. In the United States there are over 25,000 hospitalizations and 500,000 emergency department visits each year, which has remained fairly steady, despite improvements in many areas in roadway infrastructure to better accommodate bicyclists [15-17]. The average length-of-stay per bicycle-related injury requiring hospitalization in the US is four days with over $40,000 in hospital charges, which equates to over one billion dollars in hospital charges per year for all bicycle crash-related injuries[15]. The lack of decrease in injuries and fatalities may be due to increases in ridership throughout the U.S. in recent years [18]. Given the toll of bicyclist injuries and our knowledge gap in behaviour, research that identifies riding strategies that can be the focus of prevention efforts is warranted.

The goal of this study was to develop a data collection system and data coding protocol to better understand the typical riding patterns, risk exposure, and risky behaviours of both adult and child bicyclists, using a naturalistic approach. Specifically, we aimed to collect data on trip characteristics (length, day, time, surface type, etc.) and calculate error/violation, near crash, and crash rates.

2 METHODS

2.1 Guiding principles for the Pedal PORTAL study equipment

The primary objective of this study was to develop an integrated system to passively collect information on bicycle riding routes and behaviours. Several guiding principles were used in the development of the system. Because we wanted to observe children and adults, we needed a system that could be adapted to any size of bicycle. We wanted a system that was unobtrusive and naturalistic, so that riders would not be constantly reminded that their riding was being observed, and, thus, ideally, we wanted the system to be mounted on participant's personal bicycles. Our system needed to have an integrated platform so that we could track information about the trip (e.g. distance, speed, time), the route (e.g. type of road, location of bicycle relative to the roadway), and the behaviour (e.g. accompanying riders, traffic). We also needed methods to identify hazardous situations, near crashes, and crashes. We needed our system to be operable by the rider independently and that would remain functional for the 1-2 week anticipated study participation period.

2.2 Data sources and variables

In order to meet all of the guiding principles of the Pedal PORTAL study, data were collected from baseline written surveys, written trip diaries, and GPS-enabled helmet cameras (video, audio, and GPS).

2.2.1 Baseline Survey

The baseline survey was given to all participants. Children were asked the following: gender, age, race/ethnicity, grade in school, school name, zip code, riding frequency, riding experience, bicycle riding class (Yes/No), bicycle commuter (Yes/No). Adults were asked these same questions, with the addition of educational attainment, marital status, number of adults in household, employment status, occupation, annual household income, work zip code, driver's license (Yes/No), and age they learned to drive. Riding frequency was measured by asking participants to report the average number of days they ride per week for each of the four seasons.

2.2.2 Trip Diaries

During the one-week study period, riders were asked to complete a written trip diary to provide details for each of their bicycle trips. These details included: date, time of day, trip purpose, crashes, near crashes, dangerous circumstances, weather, and type of bike ridden. Trip purpose was left open-ended in the trip diary and later collapsed into commute, errand, recreation, or social. For the purposes of this study a trip was defined as a bicycle ride from one origin to one destination. For example, if a person rode from home to work and then work back to home, that would count as two trips.

2.2.3 Pedal PORTAL data acquisition system

Based on the guiding principles established for this study, we developed a system that utilized a helmet camera with built-in GPS and audio capabilities. The camera resolution was set at 1280 x 720 and the GPS was set at a sampling frequency of 5 times per second. With an added mounting device, this compact camera system could be easily mounted to bicyclists' helmets and operated via one sliding switch (Figure 1). Indicator lights on the camera showed the status of video recording, GPS satellite connection, and battery life remaining. We equipped 10 children and 10 adults with this system and asked them to record all of their bicycling trips for one week each. All participant data was captured between August and October of 2013.

Figure 1. Pedal PORTAL data acquisition system mounted on helmet.

2.3 Data Coding

2.3.1 Graphical user interface

All recorded bicycling trips from the 20 participants, that contained both video and GPS data, were reviewed coded and coded in their entirety using a graphical user interface (GUI) specifically designed for use in this study (Figure 2). The video, GPS, and audio (for clues on context) data were loaded into the GUI for each trip and reviewed in their entirety. From the GUI, surface type, riding style, errors/violations, and details on crashes and near crashes were coded. Five percent of all trip videos were coded by two coders to ensure inter-rater reliability. The reliability was high, with average discordance between ratings at 4.0%.

