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Integrated Crowdsourcing Platform to Investigate Non-Motorized Behavior and Risk Factors on Walking, Running, and Cycling Routes

FINAL REPORT

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There are several factors on the roads that impact bicyclists' safety. This research aims to find the most important risk factors on roads, mainly in infrastructure facilities, to improve the safety for walkers, runners, and bicyclists. Most mobile cycling applications currently used by cyclists and runners were reviewed in this study in order to gain insight about the features that users care about. Features, such as speed, cumulative elevation gain, and connectivity to Google Fit, were found to be the most common features in the widely-used cycling apps. In this research, we developed and launched a mobile application for crowd-sourcing of roads' risk factors. With the proposed application, some of the cycling risk factors can be mitigated. We launched the BikeableRoute mobile application allowing bicyclists to share reports of hazards encountered on roads with other fellow bicyclists and the local authorities. To achieve the goals of this study, the mobile application collects anonymous data and self-reported risk factors and biking data. This study allows collecting user's data for later processing to extract knowledge and insight. Our proposed system enables local authorities to operate more efficiently to handle the feedback provided by the citizens. Also, the local government will be able to provide statistical reports that provide estimates of the traffic on the different routes throughout the local community.</td></tr>
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1. Background

During the period from 1990 to 2009, the number of bicycle trips in the United States increased from 1.7 billion to 4 billion. Between 2005 and 2008, the percentage of people who primarily commute to work by bicycle increased from 0.4 to 0.55 percent (The National Bicycling and Walking Study: 15-Year Status Report, May 2010).

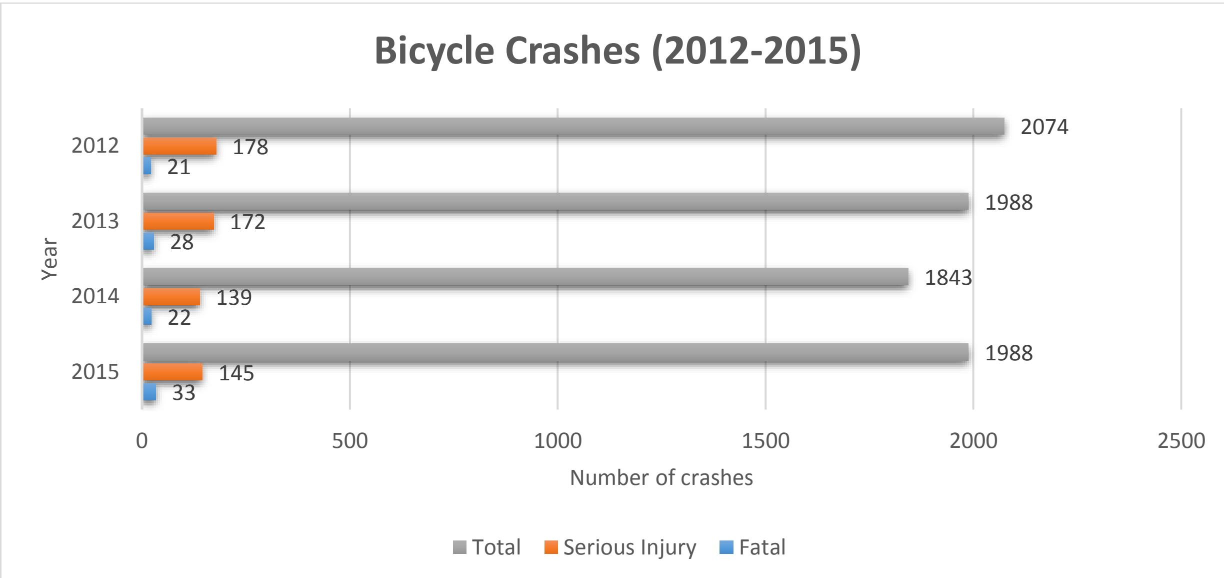


Figure 1: Bicycle crashes

This higher rate of biking has exposed bikers to higher risk, in 2015 there were 1988 crashes involving bicyclists. Of these crashes, 33 were fatal and 145 resulted in serious injuries throughout the state of Michigan. Even though the number of bicycle crashes decreased by 4.1 percent from 2012, the number of fatal bicycle crashes increased by 36.36 percent from the same year in Michigan.

It was found that walking and cycling minimize the costs associated with traffic crashes and congestion. Carbon emission from transportation can be reduced if cycling or walking are frequently used (Maibach, Steg, & Anable, 2009). Researchers in the last two decades have intensively focused on the perceived risk factors of cyclists. Lawson et al. (2013) stated that the presence and quality of cycling infrastructure, road geometry, traffic operation, and regulation of the road environment are considered as network-specific variables. (Pooley, et al., 20101) pointed out that the lack of dedicated cycle infrastructure is a significant hindrance of cycling. (Sanders, 2015) argued that traffic remains the most important anxiety for cyclists and potential cyclists. Cycle facilities change cyclists' perception of safety (Winter, et al., 2012). Eventually, the aforementioned studies lead to the conclusion that there is no doubt cyclist's decision to use a bicycle on a regular basis as a mode of commuting is related to the presence of infrastructure, traffic, and other facilities in a network.

Informing the public about the potential risk factors on walking, running, and cycling routes play a critical role in developing livable communities by saving lives and decreasing injuries. Information Technology (IT) plays an important role to keep the public and relevant city/county offices informed about risk factors on walking, running, and cycling routes in their areas of interest by adopting crowdsourcing. The deployment of intelligent systems that help the public identify, track, and monitor risk factors in their routes of interest will be of vital interest to the local communities, city/county departments, and the local economy.

This research focuses on the design and implementation of an intelligent software system that helps local authorities to track and analyze risk factor related information and disseminate alerts to the public promptly. Our research aims to exploit the ubiquity of mobile devices equipped with sensors to track and analyze the risk factors of public infrastructure. There are many mobile apps available in the marketplace that bicyclists, walkers, and runners utilize to track their exercises (BikeNet, 2015) (Biking, 2015).The mobile app that we developed in this effort does not overlap with the functionality that is offered by these apps. Instead, our app complements these functionalities by disseminating risk factor details to the public to warn them about the potential risks.

2. Literature review

Based on the bicycle hazard mitigation manual, bicycle hazards were categorized into several categories, namely: geometric design, traffic control elements, pavement condition, roadway maintenance, bike characteristics, cyclist's behavior, motorist behavior and policy & enforcement (Demers, Suddarth, Mahmassani, Ardekani, & Govind, 1995). However, in this project risk factors were categorizing under three categories: infrastructure-related, traffic-related and facility-related. (Reynolds, Harris, Teschke, Cripton, & Winters, 2009) studied the different types of transportation infrastructure that affect bicycle safety; thus, the study found that presence of bicycle facilities such as bike lanes, bike paths, street lighting, pavement surface and low-angled grades reduces the risk of crashes. There is another study that demonstrates that perceived traffic risk is multi-faceted in nature and perceived traffic risk is not monolithic (i.e., certain dangers are more worrisome). Near misses and collisions were found influencing cyclist's perception of traffic risks to varying degrees (Sanders, 2015). Furthermore, a study was conducted in Iowa that analyzed 147 bicycle crash sites found that the presence of on-road bicycle facilities such as bike lane and shared lane arrow decrease crash risks by 60% and 38% with bicycle-specific signage (Hamann & Peek-Asa, 2013). A study was conducted at the University of Maryland about bicycle facilities and policy innovations that would improve biking conditions. Thus, lack of consistency of bike lanes, high volume traffic, driver behaviors, unsafe riding habits of bicyclists and lack of bicycle route maps were found influencing the decision to bike (Akar & Clifton, 2009).

Crowdsourcing is defined as the process of acquiring needed services, ideas, or content by soliciting a contribution from a large group of people who particularly online users (Merriam-Webster, 2016). Geo-crowdsourcing is defined as data collected by ordinary citizens through digital mapping (via a web-interface) and volunteered geographic information is defined as an innovative digital technology approach to enriching available data for a wide-range of research and planning applications (Elwood, 2008).

A risk factor can be reported using direct measurement and crowdsourcing. The direct measurement is conducted by contacting cyclists directly (e.g., interview, survey, and bicycle crash data). (Poulos, Hatfield, Riddel, Grzebieta, & Mclntosh, 2011) measured and identified data about cyclists' crashes, near misses and injury rates. Cyclists survey was conducted in New South Wales over a period of 12 months, 2000 cyclists participated in the study. Another study was conducted by (Strauss, Miranda-Moreno, & Morency, 2015) aimed to estimate and map bicycle volumes and cyclist injury risks throughout the entire network of road segments and intersections on the island of Montreal, achieved by combining smartphone GPS traces and count data to map cyclists' injuries. Although the direct measurement method is an accurate method since it may have many participants, it is a tedious method that consumes a lot of time. It is also an expensive method that needs manpower to organize the study as well as it has coverage issues.

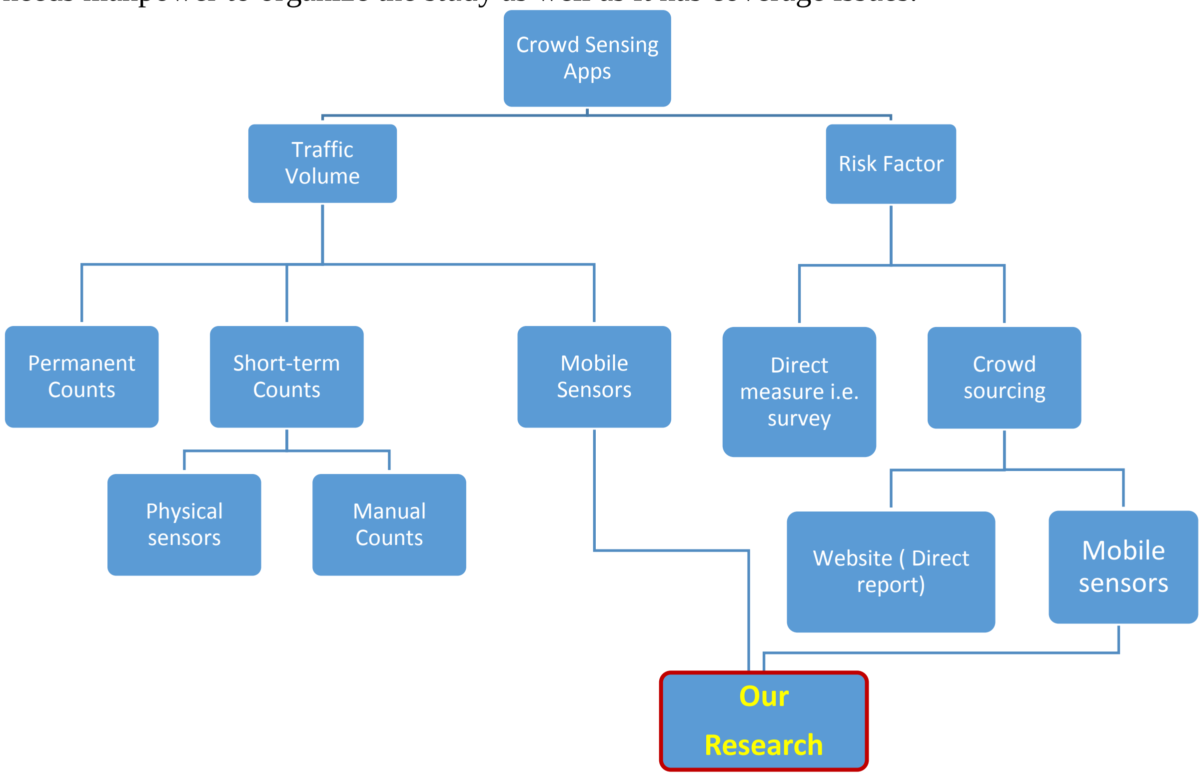


Figure 2: Literature review flowchart

Crowdsourcing is the second method used to report risk factors. Nelson et al. developed a website that allows users to map cycling risk factors such as collisions and near misses, in order to inform bicyclists about bicycle safety and risks (Nelson et al., 2005). However, their study did not allow users to report risk factors through a mobile application. Also, the website does not have the ability to inform local authorities about local hazards, besides it did not have the ability to estimate traffic volumes.

Traffic volume can be acquired using a variety of methods, in this project these methods have been classified into three broad categories, namely: permanent counts, short counts, and mobile sensors. *Permanent counts* are devices that count the traffic volume continuously during the whole year (e.g., inductive loop, infrared, magnetometer, and automated video imaging). Multiple inductive loop sensors were studied in order to sense different vehicles at the same sensors (Ali, George, Vanajakshi, & Venkatraman, 2012). Inductive loop counts and historical data were used to estimate missing daily bicycle volume data by using an auto-encoder neutral network model (El Esawey, Mosa, & Nasr, 2015). However, they found that even the conductive loops have some issues with accuracy; besides, inductive loops are relatively expensive compared to mobile sensing, physical sensors used for counting bicycle volume cost from $2000-$2500 per counter (Benz, Turner, & Qu, 2013) and do not cover a large area. Nevertheless, a study that examined inductive loops accuracy after a number of years of use by comparing it with manual count data found that inductive loop data showed 4% lower counts compared to manual counts (Nordback & Janson, 2010).

The second type to acquire traffic volume is through the use of *short-term counts* that count the traffic volume for a short period (e.g., week or month). The short-term counts can be attained through manual counts or physical sensors such as pneumatic tubes. (Strauss, Miranda-Moreno, & Morency, 2015) used manual counts and pneumatic tubes in order to validate bicycle volume in the network. (Nordback & Janson, 2010) used manual count data in order to examine the inductive loops accuracy after a number of years of use. Another study counted the pedestrian and bicycle volume in downtown Wilkes-Barre manually in order to assess downtown built environment and active living (Schasberger, Rackowski, Newman, & Polgar, 2012). Even though the short-term counts method is relatively accurate, it does not cover a large area and is somewhat expensive.

Informing the public about the potential risk factors on cycling routes has a critical role in developing livable communities, saving lives and reducing injuries. Information technology also plays an important role in keeping the public and relevant city/county departments aware of risk factors on biking routes in their areas of interest by utilizing crowdsourcing. The deployment of our BikeableRoute application helps the bicyclists identify, track, and monitor risk factors in their routes of interest and is of interest to the local communities, city, and local economy.

Our BikeableRoute mobile application is designed to help local authorities track and analyze risk factor related information and disseminate alerts to the public promptly. BikeableRoute aims to exploit the ubiquity of mobile devices equipped with sensors to track and analyze the risk factors of public infrastructure. There are many mobile applications available in the marketplace that bicyclists utilize to track their exercises. Our BikeableRoute mobile application does not overlap with the functionality that is offered by these mobile applications. Instead, our application complements these functionalities by disseminating risk factor details to the public to warn them about the potential risks. In the following paragraphs, we review some of the relevant mobile applications that are available in the marketplace as of this writing then we describe the details of our proposed mobile application.

FixMyStreet: An open source project to help people run websites for reporting infrastructure related issues seen on streets, such as potholes and broken street lights, to the appropriate authorities. Users report infrastructure related issues using the address where the issue is seen, by sticking a pin on a map, without worrying about the correct authority to report it to. FixMyStreet then reports the issues to the correct authority using the given location and type fields. FixMyStreet sends a report by email or using a web service such as Open311. Everyone can see the reported issues and leave updates. Users can also subscribe to email or RSS alerts of reported issues in their area. This service was created in 2007 by mySociety for reporting problems to UK councils and has been copied around the world. (wikipedia, FixMyStreet, 2016)

Street Bump: A crowd-sourcing project that helps residents to monitor and improve their neighborhood streets. Volunteers use the Street Bump mobile application to gather road condition data while they drive. The data provides governments with real-time information to fix problems and plan long-term investments. (StreetBump, 2013)

Grand Rapids 311: Grand Rapids 311 aims to help residents make their neighborhoods more beautiful by reporting local issues including potholes, graffiti, and streetlight outages. Residents can view the reports of others as well as track the status of reports they or other members of the community have submitted. (GrandRapid311, 2016)

Fill That Hole: In this application, users can report potholes and other road defects right from the roadside. This is enabled using smart phones' built-in cameras and GPS receivers. Working with the Fill That Hole website, the smart phone locates the user's location on the map, looks up the corresponding address and allows the user to enter details as needed. Also, users can add a picture and upload a report to the website. This application is created to report potholes in the UK. When users find a defect spot on the road and submit it through the application, Fill That Hole contacts the highway authority to get it fixed. (FillThatHole, 2014)

SeeClickFix: This service encourages residents to become proactive citizens by participating in governance and improving their community. (seeclickfix, 2015)

The focus of our Bikeableroute mobile application is on three main categories which cover most of issues encountered on roads.

3. Problem statement

Informing the public about potential risk factors on walking, running, and cycling routes plays a critical role in saving lives.

A major goal of this research is to work with the Kalamazoo Bicycle Club, the Kalamazoo Area Runners Club, and other stakeholders and the local city/county authorities to build and experiment with an intelligent software system that enables citizens to utilize a mobile application to inform local authorities of risk factors on local walking, running, and cycling routes. Our proposed system will enable local authorities to operate more efficiently to handle the feedback provided by the citizens. Also, the local government will be able to provide statistical reports that provide estimates of the traffic on the different routes throughout the local community.

4. Overview

There are several factors on the roads that impact bicyclists' safety. In our research, we aim to find the most important risk factors on roads, mainly in infrastructure facilities, to improve the safety for walkers, runners, and bicyclists. Most mobile cycling applications currently used by cyclists and runners were reviewed in this work in order to gain insight about the features that users care about. Features such as speed, cumulative elevation gain, and connectivity to Google Fit were found to be the most common features in the widely-used cycling apps. The list of applications and their features is shown in Appendix (A).

To this end, we developed and launched a mobile application for crowd-sourcing of roads' risk factors. With the proposed application, some of the cycling risk factors can be mitigated.
In Fall 2016, we launched the BikeableRoute mobile application allowing bicyclists to share reports of hazards encountered on roads with other fellow bicyclists and the local authorities. To achieve the goals of this study, the mobile application collects anonymous data and self-reported risk factors and biking data. This work aims to collect user's data for later processing to extract knowledge and insight.

The BikeableRoute mobile application can be downloaded from Apple's App Store and Google Play.

5. Development technologies

The BikeableRoute mobile application is a Cordova/Ionic based application that can be deployed on the Android or iOS platforms. For the backend, the mobile application utilizes Google App Engine infrastructure.

Apache Cordova (formerly PhoneGap) is a popular mobile application development framework. Apache Cordova enables software programmers to build applications for mobile devices using CSS3, HTML5, and JavaScript instead of relying on platform-specific APIs like those in Android, iOS, and Windows Phone. It enables intelligent wrapping of CSS, HTML, and JavaScript code for a specific target platform (e.g., Android, iOS, Windows Mobile).

Ionic is an HTML5 mobile app development framework targeted for building hybrid mobile applications. Hybrid applications are essentially small websites running in a mobile browser shell that has access to the native platform layer. Hybrid applications have many benefits over pure native applications, specifically in terms of platform support, speed of development, and access to 3rd party libraries.

Google App Engine (often referred to as GAE or simply App Engine) is a platform as a Service (Paas) cloud computing platform for developing and hosting web applications in Google-managed data centers. Applications are sandboxed and run across multiple servers. The Google App Engine offers automatic scaling for web applications—as the number of requests increases for an application, the Google App Engine automatically allocates more resources for the web application to handle the additional demand. The Google App Engine is free up to a certain level of consumed resources. Fees are charged for additional storage, bandwidth, or instance hours required by the application.

6. The scenario behind the BikeableRoute App

Users are able to send data (Track info, risk reports, feedback, and evaluation of routes) to the Google App engine when there is an Internet connection. When there is no connection, the user's data will be saved on the phone. Whenever a network connection is established, data is sent to the GAE. The vision behind creating this application is to provide safer and more comfortable trips for bicyclists. Application users can benefit from knowing the issues that they will encounter on their routes. Also, they can report hazards to the system so that other users can benefit from the added details. The reports are saved on the GAE and cannot be deleted by users. Only GAE administrators have access to the raw data. Users who track their routes allow us to collect their travel data for further analysis. The data that is collected in the users' reports include: Latitude, Longitude, Altitude, PlaceId, Highway value, date and time. Appendix C (Code snippet Part 1) illustrates the overall logic of sending reported data from Web SQL to the GAE.

We summarize the reported data and exported in Excel formal for the local authorities. This capability allows the local authorities to prioritize the remedy of reported hazards on the roads. When the hazards are eliminated, related reports are also deleted. Another feature that the mobile application provides is to track the users' routes in the background mode even when there is no network connection. In order to enable this feature, we used a Cordova plugin which works for Android and iOS devices. Appendix C (Code snippet part 2) details the process of calling the background plugin. We also provide a feedback page in the application for the users to request desirable features and report bugs. Appendix C (Code snippet part 3) shows the code that sends the users' feedback to the GAE. Below is a sample feedback that was received from one of the mobile application users:

"How about adding something like "Debris blocking bike lane" to your list of hazards? (I'm thinking tree branch down completely blocking bike lane) Unless that's not something you need to track. But DOT needs to clear that debris or there really is no bike lane if it abruptly halts due to large limb down."

Figure 3 provides a flowchart of the overall functionality of the BikeableRoute mobile applications while Figure 4 depicts the application's architecture. Figure 5 provides snapshots of the graphical user interface of the mobile application.

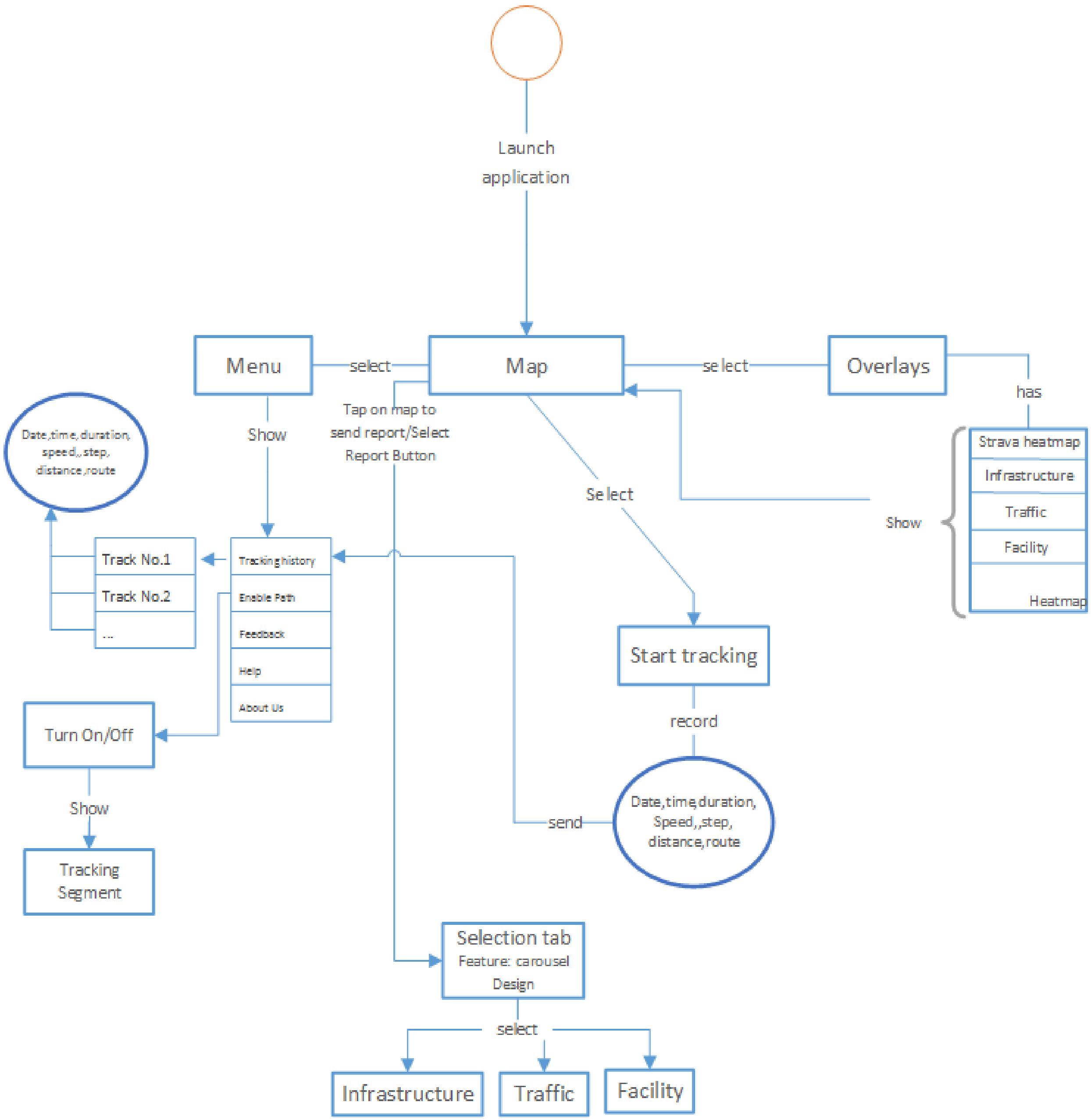


Figure 3: BikeableRoute functionality flowchart

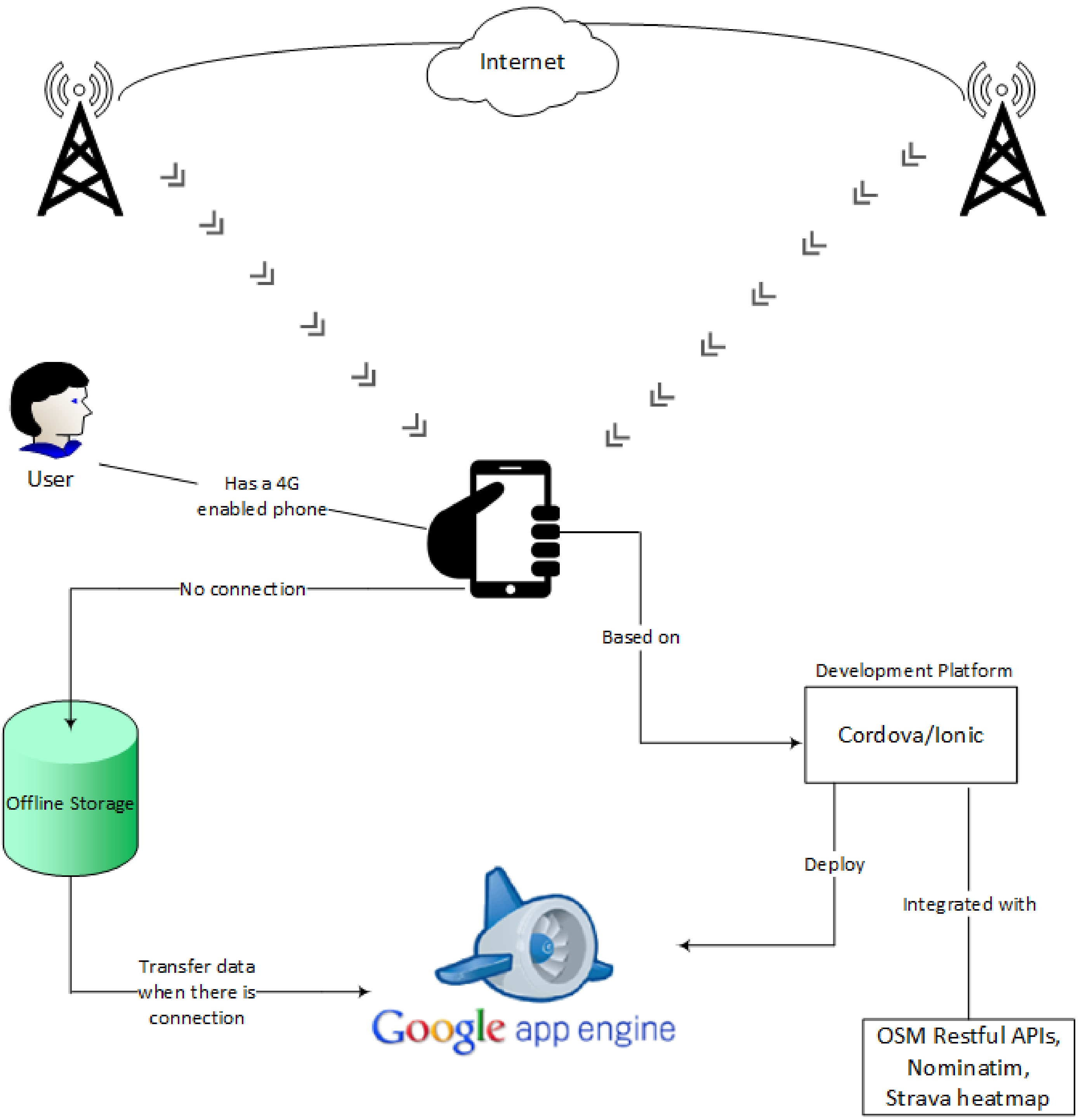


Figure 4: BikeableRoute architecture

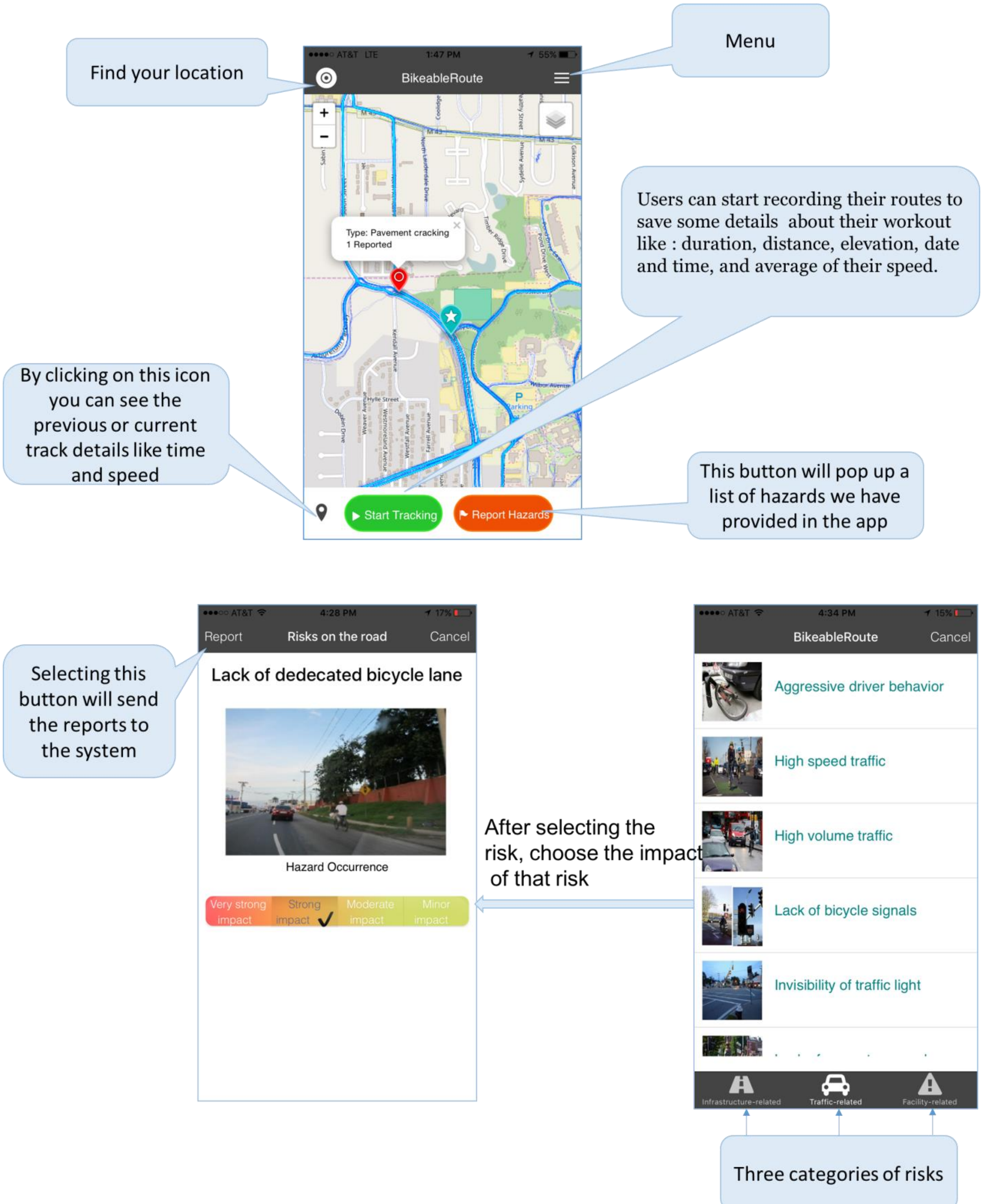


Figure 5: BikeableRoute App screenshot

7. Data structures

Our BikeableRoute mobile application integrates with Google App Engine infrastructure to store its data.

The following entities are the one utilizes in the GAE Datastore:

- **RiskReport**: Stores users' reported details.
- **UserEvaluation**: Stores the bikeability of the routes saved by users.
- **UserFeedback**: Stores the users' feedback about the application (i.e., bug reports and desirable features).
- **UserTrackData**: Stores details about the speed, duration, and distance of users' tracks.
- **Login**: Stores local authorities' authentication details to gain access to the raw collected data.

Reports are saved on the Google App Engine server. The data can be exported in Excel format for use by the local authorities. This feature allows the local authorities to prioritize the remedy of reported road/route hazards. After their elimination, hazards are deleted from the GAE reports. Figure 6 illustrates the properties that are tracked for each report. Appendix C (Code snippet Part 4) details handling of the RiskReport in the GAE.

Properties for kind "RiskReport"

Property name ^	Type	Index size	Data size
Date_Time	String	2.84 KB	439 B
Highway	String	2.27 KB	149 B
Latitude	Floating point number	2.41 KB	221 B
Longitude	Floating point number	2.44 KB	234 B
Place_id	Floating point number	2.41 KB	221 B
RiskId	String	2.66 KB	347 B
RiskType	Integer	2.41 KB	221 B
RiskValue	Integer	2.44 KB	234 B
Track_Id	Integer	2.41 KB	221 B
User_Name	String	2.95 KB	495 B

Figure 6: RiskReport properties

8. GIS data

In our mobile applications, we utilize GIS data (e.g., way-id and highway tag) in each report to pinpoint the position of the reported risk factors. Technically, we utilized the OpenStreetMap (OSM) RESTful APIs and Nominatim to Collect the GIS data. Nominatim is a tool that searches OSM data by name and address and to generate synthetic addresses of OSM points (i.e., reverse geocoding) (wikipedia, nominatim, 2017). Appendix C (Code snippet Part 5) provides the details of getting the place_id in Java. Appendix C (Code snippet Part 6) provides the details of getting the highway tag in Java. Also, Appendix C (Code snippet Part 7) details how the reports are communicated with the mobile application and its associated website.

9. Survey

The web survey was conducted, in order to collect feedback from potential users regarding the desired features of the planned mobile application and determine the most important risk factors. The survey was sent out to Kalamazoo bicycle group, WMU students, and faculties. They were asked a series of multiple-choice and free-response questions. There were a total of 182 completed responses to the survey. Respondents that claimed that they do not ride a bicycle were dropped out from the survey. A total of 24 participants were dropped based on this criterion. Those who claimed to have not used a mobile cycling application were asked a different set of questions.