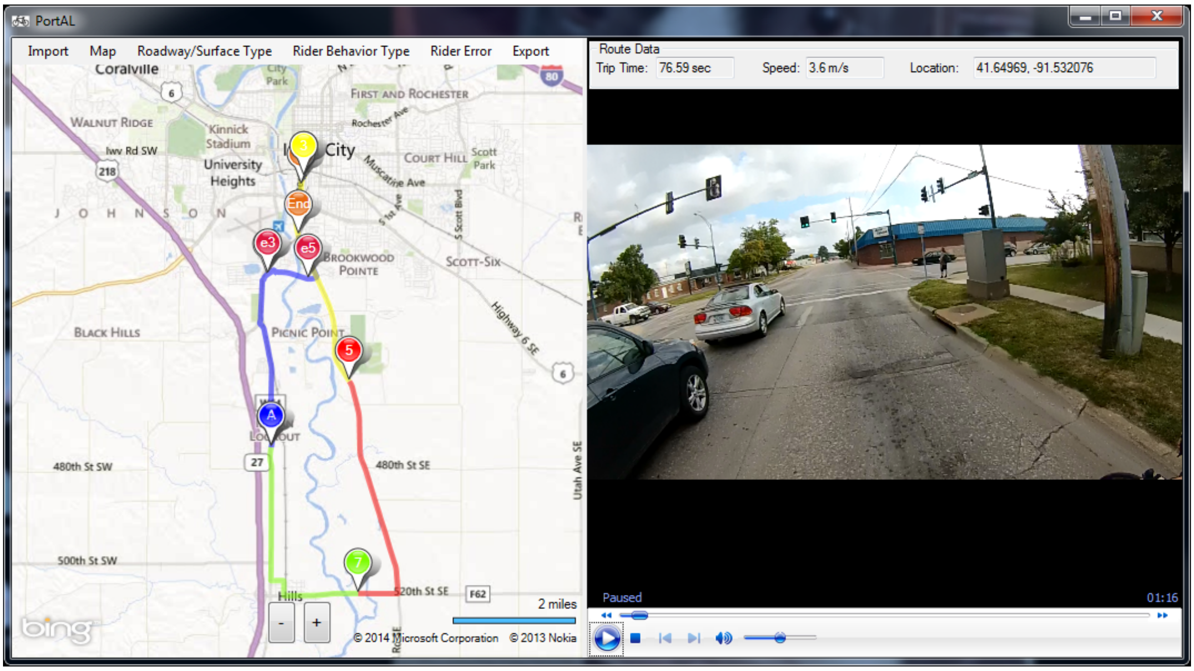

Figure 2 Graphical user interface used to code surface type ridden, riding style, and rider and motorist errors

Table 1 shows categories and classifications of the variables coded with the GUI. Percent of time on each surface type and by each riding style and error/traffic violation rates per mile were calculated at the trip level. The categories evolved throughout the coding process, as needed. For example, we found that riders often rode through parking lots or other cut-through areas which did not fit well into a particular category, so we added a category called ‘other paved’. This was also true for areas where riders went through grass or other non-paved areas, which we categorized as ‘other not paved’.

A variable called riding style was created as an attempt to better understand rider decisions and behaviours as a possible proxy to their thought process. For example, riding style ‘as a motorist’ was coded when a rider’s actions were in keeping with motorist rules of the road, while riding ‘as a bicyclist’ was coded when a bicyclist did something specific to being a bicyclist or that only a bicyclist could do (e.g., riding in a bicycle lane or riding between the gap of two rows of queued cars).

Rider and motorist errors and traffic violations were also coded using the GUI. These were either behaviours that were against the traffic code (e.g., failure to stop at a stop sign) or behaviours that put others in danger (e.g., bicyclist acting in a reckless manner that put a pedestrian at risk of being hit or having to take evasive action).