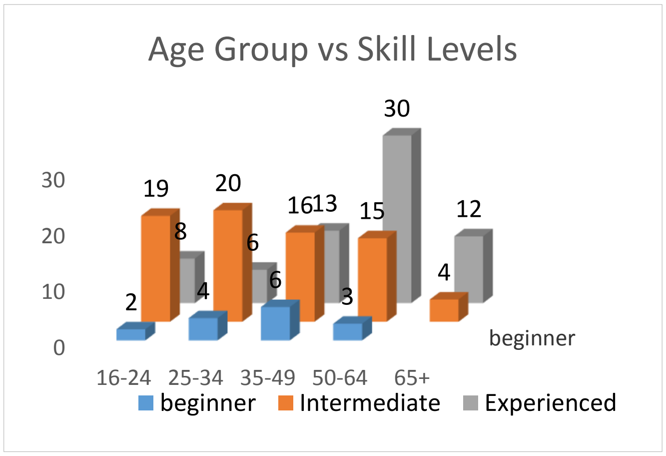


Figure 7: Age group vs skill levels

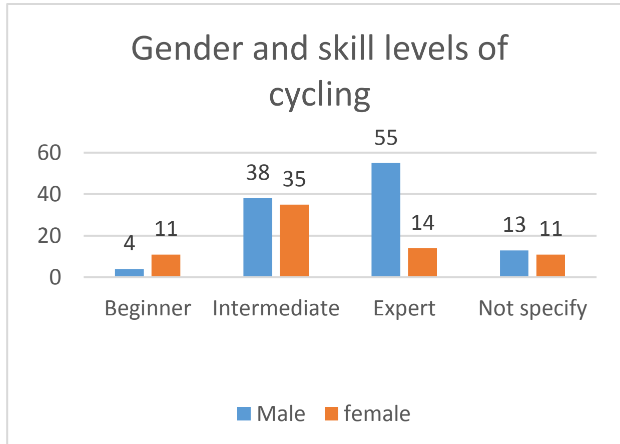


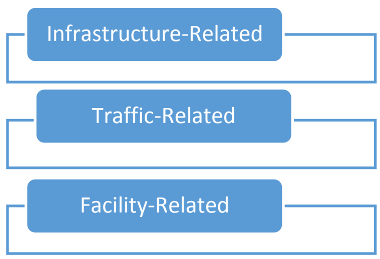
Figure 8: Gender and skill levels of participants

Out of all participants that completed the web survey, 60.77% are men and 39.23% are women. Also, 46.84% of the all participants were intermediate bikers. Based on the collected survey data, the primary purposes of the participants' bike trips are exercise and health (35%) and recreation (33%). Based on the survey, the most useful features that users use in mobile cycling applications are Mapping and Tracking. There were 92% users who would be interested in using a mobile cycling application that allows them to report risk factors. All the survey results are listed in appendix B.

We have categorized the risk factors into three categories. Survey participants were asked to rank the risk factors based on their impact of their cycling trips. The results of this part of the survey are also listed in Appendix B. For example, in the Infrastructure-related risk factors category, potholes were ranked to have the most impact, while stairways ranked as having the least impact.

10. Risk factors categories

The survey is based on cycling hazardous conditions identified from previous studies and through meeting members of the Kalamazoo bicycle group. Risk factors were classified into three categories, namely: infrastructure-related, traffic-related and facility-related. Several studies (Reynolds, Harris, Teschke, Cripton, & Winters, 2011) (Hamann & Peek-Asa, 2013) (Akar & Clifton, 2012) identified the different types of transportation infrastructure that affect bicycle safety such as bike lanes, bike paths, shared lane arrows street lighting, bicycle-specific signage, lack of bike lane continuity, high traffic volume, driver behaviors, unsafe riding habits of bicyclists, lack of bicycle route maps, pavement surface and low-angled grades reduce the risk of crashes. The survey included three main questions that addressed the risk factors relating to cycling. The first question aimed to investigate the impact of twenty infrastructure-related risk factors. The second question aimed to investigate the impact of seven traffic-related risk factors while the third one focused on the impact of twelve facility-related risk factors. The Likert scale with five levels was adopted in this survey since near misses and collisions were found to influence cyclists' perception of traffic risks to varying degrees (Sanders, 2015).



- **Infrastructure-related risk factors**
- Lack of dedicated bicycle lanes
- Lack of shared bicycle lane signs
- Lack of grade separated cycling paths (separated from motor vehicle and pedestrian)
- Narrow bicycle lanes
- Bus stop on bicycle lane
- Right-Turn channelization (bike lane being between right-turn and through lanes)
- Stairways
- Wheel-trapping catch-basin grates, gutters, and drainage grates (parallel bars)
- Pavement rutting
- Drop offs at overlays (uneven pavement)
- Open drainage ditches across the street
- Unpaved driveway and roads
- Unsmooth patches
- Wide pavement joints
- Steeply sloped gutters
- Unsafe railroad crossing (not at right angle)
- Pavement friction (slippery wet pavement)
- Potholes
- Pavement cracking
- Standing water

- **Traffic-related risk factors**
- Lack of bicycle detectors at signalized intersection
- High-speed traffic
- High volume traffic
- Inadequate cycle length
- Invisibility of traffic light

- Aggressive driver behavior

- **Facility-related risk factors**

- Unpruned trees and overgrowing vegetation.
- Speed bumps
- Rumble strips
- Insufficient lighting
- Absence bike racks
- Lack of signage devoted to bike traffic.
- Lack of information about existing facilities (i.e. maps)
- Raised lane markers
- Curbside auto parking
- Signs too close to roadway
- Blind corners (poor sight distance)
- Poorly managed work zones

Infrastructure - related	*16-24*	*25-34*	*35-49*	*50-64*	*65+*	*Beginner*	*Intermediate*	*Experienced*	*Male*	*Female*
Potholes	4.071 (1)	4.033 (1)	3.353 (3)	3.979 (1)	4.062 (1)	3.286 (4)	3.918 (1)	3.957 (1)	3.887 (1)	3.845 (1)
Lack of dedicated bike lane	3.571 (3)	3.9 (2)	3.441 (2)	3.625 (2)	3.375 (6)	3.786 (1)	3.726 (2)	3.435 (4)	3.505 (2)	3.759 (2)
Pavement rutting	3.231 (4)	3.655 (3)	3.176 (4)	3.542 (3)	4 (2)	3.769 (2)	3.38 (6)	3.522 (2)	3.406 (3)	3.571 (4)
Pavement cracking	3.607 (2)	3.31 (8)	2.824 (8)	3.417 (4)	3.875 (3)	3.077 (7)	3.288 (7)	3.464 (3)	3.247 (5)	3.526 (5)
Drop offs at overlay	3.111 (6)	3.533 (6)	3.059 (6)	3.313 (6)	3.625 (4)	3.429 (3)	3.417 (5)	3.145 (5)	3.25 (4)	3.345 (7)
Lack of grade separated	3.222 (5)	3.429 (7)	3.485 (1)	2.979 (8)	3.5 (5)	2.985 (8)	3.471 (3)	2.985 (7)	2.989 (8)	3.737 (3)
Narrow bicycle lane	3.071 (8)	3.621 (4)	3.156 (5)	3.064 (7)	3.125 (9)	3.167 (5)	3.431 (4)	2.956 (8)	3.031 (6)	3.491 (6)
Unsmooth patches	2.75 (11)	3.133 (10)	2.765 (9)	3.383 (5)	2.938 (13)	2.615 (11)	3.068 (9)	3.087 (6)	2.99 (7)	3.14 (9)
Lack of shared bicycle lane sign	2.808 (10)	3.571 (5)	2.545 (10)	2.979 (8)	3.125 (9)	2.923 (9)	3.143 (8)	2.824 (9)	2.894 (9)	3.143 (8)
Bus stop on bicycle	2.741 (12)	3.037 (11)	2.313 (15)	2.333 (18)	2.125 (20)	2.7 (10)	2.551 (17)	2.441 (15)	2.565 (15)	2.426 (19)
Standing water	2.929 (9)	3.172 (9)	2.441 (12)	2.667 (11)	3.125 (9)	2.538 (12)	3.055 (10)	2.594 (13)	2.753 (12)	2.912 (10)
Right-turn channelization	3.08 (7)	3 (12)	2.839 (7)	2.556 (14)	2.67 (17)	3.091 (6)	2.851 (11)	2.708 (12)	2.756 (11)	2.904 (11)
Wide pavement joints	2.464 (16)	2.846 (14)	2.485 (11)	2.978 (10)	3.2 (8)	2.455 (13)	2.8 (12)	2.791 (10)	2.8 (10)	2.731 (12)
Wheel-trapping catch-basin grates	2.704 (14)	2.429 (19)	2.333 (14)	2.617 (12)	3.375 (6)	2.091 (17)	2.577 (14)	2.739 (11)	2.594 (14)	2.63 (13)
Steep sloped gutters	2.385 (18)	2.654 (15)	2.121 (18)	2.442 (15)	2.875 (14)	2.333 (15)	2.485 (19)	2.418 (16)	2.407 (17)	2.538 (15)
Unsafe railroad crossing	2.571 (15)	2.963 (13)	2.344 (13)	2.34 (17)	2.813 (15)	2.4 (14)	2.577 (14)	2.536 (14)	2.604 (13)	2.434 (18)
Pavement friction	2.714 (13)	2.643 (16)	2.212 (16)	2.362 (16)	3.125 (9)	2.273 (16)	2.726 (13)	2.353 (17)	2.526 (16)	2.554 (14)
Unpaved driveway and roads	2.393 (17)	2.433 (18)	2.031 (20)	2.574 (13)	2.467 (18)	2.077 (18)	2.575 (16)	2.242 (19)	2.333 (18)	2.509 (16)

Open drainage ditches	2.37 (19)	2.56 (17)	2.034 (19)	2.318 (19)	2.8 (16)	1.778 (20)	2.515 (18)	2.286 (18)	2.319 (19)	2.457 (17)
Stairways	2.231 (20)	2.2 (20)	2.129 (17)	1.854 (20)	2.267 (19)	1.909 (19)	2.167 (20)	2.049 (20)	2.161 (20)	1.96 (20)

Table 1: Overall mean scores of different skill levels, age groups, and gender

The highest ranked hazards, based on the mean score for infrastructure-related questions, are highlighted in bold and shown in Table 1. The three highest perceived risk factors are potholes, pavement rutting, and lack of a dedicated bicycle lane. It can be noticed that there is a clear difference in the mean scores for beginners, intermediate, and experienced cyclists. Traffic-related facilities were ranked based on mean score. Aggressive driver behaviors, high-speed traffic, and high traffic volume were the highest three perceived risk factors. Finally, debris, lack of signage devoted to bicycle, and lack of bike racks were the highest in the facility-related risk factors.

11. Ordered Probit Model

An OPM is a powerful tool used to establish probabilities related to ordinal dependent variables. For this study, it was used to develop a model for each hazard in the survey questions. Table 2 shows how participants perceived narrow bicycle lanes within different categories considering age and skill level. Results from the model showed that the likelihood that beginner and intermediate cyclists would perceive narrow bicycle lanes as a hazard increased by 0.85 and 0.20, respectively, when compared to experienced cyclists. Narrow bicycle lanes were considered more dangerous by the age groups of 25-34 and 65+ by 0.5 and 0.28, respectively, in comparison to the 16-24 age group. The significant results were summarized in Table 2.

Narrow Bicycle Lane						
Ordered Probit Regression					Number of obs =	151
					LR chi2(4) =	13.69
					Prob > chi2 =	0.0083
Log likelihood = -227.18557					Pseudo R2 =	0.0293
Variable	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
Beginner	0.8536477	0.331933	**2.57**	0.01	0.2030716	1.504224
Intermediate	0.1999738	0.186711	1.07	0.284	-0.1659735	0.5659212
Age (25-34)	0.5058974	0.227035	**2.23**	0.026	0.0609171	0.9508777
Age 65+	0.2802477	0.303684	0.92	0.356	-0.314962	0.8754573

Table 2: OPM(age, and experience) perceived likelihood of Narrow bicycle Lane

As summarized Table 3, statistically significant differences were observed between skill levels and twelve risk factors, including narrow bicycle lane, bus stop on bicycle lane, unsmooth patches, pavement friction, standing water, lack of information, rumble strips, speed bumps, debris, and poorly managed work zones. Age groups were significantly different for eleven risk factors, which consisted of lack of shared sign, narrow bicycle lane, bus stop on bicycle lane, parallel bars, open drainage ditches, unsmooth patches, wide pavements joints, steep sloped gutters, aggressive drivers, rumble strips, and lack of bike racks. In addition, gender was significantly different for two risk factors, including raised lane markers, and sign too close to roadway.

Category		Significant Perceived Risk Factors
Gender	***Male***	• Raised lane markers • Signs too close to roadway
	Female	-
Age Group	***16-24***	-
	25-34	• Lack of shared bicycle lane signs • Narrow bicycle lanes • Bus stop on bicycle lane • Aggressive driver behavior • Lack of bike racks
	35-49	-
	50-64	• Unsmooth patches
	65+	• Parallel bars • Open Drainage Ditches • Wide pavement joints • Steep sloped gutters • Rumble strips
Skill Level	***Beginner***	• Narrow bicycle lanes • Bus stop on bicycle lane • Unsmooth patches • Pavement friction • Rumble strips • Speed bumps
	Intermediate	• Standing water • Lack of information about existing facilities • Curbside auto parking • Signs too close to roadway • Unpruned trees and overgrowing vegetation • Poorly managed work zones
	Experienced	-

Table 3: OPM(gender, age groups, and skill levels) significant finding of perceived risk factors at different levels

Results showed that beginner cyclists were more likely to perceive narrow bicycle lanes, bus stops on bicycle lanes, unsmooth patches, pavement friction, rumble strips, and speed bumps as a hazard, while these factors were not considered hazardous by experienced cyclists. On the other hand, the 65+ age group considered parallel bars, open drainage ditches, wide pavement joints, deep sloped gutters, and rumble strips to be riskier than these factors were perceived by the 16-24 age group as shown in Tables 1 and 3.

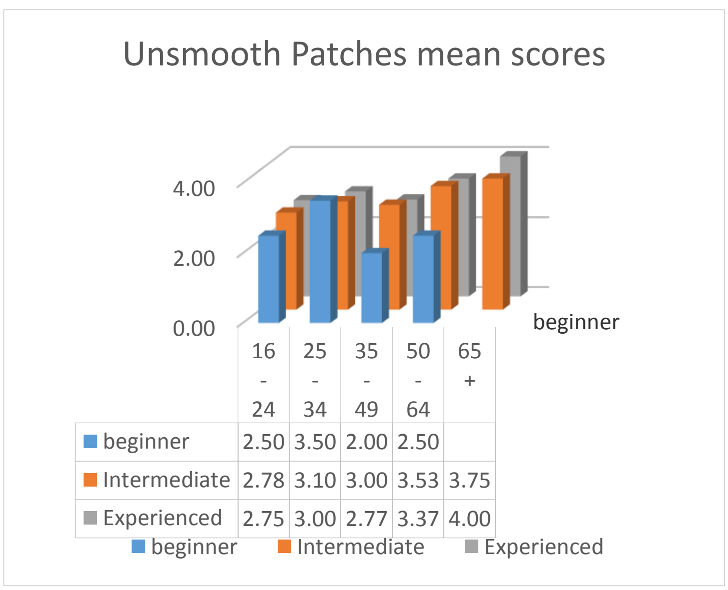


Figure 9: Unsmooth patches mean scores

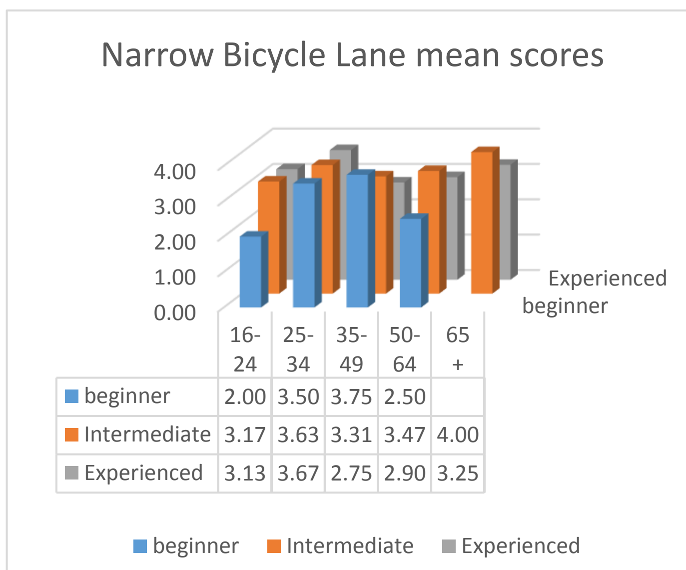


Figure 10: Narrow bicycle lane mean scores

The unsmooth patches mean scores shown in Figure 9 indicate that intermediate cyclists perceived unsmooth patches differently compared to experienced cyclists and age group 50-64. Figure 10 shows the mean score of different skill levels versus age groups for "narrow bicycle lane." Mean scores and the OPM point that beginner cyclists were more likely to perceive narrow bicycle lanes as hazardous compared to experienced cyclists. In other hands, age group 25-35 considered narrow bicycle lanes riskier than age group 16-24 as shown in mean score and the OPM. This study consisted of a survey that addressed how cyclists perceived risk factors when considering skill level, age, and gender. Risk factors were classified into three categories: infrastructure-related, traffic-related, and facility-related. Descriptive statistics and OPM were used for analyzing the survey responses. Mean scores were used to rank the risk factors. Potholes, lack of a dedicated bicycle lane, and pavement rutting were the severest risk factor based on mean scores. Traffic-related facilities were also ranked based on mean score. Aggressive driving behavior, high speed traffic, and high traffic volume were the highest three perceived risk factors, respectively. Finally, debris, lack of signage devoted to bicycle traffic, and lack of bike racks were the highest ranked facility-related risk factors. Significant differences were observed in the mean scores for beginners, intermediate, and experienced cyclists. The OPM was utilized to examine perceived risk factors among different skill levels, gender, and age groups. Gender was found to be statistically significant for two hazardous actions in facility-related factors. Age group was found to be statistically significant for eight risks in infrastructure-related factors. Finally, skill level was found to be statically significant for twelve risks. Therefore, these results indicate that perceived risk of cycling hazards may be dependent on the cyclist’s age group, gender, and skill level. However, the results do not disclose the reason of these differences. Further research on perceived risk of cycling could be expanded by exploring behavioral responses to certain risk factors. Different risk scenarios could be studied through use of a bicycling simulator or interviewing cyclists where the risk factors are found.

Users’ reported hazards were collected after releasing the application in October 2016. Figure 11 shows a sample report from the BikeableRoute App and Table 6 in Appendix C shows the corresponding data in the GAE datastore.