Table 1 Surface, behavior, and error categories used for video coding

Roadway Surface Type
Street
Bike Facility (bike infrastructure on street)
Sidewalk
Bike Path (pathway not immediately adjacent to street)
Gravel
Other Paved
Other Not Paved
Riding Style
As a Motorist
As a Bicyclist
As a Pedestrian on a bike (riding bike, but using pedestrian facilities)
As a Pedestrian off a Bike (walking while pushing bicycle)
Errors, Violations, and Interactions
Failure to Stop or Yield to another road user
Slow and Look (incomplete stop), no traffic present
Reckless toward a pedestrian
Reckless toward another bike
Riding Against Traffic
Motorist Error
Defensive Action

2.3.2 Utilization of GIS to determine spatial relationships and bicycle route choice

All GPS data were imported into the ESRI ArcMap geographic information system (GIS)[19] with the corresponding roadway network for Johnson County, Iowa. ArcGIS was used to examine the GPS data for spatial pattern analysis of rider trips, as well as route preference/choice, and roadway classification assignment to routes. GPS data essentially provide a "breadcrumb" trail – allowing for reconstruction of routes ridden. However, consumer level GPS devices are only accurate from 7 to 10 meters[20], which can be reduced in urban areas[21], but sometimes places points well off a street or known bicycle facility.

Working under the assumption that GPS points are correct, or near the actual path travelled, map-matching allows for the points to be joined to the street network to reconstruct the actual route. Two different approaches were employed to determine actual bicyclist route choice on the street network and the proportion of each trip occurring on each functional class type.

To determine route choice we elected to use the same methods as Hudson et al (2012)[22]. Hudson and colleagues employed Dalumpines and Scott's (2011)[23] map-matching algorithm which utilizes the Make Route Layer in ArcGIS and Dijkstra's shortest–path algorithm to find the shortest path a cyclist travelled on the road/bicycle network within the given confines of their GPS traces (see Figure 3 for example). Hudson and colleagues generously shared the GIS model with us, which was developed for the exact purpose of determining routes of travel for realistic and accurate assessment of bicyclist route choice.

Data were formatted such that all trip origin, destination, and GPS traces could be selected using the same query in ArcGIS. Origin and destination for each trip were input as stops in a Network Analyst Route Layer in ArcGIS. A buffer was created around each GPS trace and converted to a line barrier in the route layer. This effectively confined the potential route options from an origin to a destination to stay within the buffer created around the GPS trace. This formatting allowed the model to iterate through all the trips individually and solve the route most likely travelled on the road network for each trip.

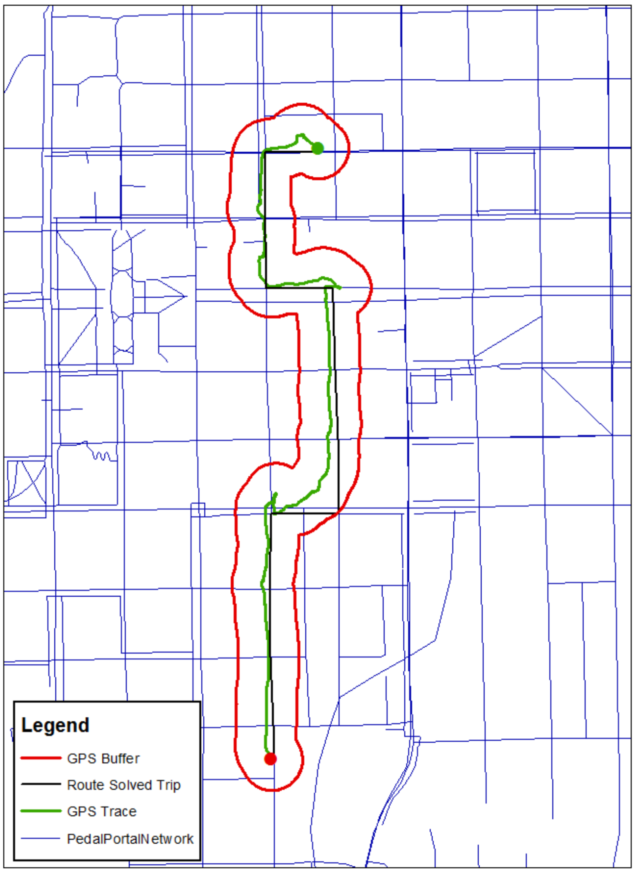

Figure 3. Example GPS trace of a bicycle trip for which the route was solved using a GIS

The model provided by Hudson and colleagues was altered slightly to carry individual Trip IDs throughout the process, as well as append each individual trip to an aggregate trip feature class that contained all trips with valid GPS data. A trip count variable was then used to aggregate the number of trips occurring on each roadway segment (Figure 4). Functional class could be aggregated at this trip level, looking at the number or percent of trips occurring on each functional class type. However, the Hudson model did not allow for the use of a time variable (percentage of trip time) to compare the functional class data from GIS with the surface type coded from the video data. We opted to aggregate by time instead of distance because it more accurately represented the exposure of the rider on certain surface types and functional class compared to distance or trip because it takes into account rider speed. Furthermore, variability in GPS traces and buffers from which they were based using the Hudson method, occasionally prevented the solver from finding a suitable route on the network which produced an output error which had to be corrected manually.