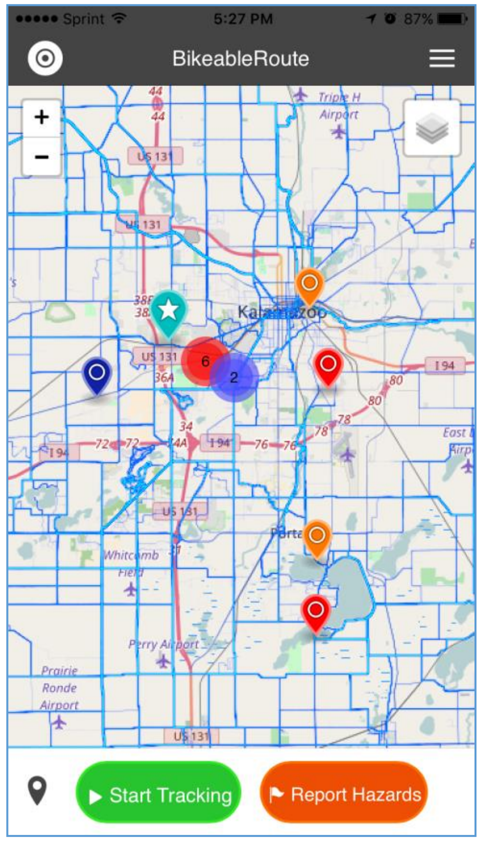


Figure 11: Map report on Oct 2016

12. Traffic volume

Cycling volumes enable decision makers and researchers to investigate many factors that prevent cyclists from using certain roads (Griswold, Medury, & Schneider, 2011). In addition, cycling volumes are used to determine the exposure when evaluating the cycling safety (Nelson, Denouden, Jestico, Laberee, & Winters, 2015). The traditional methods to collect cycling traffic volumes include: manual counts, permanent count stations, and surveys. The Global Position System (GPS) is a new method for collecting cycling volumes. Smartphones have GPS receivers that allow them to track and map users' locations (Le Dantec, Asad, Misra, & Watkins, 2015). (Casello & Usyukov, 2014) used GPS to determine which routes were chosen by cyclists in order to know the variables that influence the cyclist's decision. Our BikeableRoute mobile application quantifies and maps the activities of cyclists who used the BikeableRoute app spatially and temporal. The crowdsourced BikeableRoute mobile application data was collected in the period from October 15, 2016, to March 25, 2017, in Kalamazoo, MI.

Since the release of the BikeableRoute mobile application, the total number of distinct devices that used the application is 27. We conducted traffic volume estimation based on a total number of devices on each road segment. To recognize each segment, we retrieve its associated Place-ID through reverse geocoding using the Nominatim API.

Figure 12 shows the traffic volume estimates based on the data reported through the BikeableRoute mobile application. Figure 13 shows the traffic volume in a specific Place-ID where the total number of distinct devices that pass this area was 7.

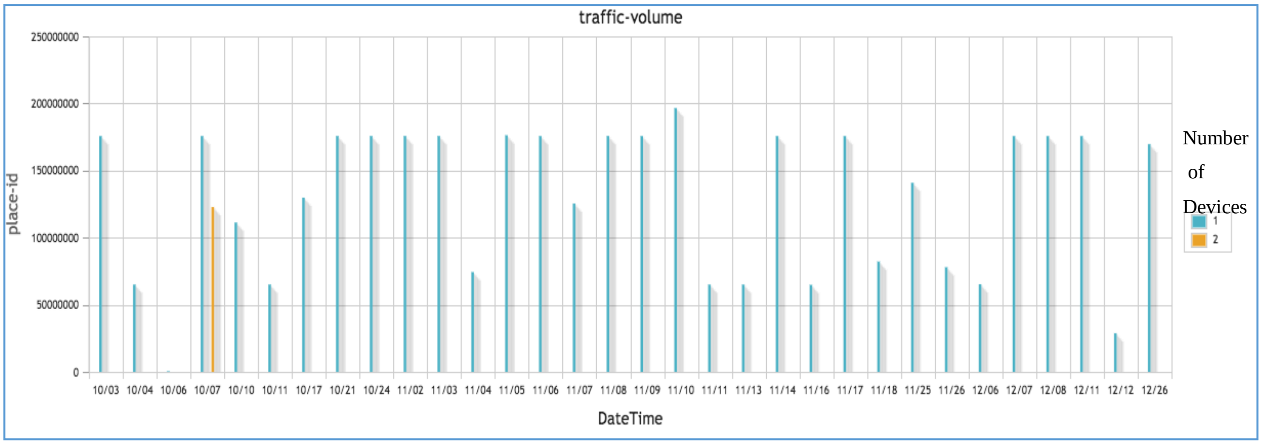


Figure 12: Traffic volume

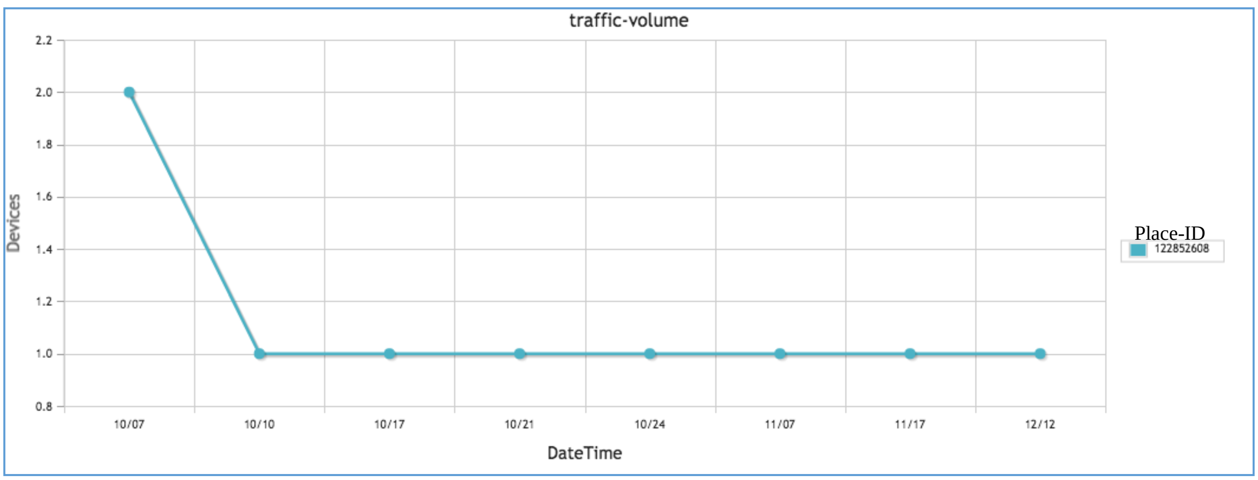


Figure 13: Traffic volume in a specific Place_ID

13. IMU Data vs. Mobile Data

A comparative study was conducted between the BikeableRoute mobile application and Instrumented Probe Bicycle (IPB) in order to assess their performance in measuring the bikeability of cycling routes. The experiment was designed to collect the necessary data, including: GPS, accelerometer, and gyroscope data. The IPB is an equipped bicycle that was designed and built by a research group in the Transportation Research Center for Livable Community (TRCLC). The IPB has various individual sensors that were connected to a laptop. The sensors are able to collect data such as the angular velocity of the front and rear wheels, bicycle linear accelerations, angular velocities, GPS, angular of displacement of the handle bar, and lean and pitch angle of the rider. The inertial measurement unit (IMU) considered the most important sensor on the IPB includes:

three accelerometers, three rate gyroscopes, three magnetometers, and GPS receiver. The way the sensor was built makes it robust and accurate, albeit expensive. In addition, the IMU was factory calibrated prior to being used.

The experimental trial process was designed to engage a rider in a handful of different situations. These situations include: bike lane with the smooth road surface, unpaved road, and sidewalk. It was decided to use a route of relatively short overall distance. The experimental route described was slightly less than one mile. In this experiment, we compared the accelerometer and gyroscope measurements collected using the smart phone (Android) with that collected using the MU sensor. We compared the latitude and longitude collected by the IMU with the ones collected by the smart phone. The readings were quite similar. This provides the insight that smart phones can be used to quantify the bikeability of cycling routes without the need to use expensive IMUs. A subset of the data samples that we collected in our experiments is included in Appendix D.

It should be emphasized that this comparison is based on the analysis of a single trial. Therefore, more trials are required to make a statistical comparison between the two data sets. In addition, different smart phone types should be tested, in ordered to know if they the Operating System (OS) or the specific hardware of the smart phone plays a significant role on the usability of its sensory data in support of quantifying the bikeability of cycling routes.

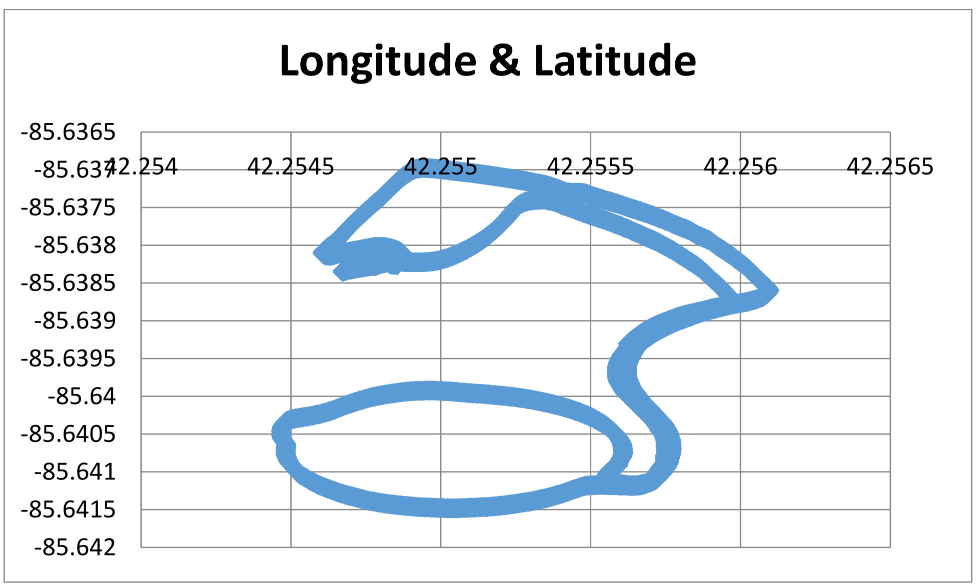


Figure 14: IMU latitude and longitude Data

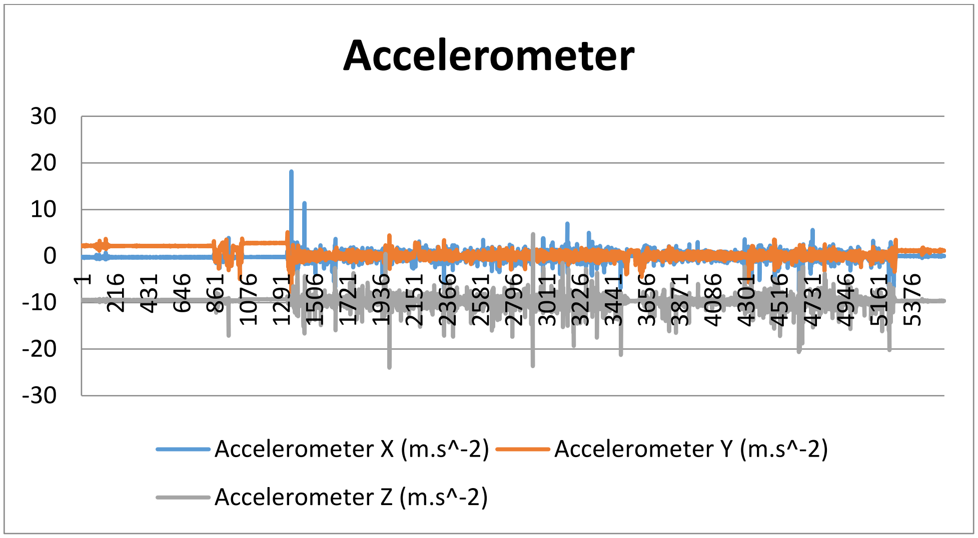


Figure 15: IMU Accelerometer Data

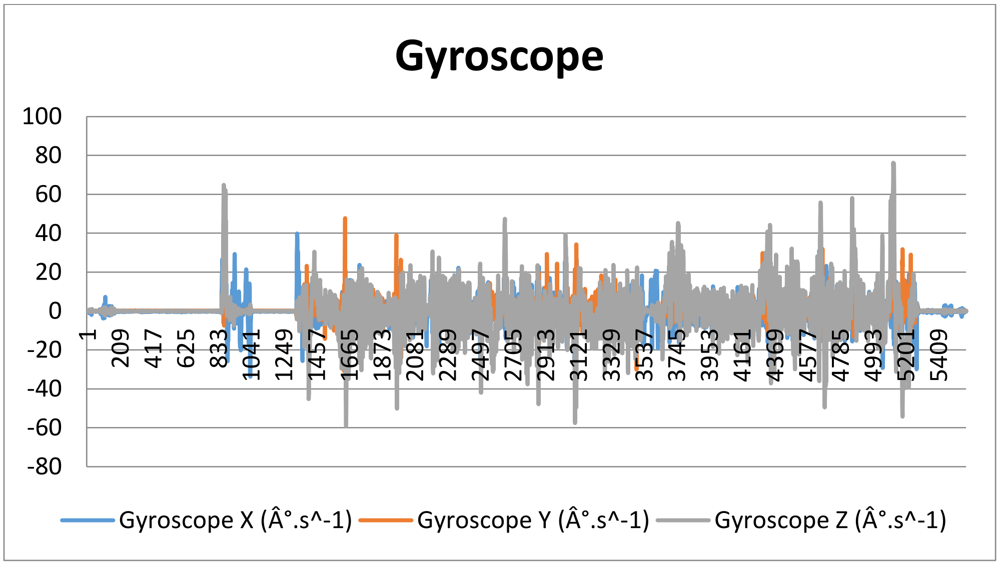


Figure 16: IMU gyroscope Data

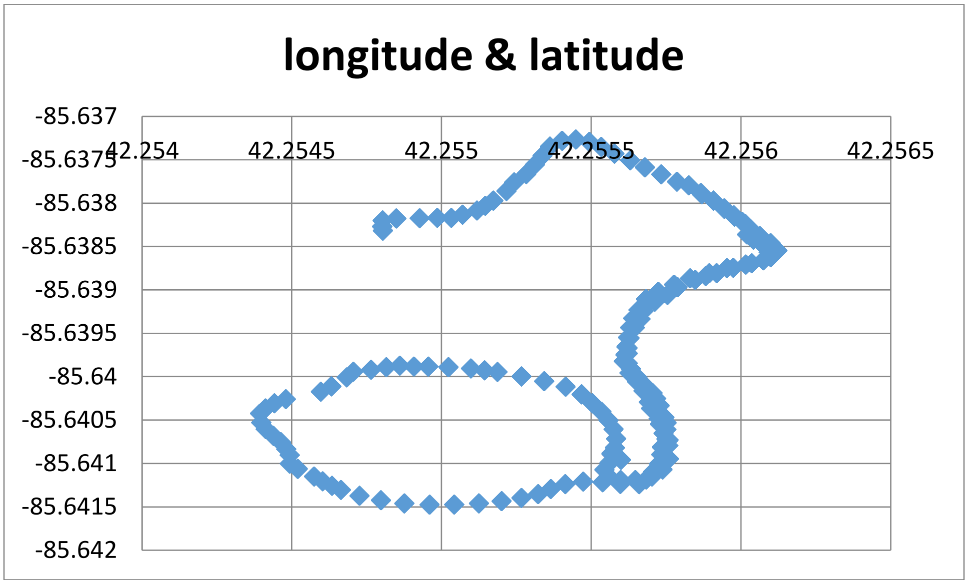


Figure 17: Mobile App latitude and longitude Data

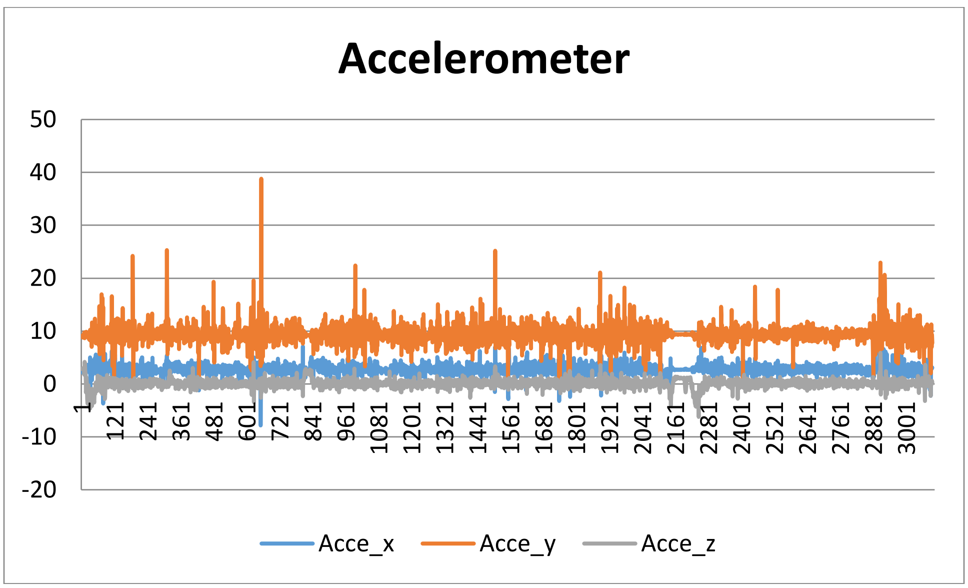


Figure 18: Mobile App Accelerometer

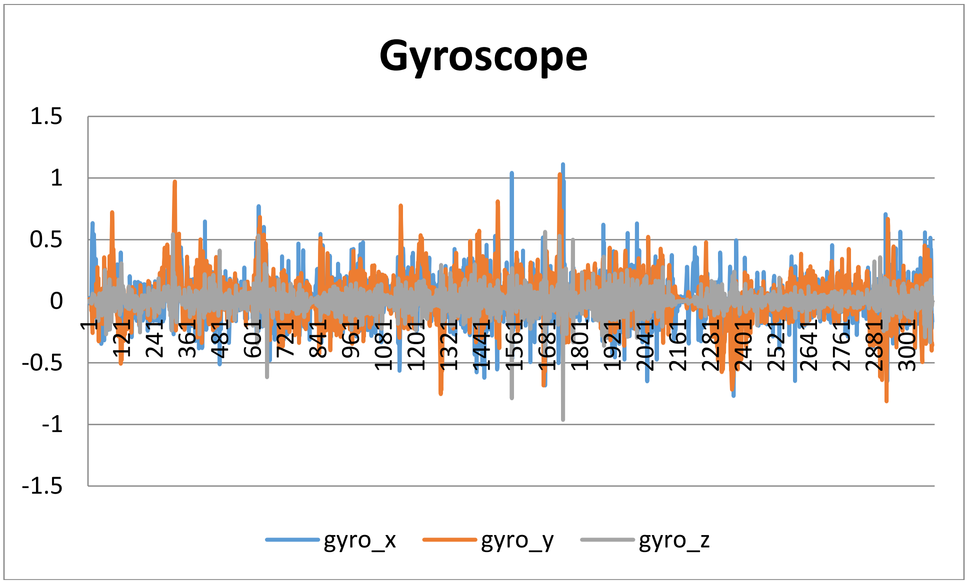


Figure 19: Mobile App Gyroscope Data

14. Conclusion

In this research, we designed and experimented with a mobile application for citizens to report risk factors encountered on cycling routes. The risk factors are categorized into three major categories. Risk factors reported through the mobile application are sent to fellow citizens and local authorities to benefit from.

In our future work, we plan to introduce Integrated Intelligent Transportation Systems (ITS) features into the mobile application (e.g., collision/Hazard warning). We also plan to benefit from off-the-shelf M2M communication technologies (e.g., WiFi-Direct, LTE-Direct, and Bluetooth smart). These technologies are becoming more widespread in smartphones. This technology allows Vehicle-to-Device (V2D) communications with contributes to pedestrian safety. Also, we aim to utilize machine learning techniques to extract hidden patterns from collected risk factor data.

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16. Appendix

List of Best Bicycle Mobile Applications

NO.	Apps' Name	Apple Store	Google play	Basic Feature		
1	**Starva (GPS)** Fast company track your rides with GPS	**14911 rating** **4.5 stars**	Installs (5-10) millions -142240 rating 4.6 stars	Follow routes you have created or found and view your activity map as you record	Tracks and records (speed, time, elevation, calories burned, and distance) while you riding	how is your performance and if you set a new record
				Collect heart rate, power and cadence data from ANT+	Provide statistics such as calories burned and elevation ridden.	Socialize: follow friends and their activates. (Find you friends and motivate them). Join clubs and create new one take part of challenges.
				Filtered leaderboards by age and weight / Control your privacy setting	Record maintenance	Provide information about most popular(competitive) segment anywhere you go
				Share your activates on social media	heart rate analysis and see your Suffer Score	Set weekly mileage or time-based goals and keep tracking your effort against past effort, as well as with other athletes.
				See which from your friends out riding or running	Visualize your training with Power Zone and Pace Distribution analysis	Stay on top of your game throughout the year with training videos
2.	**MapMyRide** For plotting routes	**36446 rating**	Installs (1-5) million 59,320 rating (4.4) stars	**How many calories you have burned	24/7 Activity Graph (sleep, workouts)	Import data from best activity tracking devices i.e. Jawbone, Misfit, Fitbit, Garmin, Withings and more (Bluetooth Smart™ and ANT+
				Workout Stats (GPS / pace / route / distance/ calorie burn/	*Sync your account with other health and nutrition apps i.e (my fitness pal)	Share your progress in social media and other health and nutrition apps

				elevation profile)		
					Join community (share the progress and see what friends are in your activity feed.	Challenges (join challenges for some friends) and win prizes
					Heart rate analysis, personal training plans, audio coaching, and live tracking	Gear Tracker - Add your athletic shoes and start tracking mileage with Gear Tracker. Help yourself avoid common injuries and get notified when it’s time for a new pair
						Avoid bad parts
3.	**Runtastic Road Bike Tracker**	**2202 rating (4.5)**	Installs (1-5) million 73,927 rating (4.5) stars	Track bike tours via GPS: Distance, duration, speed, elevation gain, pace, calories burned	LIVE Tracking & Cheers	Plotting routes or finding other routes in your area good option for those wanting to discover a part of the county
				Route search: Browse & search thousands of bike routes	Voice Coach: Keeps you posted on speed, distance, elevation gain	Display your current rate of climb during a tour (elevation gain/minute
				Maps (Google Maps) Offline Maps: Download & save maps	Show current grade in %	Determine cadence & speed during your velo tours with the Runtastic Speed & Cadence Sensor
				Heart rate measurement	Configure your display	Auto Pause
				Music: Create a playlist for your tours & activate Powersong	Wind & weather conditions	Detailed post-tour analysis incl. time rode uphill, downhill, flat, as well as graphs & training progress
				Share your routes & success on Google+, Facebook, Twitter and via email	Open Street Map/Open Cycle Map Integration	

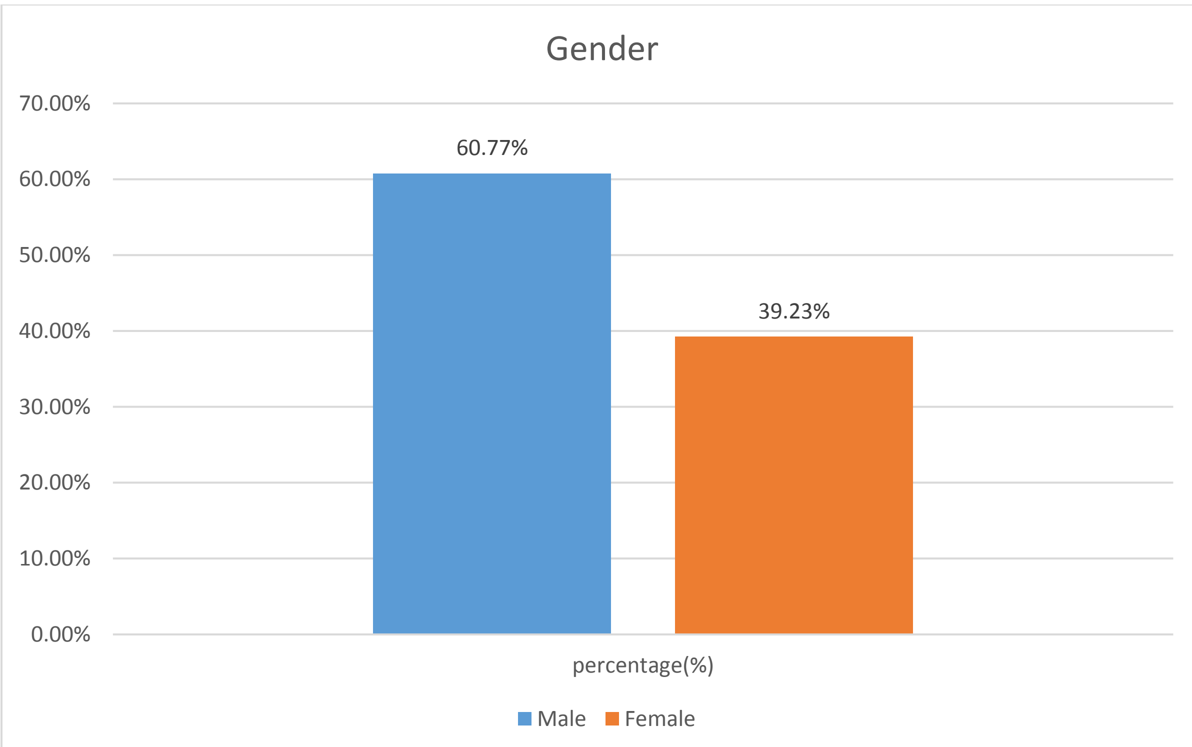
4.	**Google Maps**		Installs (1-5) billion 5.1 million reviews (4.3)stars		Audio urn-by-turn instructions (Voice-guided)	Live traffic conditions, incident report, automatic rerouting to find the best route
					Transit directions	Street view
5.	**Cyclemeter GPS**	**7024 rating 4.5 stars**		Connect with social media	Automated posting features and you can (customization)	Startup quick and effortlessly connects other sensors i.e. Polar HR Chest and Bontrager Doutrap sensor
				Average speed, riding time, stopped time, heart rate, cycle cadence, calories and weather	Does not drain the phone battery	For safety, you can set it emails of your location to anyone you want every 15 min and while you riding and if stop
				Records steps all day and cadence during workouts	View terrain and traffic maps with Google maps	Records an unlimited number of workouts
				No website login required	Swipe across the stopwatch to see pages of stats, maps, and graphs - completely configurable.	View your workouts on a calendar, and by routes and activities
				Exclude stopped time with automatic stop detection	Record heart rate, bike speed, bike cadence, and bike power with sensors	Automatically record the weather
				Start and stop with your earphone remote	Keep on track with extremely configurable interval training, zones, and target	Hear announcements that keep you in the zone
				Analyze your split, interval, and zone performance	Hear stats automatically at time or distance intervals, or on-demand with your earphone remote	Listen to comments from friends and followers on Facebook
				Compete against your previous workouts along a route	See your virtual competition on a map and in graphs	Design your own training plans

				Synchronize your plan with your iPhone calendar and your online calendars		
6.	**Wahoo Fitness: Workout Tracker**	**1834 rating 4.0**	Installs (50-100)K 2,043 reviews (4.0)	GPS map	Upload workouts to your favorite training website, including Strava, RunKeeper, MapMyFitness	Pair with other BTLE and ANT+™ heartrate, footpod and bike speed/cadence/power devices
					Get comprehensive cycling power data. Offers multiple power screens	Use multiple sensors at once. You can use multiple sensors at the same time without interference
					Heart rate/ calculate HR zones and average / max heart rate and how much	Get the most accurate calorie burn count. Add your user data such as age, weight, and height to get personalized calorie burn information
					See a summary of the results from your entire workout history,	Dedicated KICKR workout screen with four modes including Resistance Levels, Ergo Mode, Simulation Mode and Manual mode
7.	**BikeComputer**		Installs (500k-1 million) 5282 reviews (4.3)	follow your trip on the map and see distance, speed, and all other relevant data	plan a route by setting points on the map (calculate the track and distance)	move waypoints of the route using drag-drop and discover new trails or unknown roads
				elevation profile	Offline map	
				Share your trip on social media	Back up to another phone	English and metric system
8.	**CycleDroid – bike computer**		Installs (100-500)k 6761 reviews (4.4)	Display (speed/ distance / time / altitude/ elevation / slop/ burned calories/ fat)	creating trips and assigning collected data to a specified trip/ creating trips and assigning collected data to a specified trip	All data collected by the application can be exported to an SD card
				precise location (GPS and network-based)	Drawing graphs: altitude/distance, speed/distance, speed/time. You can easily zoom	prevent the device from sleeping

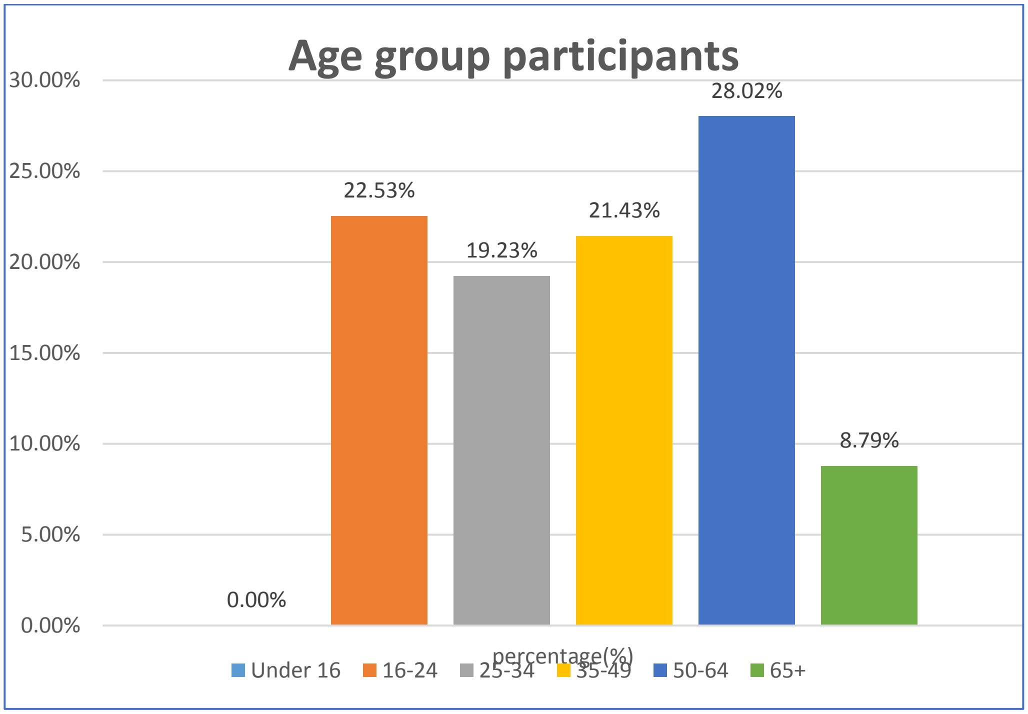
					in/out a graph using multi-touch	
				full network access		
9.	**iBiker**	**361 rating (4.5)**		Distance, time, pace/speed and splits tracker	Complete route mapping for outdoor activity	Listen to voice feedback as you workout
				See your results and charts for all workouts	Track your weight, blood pressure, and sleep scores, integrates with Withings, Jawbone UP, Fitbit, Misfit Shine	Sync data to multiple devices and view online
				Share on social media		
10.	**BikeMaps (to make biking safer)**		Installs (500-1000) 16 review (4.7)	Map the trouble spot	He feedback of safety, hazards, and thefts will be analyzed on GIS	Identify hot spot of cycling safety/ risk and crime

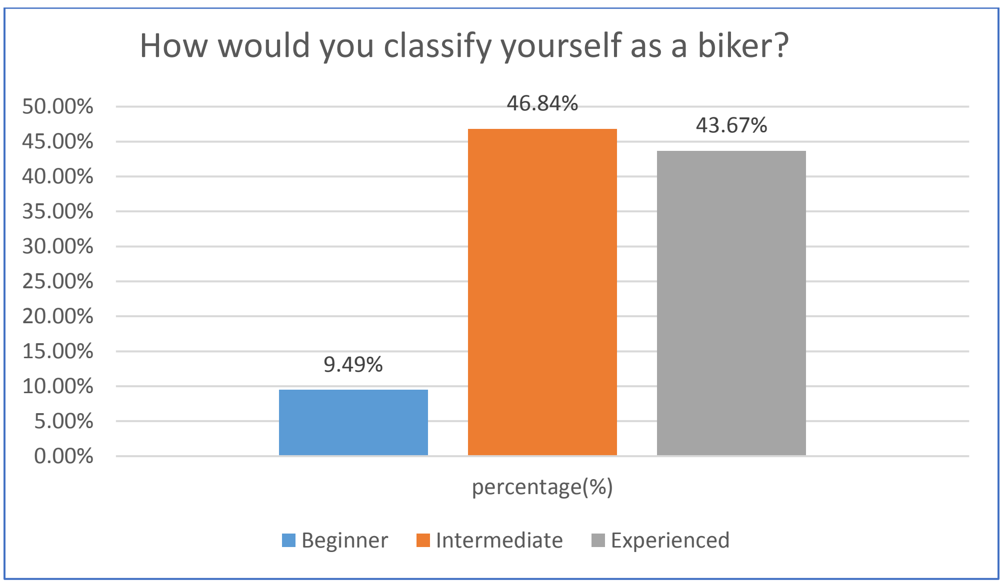
Survey Results

Answer	percentage(%)	No. of participant
Male	60.77%	110
Female	39.23%	71
Total	100.00%	181