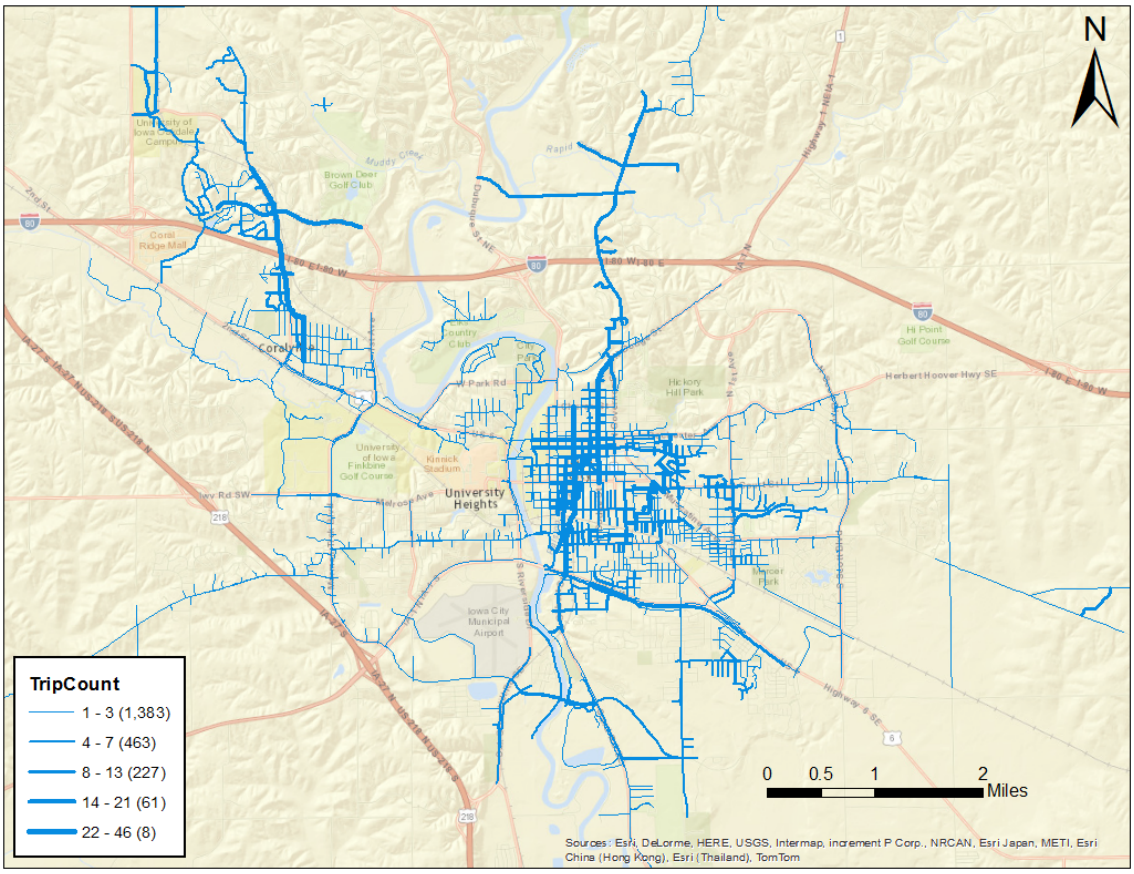

Figure 4 Trip counts per roadway segment for all participant trips during study period, Johnson County, Iowa.

2.3.3 Joining roadway functional class to GPS data

In order to effectively compare video coded data (based on time) and GPS data, roadway functional classes were joined to the GPS traces using the spatial join function in ArcMap proportion of total trip time on each roadway functional class was determined.