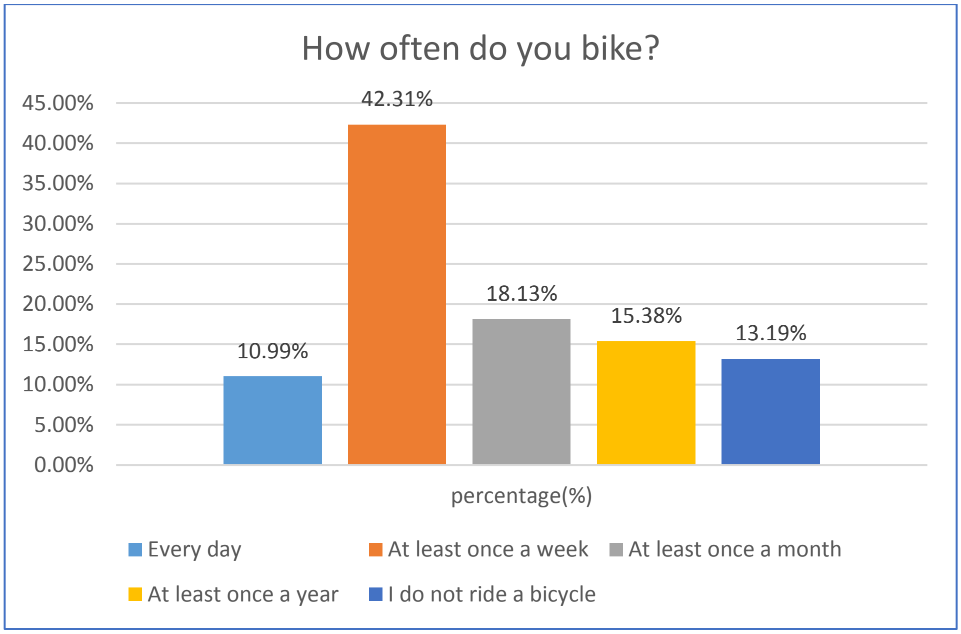


Age Group and Skill Level

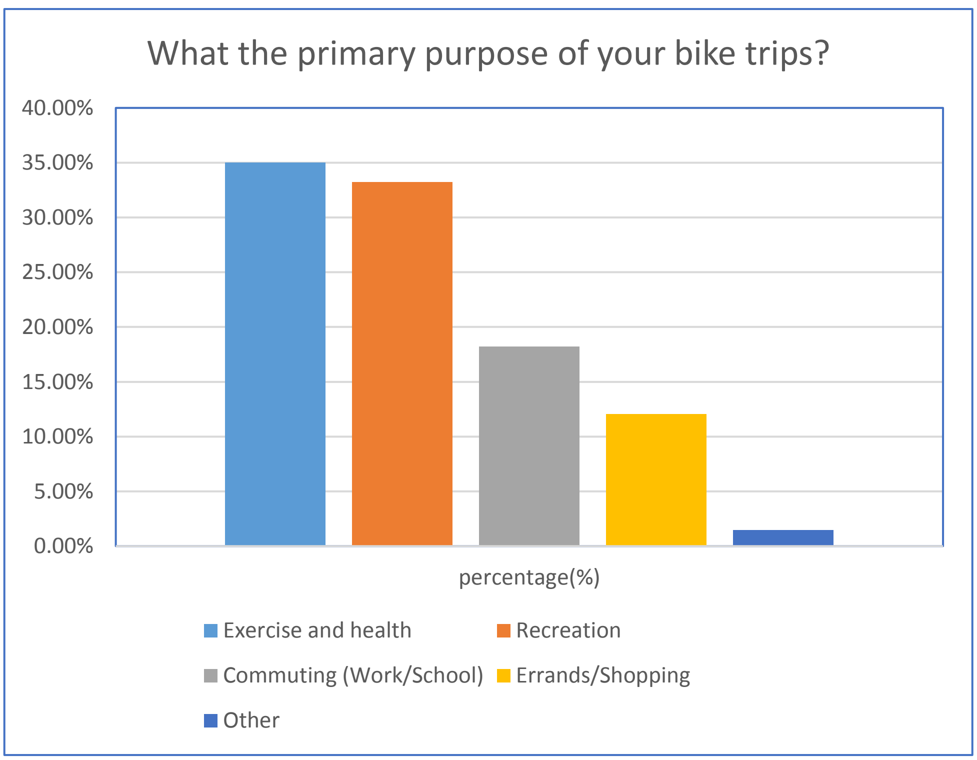


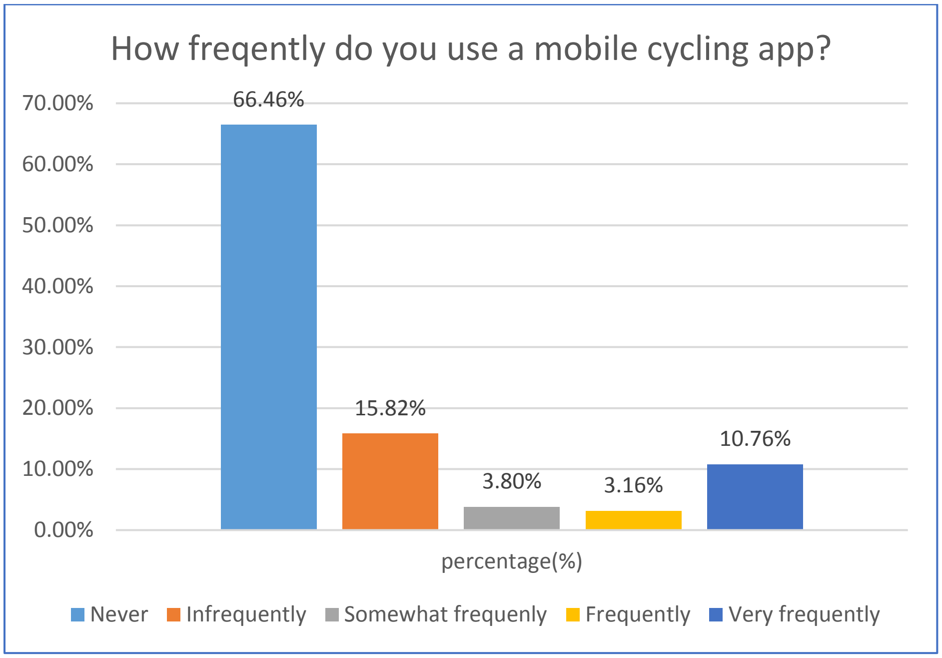


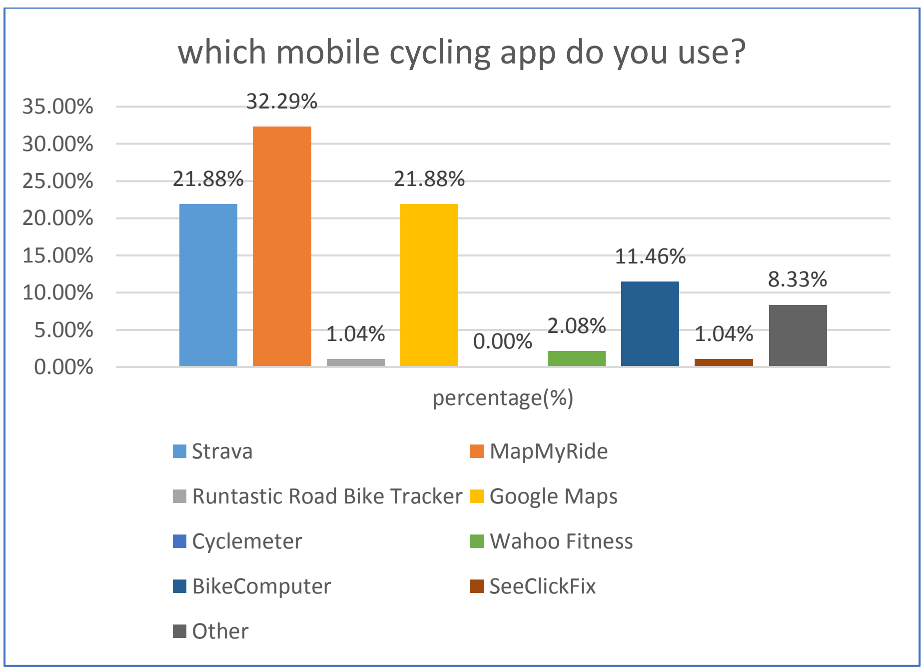
Biker Experience



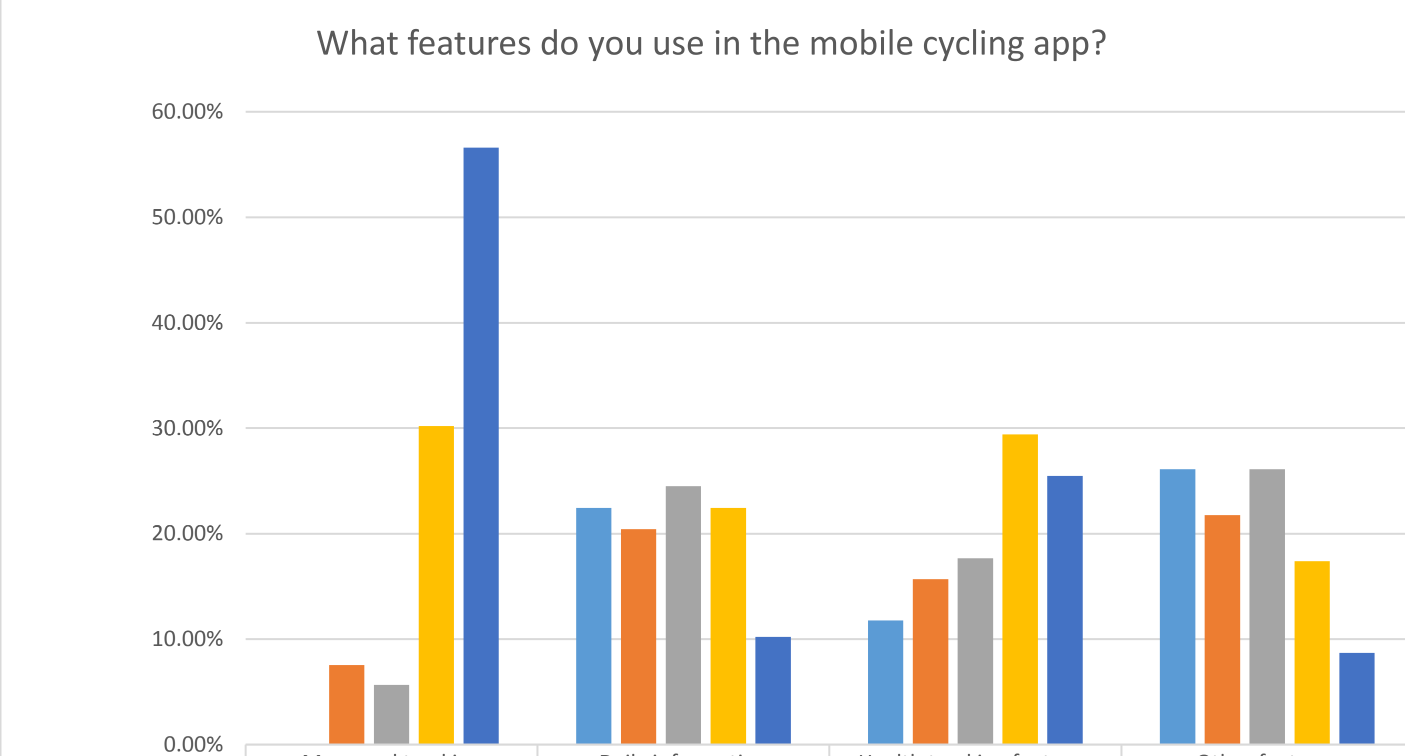
Cycling App Usage




How freqently do you use a mobile cycling app?
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
66.46%
15.82%
3.80%
3.16%
10.76%
percentage(%)
Never
Infrequently
Somewhat frequenly
Frequently
Very frequently


which mobile cycling app do you use?
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
21.88%
32.29%
1.04%
21.88%
0.00%
2.08%
11.46%
1.04%
8.33%
percentage(%)
Strava
MapMyRide
Runtastic Road Bike Tracker
Google Maps
Cyclemeter
Wahoo Fitness
BikeComputer
SeeClickFix
Other

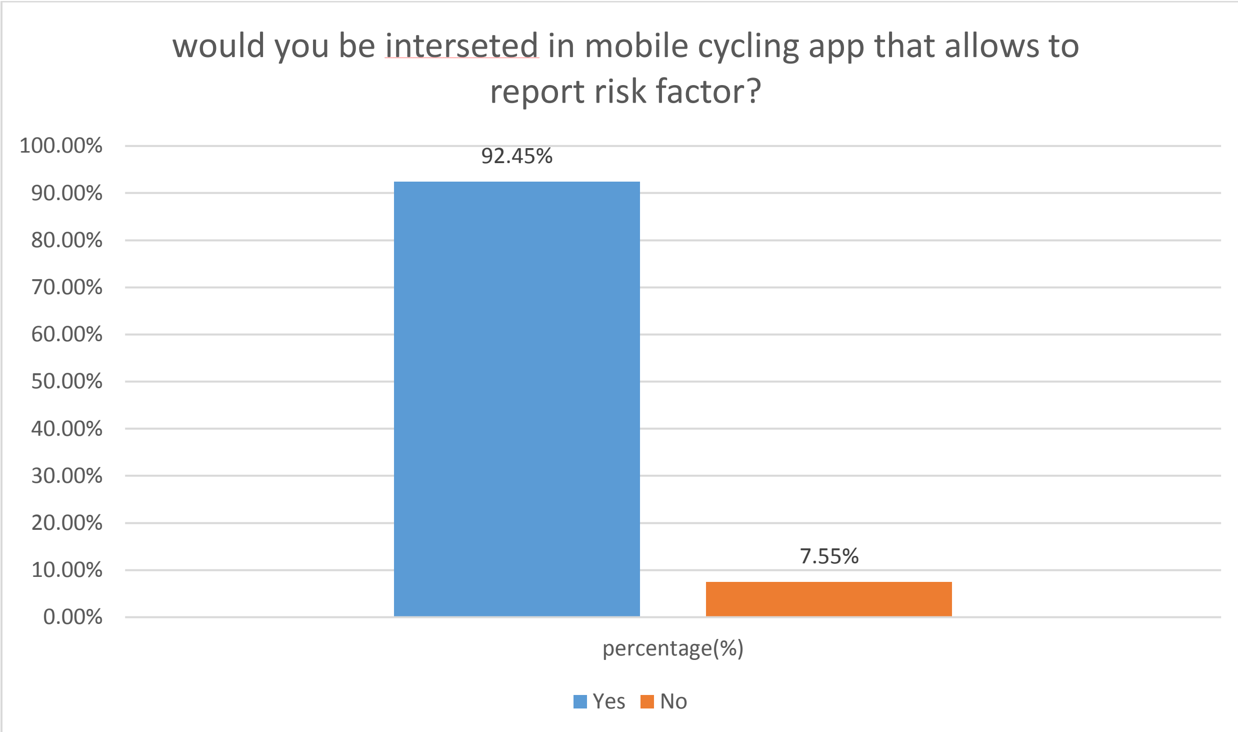
Useful Mobile app feature



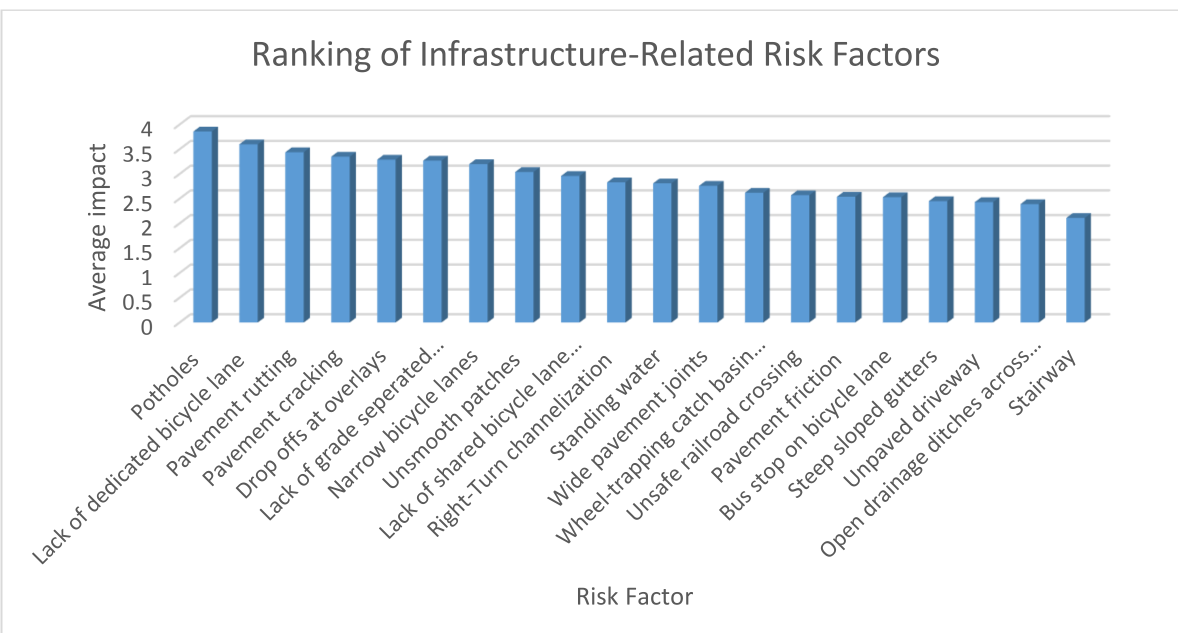
	Maps and tracking	Daily information	Haelth tracking features	Other features
Not at all useful	0.00%	22.45%	11.76%	26.09%
Slightly useful	7.55%	20.41%	15.69%	21.74%
Moderately useful	5.66%	24.49%	17.65%	26.09%
Very useful	30.19%	22.45%	29.41%	17.39%
Extremely useful	56.60%	10.20%	25.49%	8.70%

Not at all useful · Slightly useful · Moderately useful · Very useful · Extremely useful

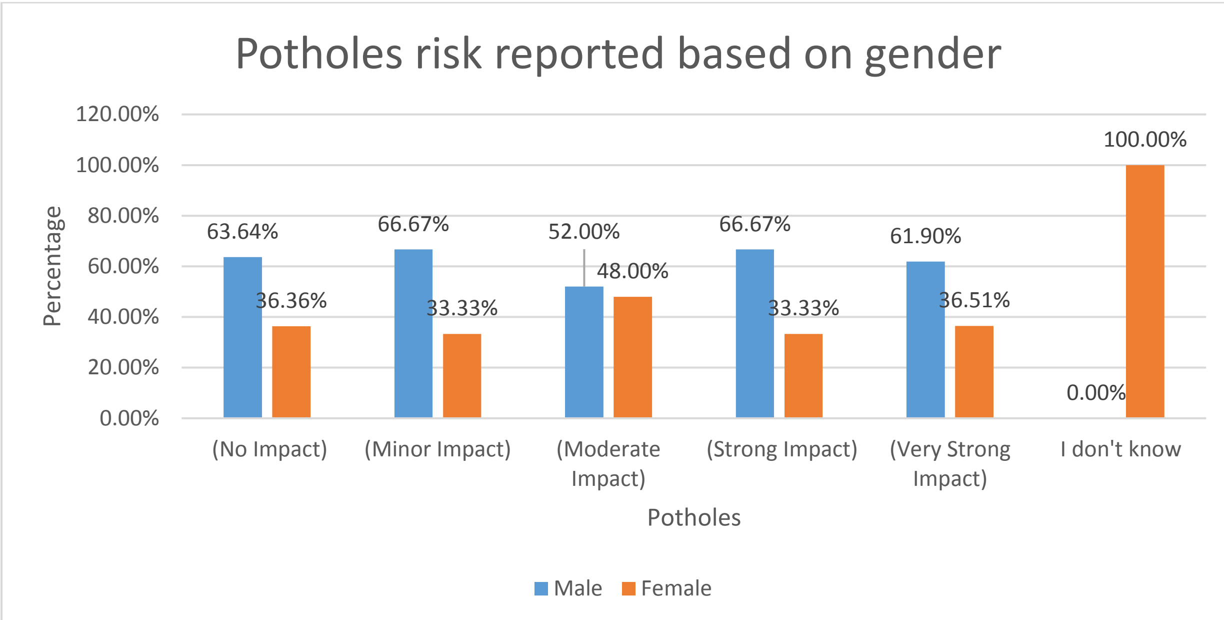
Need for Risk Factor Reporting App



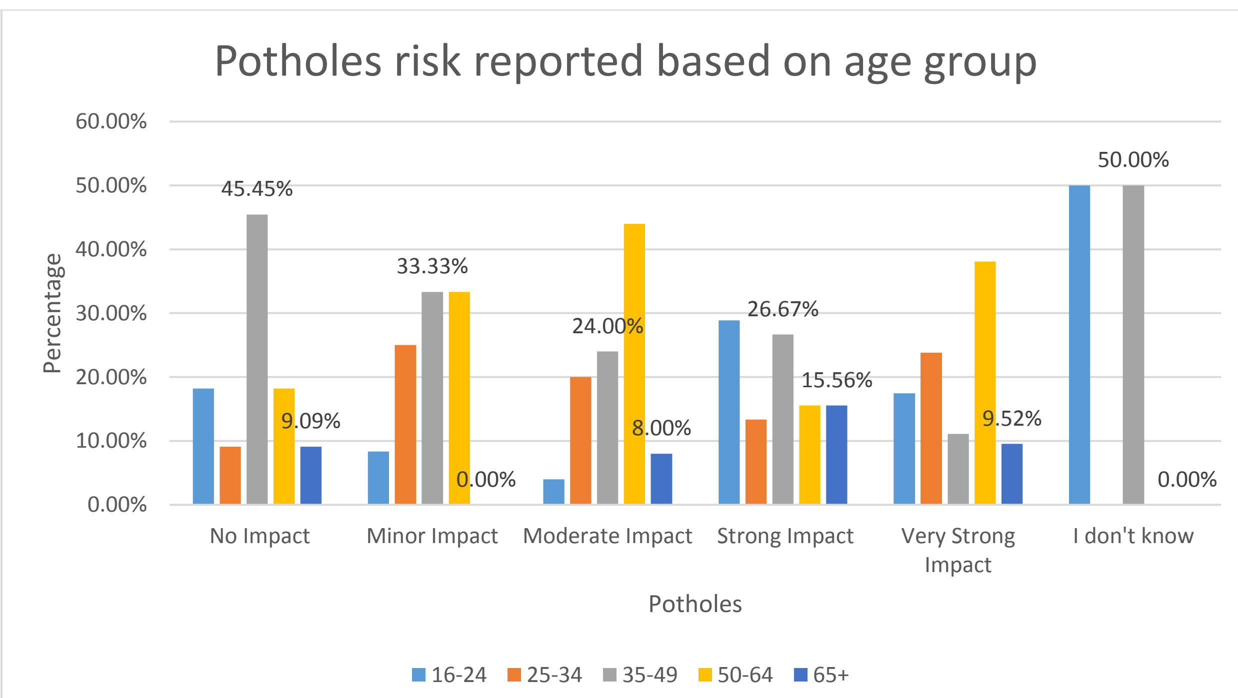
Rank of Infrastructure Risk Factors



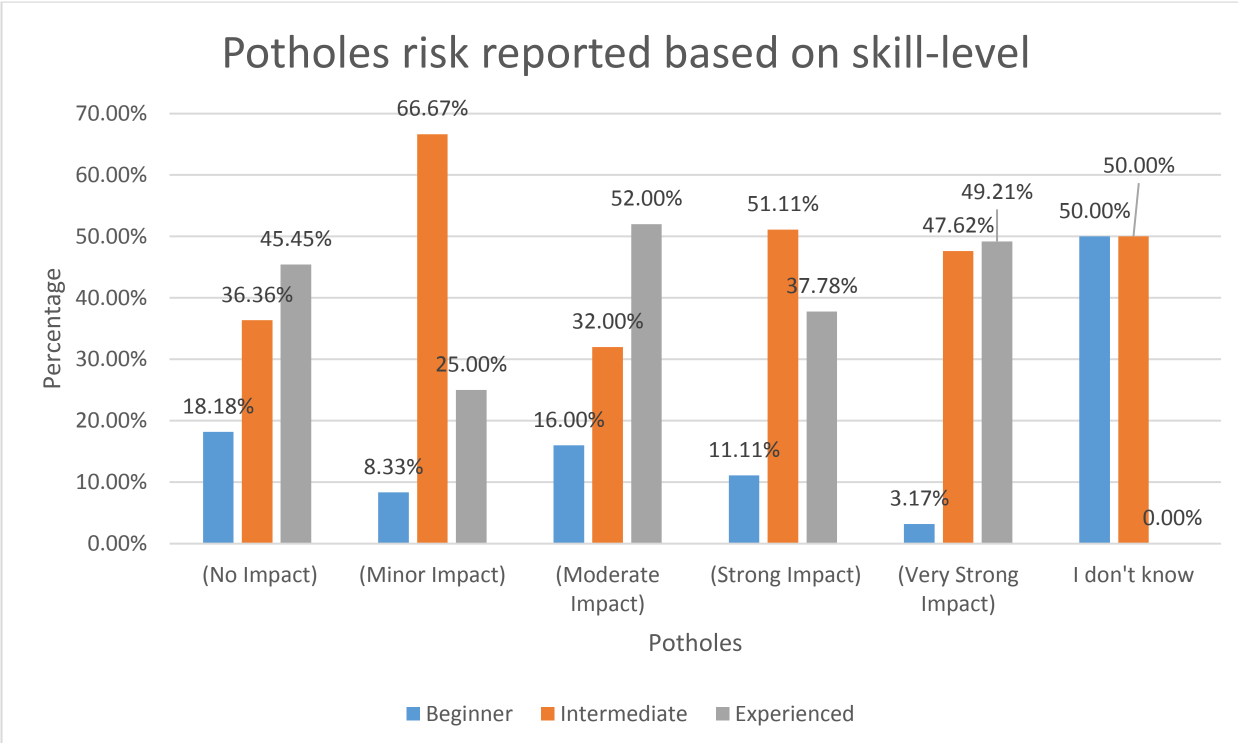
Potholes Risk vs. Gender



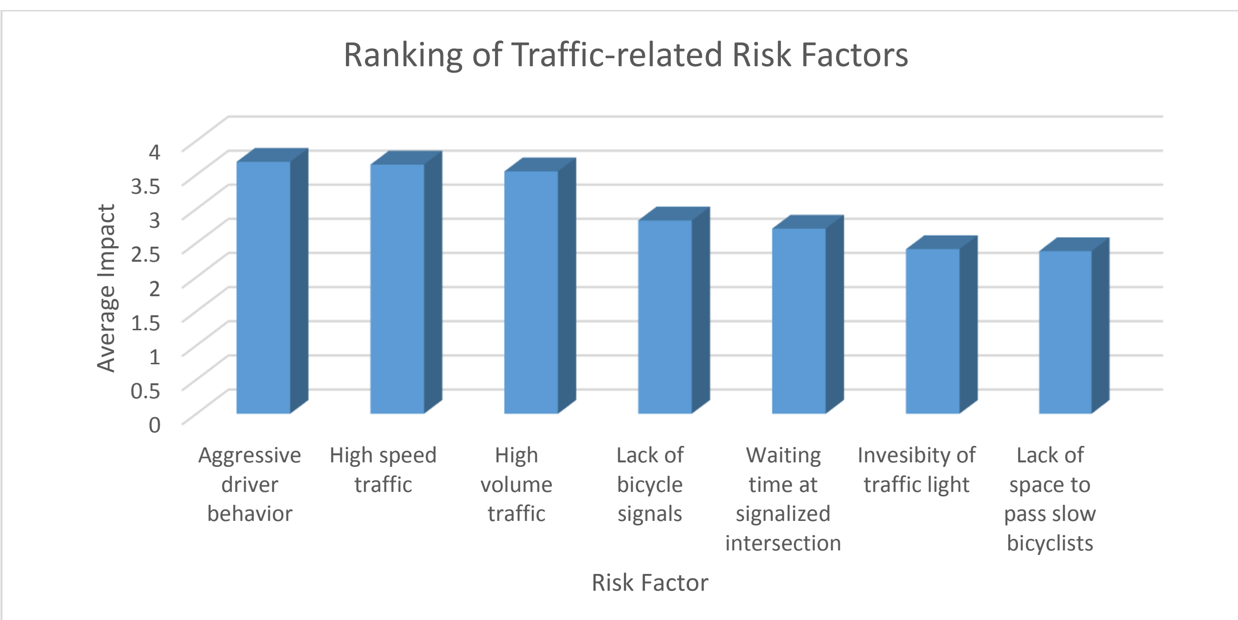
Pothole Risk vs. Age Group



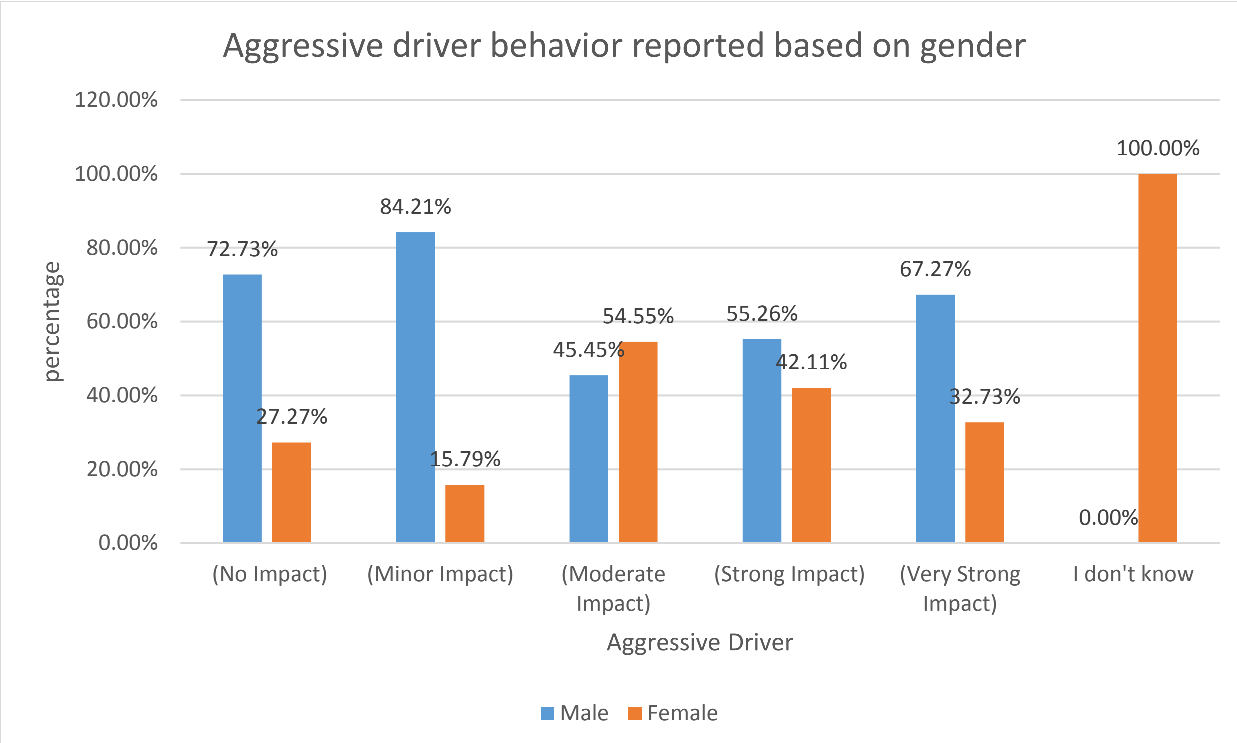
Potholes Risk vs. Skill-Level



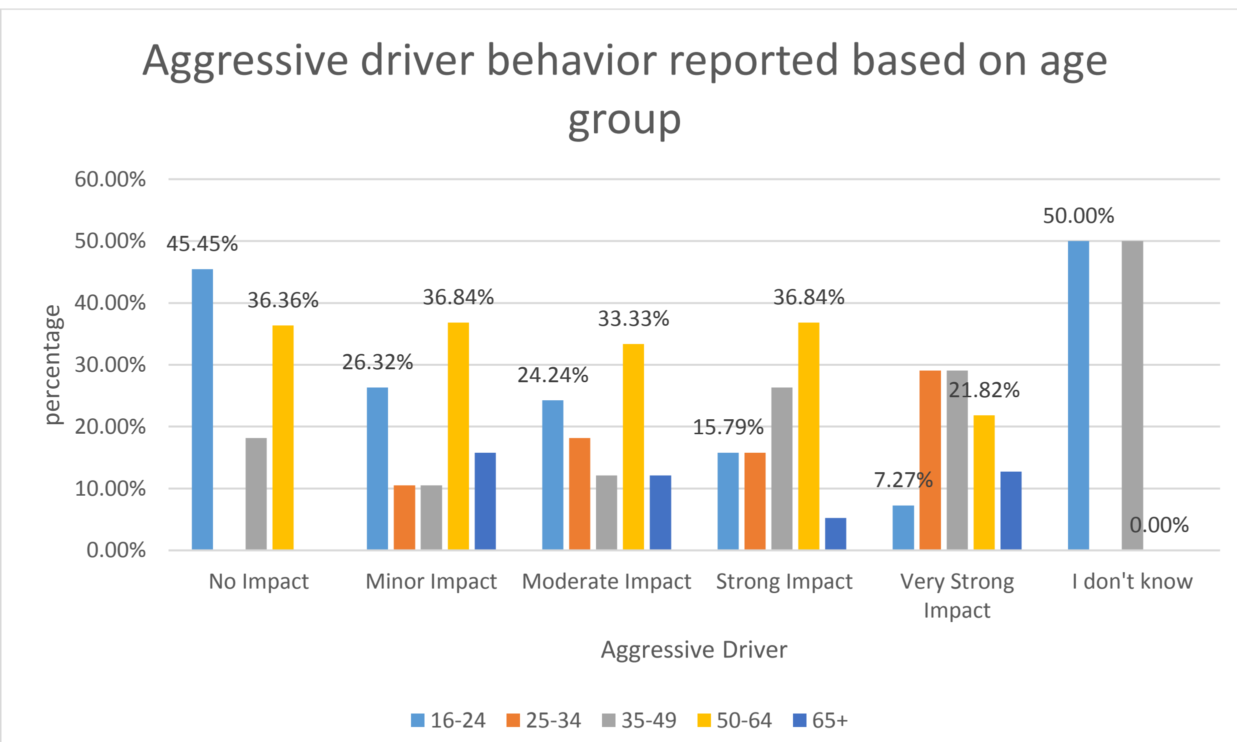
Rank of Traffic Risk Factor



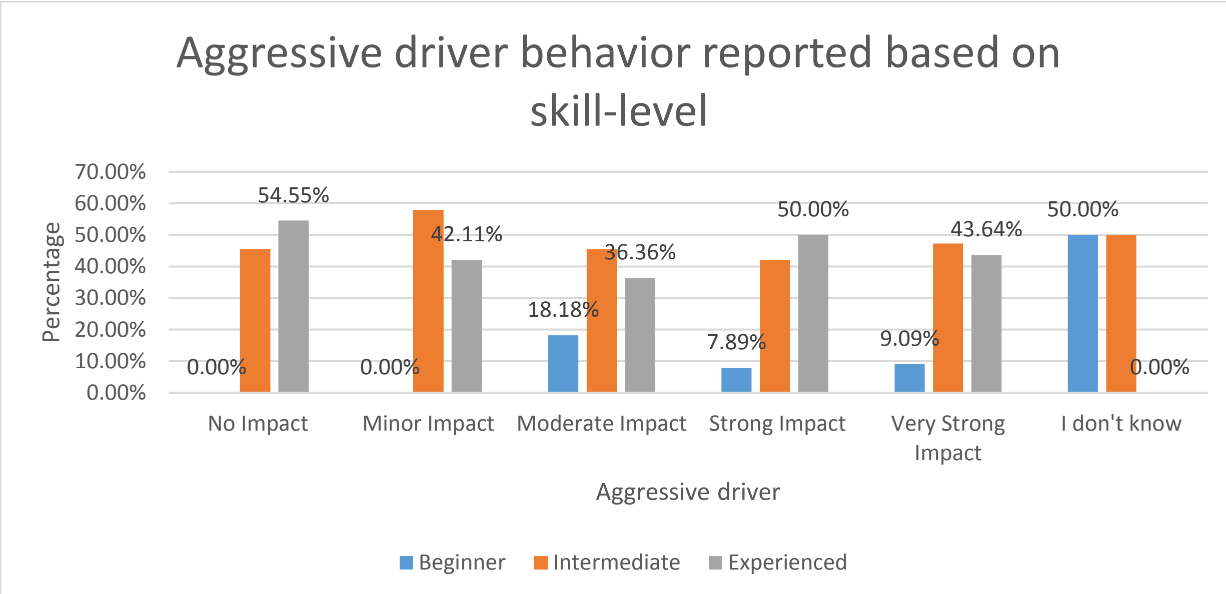
Aggressive Driving vs. Gender



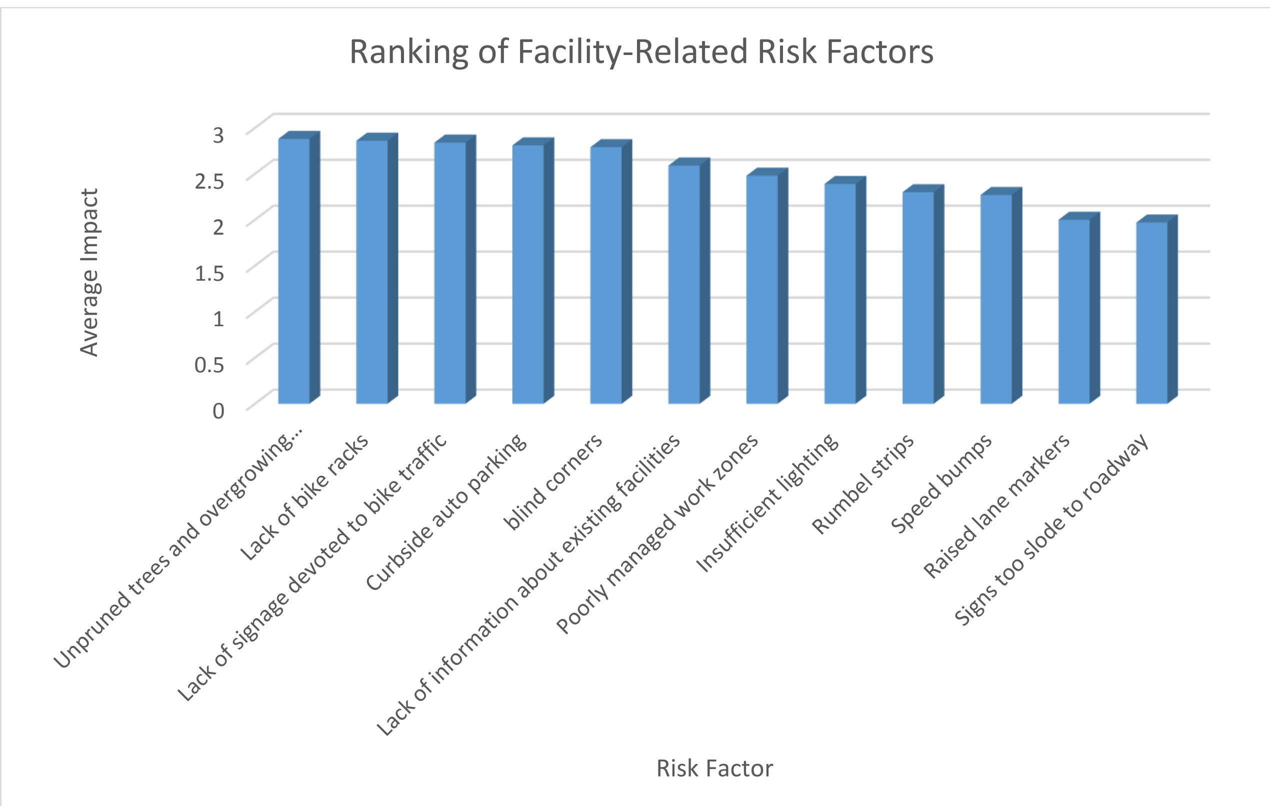
Aggressive Driving vs. Age Group



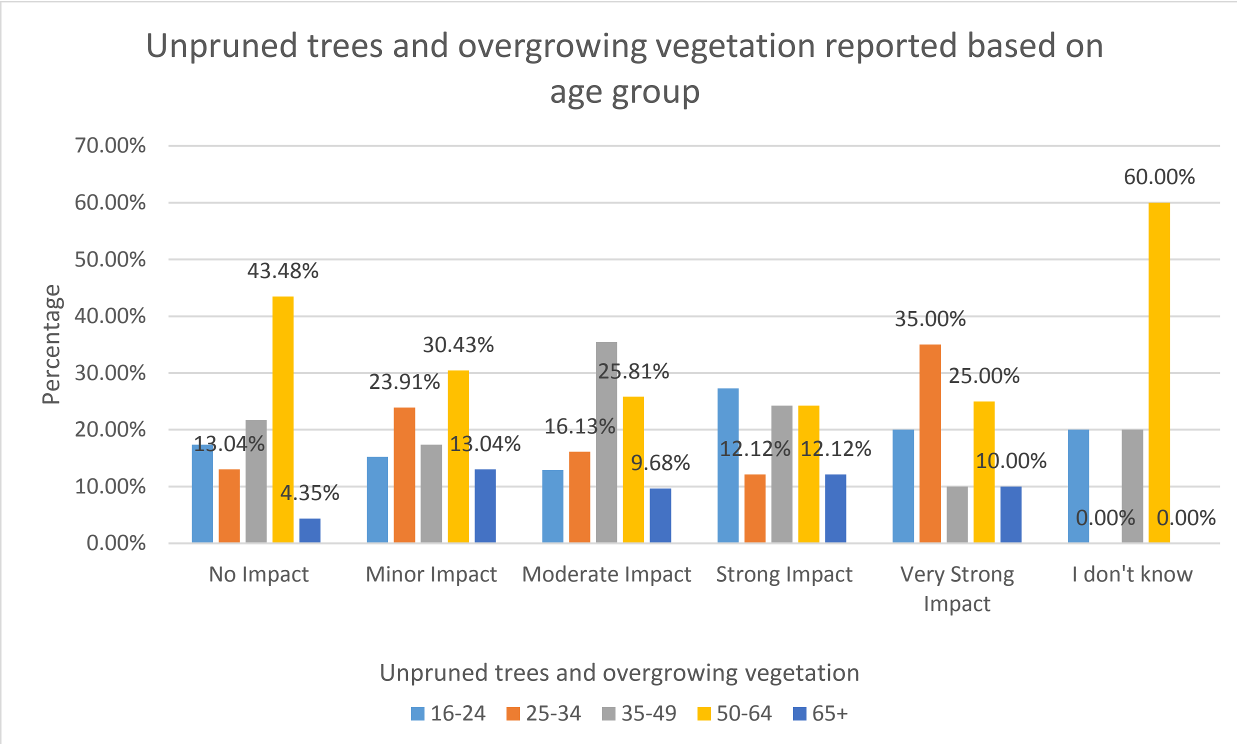
Aggressive Driving vs. Skill-Level



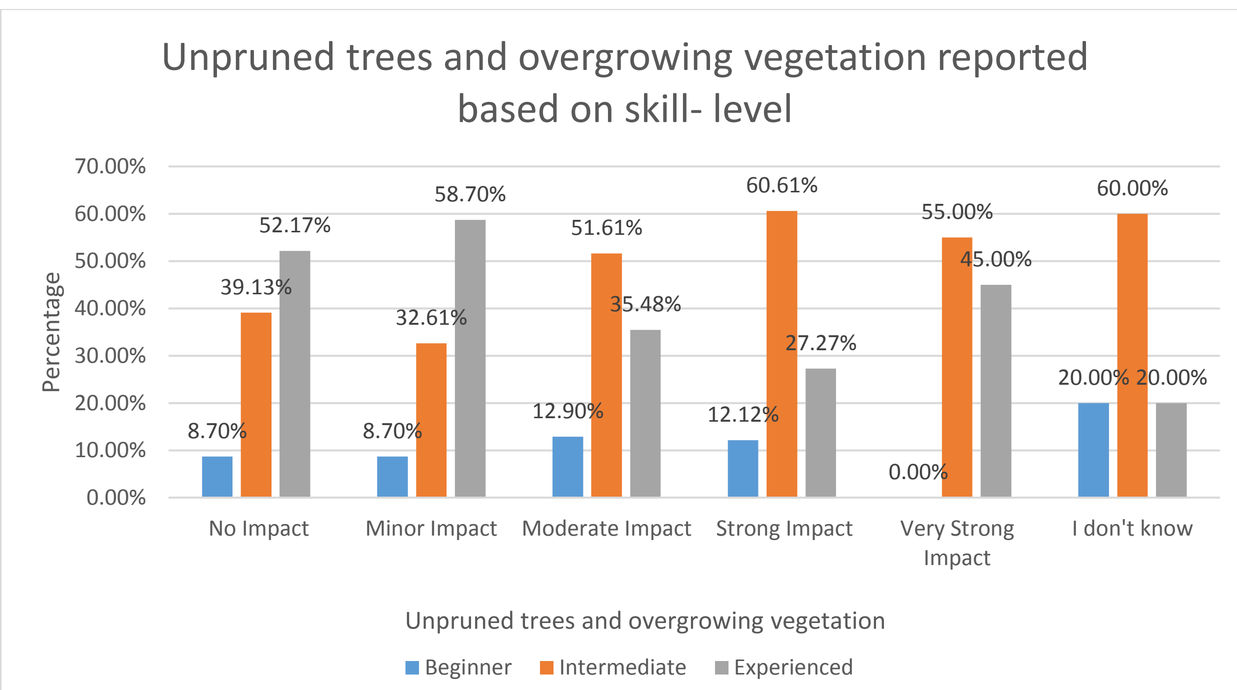
Ranking of Facility Risk Factors



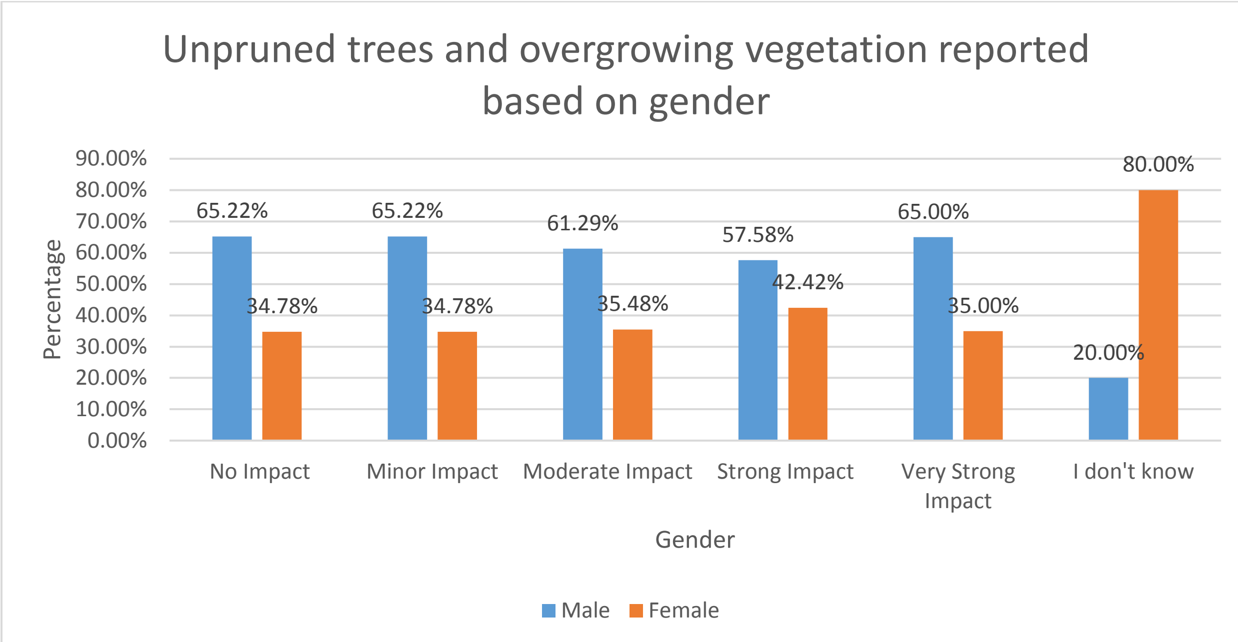
Unpruned Trees vs. Age Group



Unpruned Trees vs. Skill-Level



Unpruned Trees vs. Gender



Code snippets

Part 1: Sending Reports' Data from Web SQL to GAE.

```
// send the reports table to GAE datastore every 30s
setInterval(function(){
  if (isOnline == true){
    db.transaction(function (tx) {
      var result;
      tx.executeSql("SELECT * FROM reportrisk where deleted = 0;", [], function(tx, rs){
        for(var i=0; i<rs.rows.length; i++) {
          var row = rs.rows.item(i);
          result = { 'Track_Id': row['TrackId'],
          'User_Name': row['UserId'],
          'Risk_Id':row['riskId'],
            'RiskType' :row['riskType'],
          'RiskValue':row['Value'],
          'Date_Time': row['date'],
  'Latitude': row['lat'],
  'Longitude': row['lng'],
  'Place_id' : row['place_id'],
  'Highway':row['highway']
  };
  gapi.client.helloworldendpoints.saveReport(result).
  execute(function (resp) {
    if (resp.error) {
      // The request has failed.
    }
    else {
      updateReport(resp.TrackId, resp.UserName, resp.RiskId, resp.riskType, resp.riskValue,
resp.Date, resp.Lat, resp.Lng, resp.Place_id, resp.Highway);

                }
   });
 }
});
  tx.executeSql('Delete From reportrisk where deleted = 1');
});
}
},1000*30);
```

Part 2: The Background Plugin.

```
//Get plugin                    navigator.geolocation.getCurrentPosition(function(p){})
        bgLocationServices =  $window.plugins.backgroundLocationServices;
```

```
//Configure Plugin
  bgLocationServices.configure({
//Both Devices
  desiredAccuracy:      0,
  distanceFilter:       2,
  debug:                false,
  interval:             2000,
  fastestInterval:      2000,
  useActivityDetection: false,
  notificationTitle: 'BikeableRoute', // customize the title of the notification
  notificationText: 'BikeableRoute in Background', //customize the text of the notification
  });
bgLocationServices.registerForLocationUpdates(function(location) {
  var position = encapsulateLocation(location);
  counter = counter+1;
  if($scope.started){
    showPosition2(position);
    }
    , function(err) {
      //console.log("Error: Didnt get an update", err);
  });
  bgLocationServices.registerForActivityUpdates(function(acitivites){
// console.log("We got an BG Update" + activities);
  }, function(err) {
// console.log("Error: Something went wrong", err);
});
bgLocationServices.start();

});
```

Part 3: Sending Users' Feedback to the GAE.

```
function sendUserFeedback(uname){
  db.transaction(function (tx) {
  var result;
  tx.executeSql("SELECT * FROM feedback WHERE name = ?;",     [uname], function(tx, rs){
    for(var i=0; i<rs.rows.length; i++) {
      var row = rs.rows.item(i);
      if(row['name']!= null && row['emailAddress'] != null && row['message'] != null) {
        result = { 'Name': row['name'],
        'EmailAddress':row['emailAddress'],
  'Message': row['message'],
  'Date':row['date']
  };
  gapi.client.bikeablendpoints.saveFeedback(result).
```

```
  execute(function (resp) {
  if (resp.error) {
    // The request has failed.
  } else {
    // The request has succeeded.
    }
  });
}
} // end for loop
}); });
```

Part 4: RiskReport in the GAE.

```
@ApiMethod(name = "saveReport", path = "saveReport",
  httpMethod = HttpMethod.POST)
  public RiskReport saveReport (@Named("Track_Id") int id, @Named("User_Name")
String name, @Named("Risk_Id") String riskId,
  @Named("RiskType") int riskType, @Named("RiskValue") int riskVal,
@Named("Date_Time") String date,
  @Named("Latitude") double lat, @Named("Longitude") double lng,@Named("Place_id")