Federal Functional Classification codes provide a standard system of categorization for roadway networks ranging from 1 to 7, with 1 being interstates, and 7 being local roads [24]. We found that participants often used alleys, parking lots, cut-throughs, etc., which were not on the original street network and had to be manually added for the for the aforementioned route analysis using the Hudson approach. Additional classes were created to account for trip portions occurring in parking lots, off pavement (e.g., grass), and bike paths. The final list of functional class categories used for this study were: arterial, collector, local, bike path, bike lane, shared lane arrows, and other.

Once GPS and roadway network data were joined, the percentage of time spent on each functional class was aggregated for each trip and this could then be compared to the actual surface ridden coded from the video data. For example, from the video coding we know that participant A on Route 1 rode from home to work on a route that was 1 mile long and took 6 minutes 16 seconds. 94.5% of that trip was ridden on a paved street and the remaining 3.5% was ridden in a bike lane. We could then compare this to the functional class data derived in GIS to know that 51.4% of the route was on local roads, 34.2% on collectors, 4.6% on arterials, and 9.8% on a route with a bike lane. The discrepancy between the 9.8% of the time a bike lane was available on the route versus the 3.5% of time a bike lane was actually used by participant A suggests that this rider chose not to ride in a bike lane during part of their trip, even though it was available to them on the route.

However, similar to the Hudson model which had some error, this GIS join technique did not perform perfectly, because it joins to the nearest network link, which does not always correspond to the route taken. Each intersection a cyclist travelled through provided an opportunity for error in GPS point functional class assignment. Figure 5 shows GPS points from one trip with arrows indicating where roadway functional class attributes were assigned to points from the nearest roadway segment link, but should have been assigned from the link parallel to the contiguous GPS trace. In aggregate, we roughly estimate this results in 2-3% error in functional class assignment, which we have not found a suitable correction for without very tedious manual corrections.

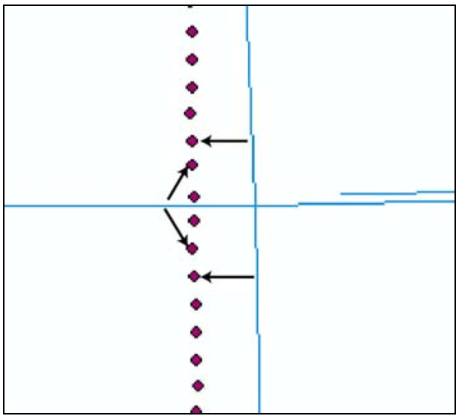

Figure 5 Illustration of functional Class Assignment to GPS points using nearest spatial join

2.4 Analysis

Total frequencies and proportions of child and adult characteristics and their corresponding bicycle trip characteristics were calculated. T-tests were used to compare trip characteristics between adults and children. Rates of errors, traffic violations, near crashes, and crashes were calculated per mile.

3 RESULTS

3.1 Child characteristics

All children in the study were between ages 11 and 13 (Mean Age = 12). However, their grade in school ranged from 5th (elementary) to 9th (high school), with the majority in 7th grade (middle school/junior high). Children rode most frequently in the summer and least in the winter. Overall, children had an average of 5.3 years riding experience. The majority of children reported that they ride their bicycle to school (80%) and had not taken a bicycle riding class (80%) (Table 2).

Table 2. Child Participant Characteristics

Age, Mean(SD)	12.0 (0.8)
Gender, N	
Male	5
Female	5
Grade, N	
5	2
6	1
7	4
8	2
9	1
Riding frequency (days per week), Mean (SD)	
Winter	0.6 (0.8)
Spring	3.7 (1.6)
Summer	4.7 (1.8)
Fall	3.7 (1.8)
Years of regular biking, Mean (SD)	5.3 (1.9)
Taken a bicycle riding class, N	
Yes	2
No	8
Ride bike to school, N	
Yes	8
No	2

3.2 Adult characteristics

The 10 adults included in this study ranged in age from 21 to 59, with an average age of 38.4. The sample was highly educated, with 80% having a 4-year college degree or higher. The majority of the sample were single, never married (70%) and employed (80%). Annual household income ranged fairly evenly across all categories from <$20,000 to >$59,999. Adults rode least frequently in winter, but otherwise evenly in frequency in spring, summer, and fall. The majority of adults reported that they ride their bicycles to work (80%) and had not taken a bicycle riding class (60%) (Table 3).

Table 3. Adult Participant Characteristics

Age, Mean (SD)	38.4 (13.6)
Gender, N	
Male	5
Female	5
Education, N	
Post high school	2
4-year college degree	7
Master's or doctorate	1
Marital Status, N	
Married	2
Single, Never Married	7
Widowed	1
Employed, N	
Yes	8
No or Retired	2
Annual Household Income, N	
< $20,000	2
$20,000 to $39,999	3
$40,000 to $59,999	1
>$59,999	3
Refused	1
Riding Frequency (days per week), Mean(SD)	
Winter	3.4 (2.7)
Spring	5.2 (1.5)
Summer	5.4 (1.3)
Fall	5.1 (1.4)
Years of regular biking, Mean (SD)	16.2 (12.1)
Taken a bicycle riding class, N	
Yes	4
No	6
Ride bike to work, N	
Yes	8
No	2
Age Learned to Drive, Mean (SD)	15.5 (1.7)

3.3 Trip characteristics

During their respective one week study periods, the 10 child participants rode an average of 10.7 trips, 12.8 miles, and 87.8 minutes (Table 4). Adults rode an average of 15.4 trips, 54.1 miles, and 254.3 minutes. From the federal functional class, derived from GPS points in GIS, we found that the majority of participant bicycle trips were along local roads, followed by collector roads. Average adult bicycle trips had more accumulated time on routes with bike paths and bike lanes than children, but also more route time on more heavily trafficked arterial roads. From video coding we were able to more precisely indicate where a bicyclist positioning along the route. For example, the federal functional class showed that 62.7% of average child trips were on local roads, but surface type ridden (from video coding) tells us that 56.4% of an average child bicycle trip was on sidewalks and only 25.1% were on paved streets with no bicycle facility, giving us a clearer picture. Comparing functional class to actual surface ridden also allows us to compare how often facilities were available to how often they were used. For example, average child bicycle trips had bike lanes and shared lane arrows available 6.8% of the time, but they were only used by the children 1.3% of the time. However, it is important to note that the way the federal functional class was derived in GIS introduced some error, so we cannot make definitive conclusions in the amount of difference in this type of comparison.

Table 4. Trip characteristics (N=261)

	Children		Adults		
Characteristic	**Mean**	**Range**	**Mean**	**Range**	**Adult vs. children p-value**
Number of trips, 1 week study period	10.7	2-25	15.4	2-25	0.16
Total distance, 1 week study period	12.8	5.1-31.9	54.1	19.9-113.5	**<0.01**
Total time, 1 week study period	87.8	26.2-154.1	254.3	139.3-445.4	**<0.01**
Federal Functional Class of Route (Average % time during trips)*-FROM GIS (GPS)					
Arterial (principal or minor)	0.04	0-1.5	3.1	0-39.2	**<0.01**
Collector (major or minor)	19.2	0-93.0	23.5	0-100	0.12
Local	62.7	7.0-100	48.2	0-100	**<0.01**
Shared Lane Arrows	6.8	0-52.3	5.5	0-78.9	0.36
Bike Lane	0	0	2.4	0-48.4	**<0.01**
Bike Path	6.9	0-66.6	14.1	0-99.5	**<0.01**
Other	4.3	0-71.4	3.1	0-51.1	0.37
Actual Surface Type Ridden (Avg % time of trips) –FROM GUI (video)					
Paved street no bike facility	25.1	0-100	60.1	0-100	**<0.01**
On-street bike facility (bike lane or shared lane arrows)	1.3	0-99.2	10.6	0-84.4	**<0.01**
Sidewalk or Side Path[d]	56.4	0-100	12.7	0-100	**<0.01**
Bike path	5.8	0-59.4	9.2	0-100	0.10
Gravel road	1.7	0-86.2	1.3	0-69.6	0.75
Other paved (e.g., parking lot)	4.6	0-42.0	5.8	0-100	0.29
Other unpaved (e.g., grass, dirt)	5.1	0-64.1	0.4	0-20.1	**<0.01**
Riding style (Average % time during trips, SD)*					
As a motorist	29.3	0-100	68.1	0-100	**<0.01**
As a pedestrian on bike	55.5	0-100	10.8	0-100	**<0.01**
As a pedestrian off bike	1.7	0-34.3	0.5	0-19.9	**0.03**
As a bicyclist	11.4	0-64.1	20.2	0-100	**<0.01**

*23 trips are not included because they did not have complete trip data or were outside of the 1 week study period, N=261

3.4 Safety-critical events

Safety-critical events were determined both by the riders themselves, as indicated from trip diaries, and from review of trip video footage by our research team. It was clear from both counts and rate calculations that some of the large differences in child and adults was likely an artifact of our coding scheme, which primarily relied upon traffic violations (Table 5). Adults had much higher rates per mile of both failure to stop or yield and failure to make a complete stop, however they also rode much more frequently on the street compared to children, who rode more frequently on sidewalks where the traffic rules do not equally apply. For all participants, the crash, near crash, and dangerous circumstance rates were low. Two crashes were captured in this study. Both of the crashes were a result of bicyclist handling errors and neither involved motor vehicles or significant injuries.

Table 5. Errors, traffic violations, near crashes, and crashes*

	Children		Adults	
Rider & Driver Errors/ Traffic Violations	**n**	**Rate per mile**	**n**	**Rate per mile**
All error/violation types	17	0.133	166	0.307
Slowed and looked, no complete stop, no traffic present	11	0.086	110	0.203
Failure to Stop or Yield	1	0.008	55	0.102
Reckless toward Ped[a]	1	0.008	0	0
Reckless toward Bike[b]	2	0.016	0	0
Against Traffic	2	0.016	0	0
Motorist Error	0	0	1	0.002
Crashes, near crashes, and dangerous circumstances				
Crash	1	0.008	1	0.002
Near crash	3	0.023	3	0.006
Dangerous Circumstance	0	0	1	0.002

*23 trips are not included because they did not have complete trip data or were outside of the 1 week study period, N=261
[a]Reckless toward ped = any action by participant bicyclist that impeded or endangered pedestrian
[b]Reckless toward bike = any action by participant bicyclist that impeded or endangered another bicyclist
[c]A sidepath is a bike or multi-use path that is directly adjacent to a road.

DISCUSSION

4.1 Challenges and lessons learned

Overall, participants were able to successfully record nearly all of their bicycling trips, resulting in a wealth of data. The GUI designed for this study allowed for accurate coding of trip surface type, rider behaviors (riding style, errors, crashes), and motorist errors. Risky behaviors were coded primarily in relation to traffic violations (e.g., failure to stop at a stop sign). Once the data were coded we found that children spent the majority of their ride time on sidewalks, where stop signs and pedestrian lights often did not exist, thus the number of traffic violations was much lower for children. However, subjectively, we found that children often did things that may have increased their risk (e.g., riding through an intersection via sidewalk without appropriately pausing/stopping to check for traffic). We could not count these types of scenarios as errors/violations to be in keeping with our coding scheme, which made the final comparison between adults and children appear skewed.

We found that GIS was a useful tool for coding roadway functional classification, aggregating time, and examining route choice. Two GIS approaches were utilized to extract and join information between the recorded GPS points and the roadway network information. We found that both methods were useful, but introduced some level of error because they both involved automated, imperfect, processes. Although we could not determine the exact amount of error this introduced, we estimate it was fairly small and, therefore, the information gained was still valuable.

4.2 Next steps

To address the limitations in our coding of bicyclist errors, especially among children, we plan to examine error rates by surface type (street, bike facility, sidewalk, etc.) and riding style (as motorist, as bicyclist, as pedestrian) to determine where exactly the current coding scheme fails. We hypothesize that the current way of coding traffic violations is not robust enough to account for riding on sidewalks and that modifications to our coding to capture risky behaviors that are not technical traffic violations would be beneficial. We will also continue to investigate ways to improve the performance of our GIS modeling to reduce error.

Finally, our future plans include enhancing our data collection system to capture variables our current system was not able to collect, but would be informative. We envision this improved instrumentation to include as braking force sensors, an accelerometer, and a handlebar push button to allow participants to record safety-critical events in real-time.

5 CONCLUSIONS

The naturalistic study of bicycling behavior is needed to build an evidence base for a comprehensive safety road safety strategy that can reduce injuries and fatalities among bicyclists. The data acquisition system and data coding methodology used in this study demonstrate that naturalistic bicycling research is feasible. The results begin to provide evidence for the variations in risk exposure and behaviors among cyclists of different ages and characteristics. Data from this study can be used to answer further research questions and establishes the utility in collecting naturalistic cycling data, which provides a robust picture that could be further enhanced if collected from a larger sample of bicyclists of different types and in different locations, as bicycling experience varies widely throughout the world.

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