double place_id,@Named("Highway") String highway) {

  double placeId = 0;
  String hiway = "NA";
  try{
    OSMData osmData = getPlaceId(lat, lng);
    placeId = osmData.PlaceId;
    String osmId = osmData.OsmId;
    hiway = getHighway(osmId);
  } catch(Exception ex){}
  RiskReport h1 = new RiskReport(id, riskId, riskType, name, date, lat, lng,
riskVal,placeId,hiway);
  Entity riskRep = new Entity("RiskReport");
  riskRep.setProperty("Track_Id", h1.TrackId);
  riskRep.setProperty("RiskId", h1.RiskId);
  riskRep.setProperty("RiskType", h1.RiskType);
  riskRep.setProperty("User_Name", h1.UserName);
  riskRep.setProperty("RiskValue", h1.riskValue);
  riskRep.setProperty("Date_Time", h1.Date);
  riskRep.setProperty("Latitude", h1.Lat);
  riskRep.setProperty("Longitude", h1.Lng);
  riskRep.setProperty("Place_id", h1.Place_id);
  riskRep.setProperty("Highway", h1.Highway);
  datastore.put(riskRep);
  return h1;
```

```
}
```

Part 5: Get place_id in Java.

```
private OSMData getPlaceId(double lat, double lng)
throws IOException {
  String req_url =
"https://nominatim.openstreetmap.org/reverse?format=json&lat="+lat+"&lon="+lng;
  URL url = new URL(req_url);
  BufferedReader reader = new BufferedReader(new InputStreamReader(url.openStream()));
  StringBuffer json = new StringBuffer();
  String line;
  while ((line = reader.readLine()) != null) {
    json.append(line);
  }
  reader.close();
  JSONObject jo = new JSONObject(json.toString());
  String placeId = jo.getString("place_id");
  String osmId = jo.getString("osm_id");
  OSMData osmData = new OSMData(Double.parseDouble(placeId), osmId);
  return osmData;
}
```

Part 6: Get Highway Tag in Java.

```
private String getHighway(String osmId)
throws IOException {
  String txt1="";
  String txt2="NA";
  String req_url="http://www.openstreetmap.org/api/0.6/way/"+osmId;
  try {
    DocumentBuilderFactory dbFactory = DocumentBuilderFactory.newInstance();
    DocumentBuilder dBuilder = dbFactory.newDocumentBuilder();
    Document doc = dBuilder.parse(req_url);
    doc.getDocumentElement().normalize();
    NodeList nList = doc.getElementsByTagName("tag");
    if (nList.getLength()>0) {
      Node nNode = nList.item(0);
      if (nNode.getNodeType() == Node.ELEMENT_NODE) {
        Element eElement = (Element) nNode;
        txt1 = eElement.getAttribute("k");
        if(txt1.equals("highway"))
        txt2 = eElement.getAttribute("v");
      }
    }
  } catch (Exception e){}
```

```
    return txt2;
    }
```

Part 7: Show Reports on the Mobile Application and the Website.

```
@ApiMethod(name = "getReportsByType", path = "getReportsByType",
  httpMethod = HttpMethod.POST)
  public List<RiskReport> getReportsByType (@Named("RiskType") int riskType) {
    Filter riskTypeFilter =new FilterPredicate("RiskType", FilterOperator.EQUAL, riskType);

    Query q = new Query("RiskReport").setFilter(riskTypeFilter);
    PreparedQuery pq = datastore.prepare(q);
    HashMap<GeoKey, RiskReport> accumulativeRisks = new HashMap<GeoKey,
RiskReport>();
    for (Entity result : pq.asIterable()) {
      long trackId = (long) result.getProperty("Track_Id");
      long rtype = (long) result.getProperty("RiskType");
  String uname = (String) result.getProperty("User_Name");
  String riskId = (String) result.getProperty("RiskId");
  long riskValue = (long) result.getProperty("RiskValue");
  double lat = (double) result.getProperty("Latitude");
  double lng = (double) result.getProperty("Longitude");
  double place_id = (double) result.getProperty("Place_id");
  String date = (String) result.getProperty("Date_Time");
  String highway = (String)result.getProperty("Highway");
  GeoKey lat_lng_key = new GeoKey(lat, lng);
  if(accumulativeRisks.containsKey(lat_lng_key)){
    RiskReport val = accumulativeRisks.get(lat_lng_key);
    val.incCount();
  }
  else {
    RiskReport rp = new RiskReport((int)trackId, riskId, (int)rtype, uname, date, lat, lng,
(int)riskValue,place_id,highway);
    accumulativeRisks.put(lat_lng_key, rp);
  }
}
  List<RiskReport> riskList  = new ArrayList<RiskReport>( accumulativeRisks.values() );
return riskList;
}
```

IMU Data

Latitude (Â°)	Longitude (Â°)	Accel X (m.s^-2)	Accel Y (m.s^-2)	Accel Z (m.s^-2)	Gyro X (Â°.s^-1)	Gyro Y (Â°.s^-1)	Gyro Z (Â°.s^-1)
42.254673	-85.638342	-0.252	2.271	-9.481	-0.278752	0.174804	-0.061622
42.254673	-85.638342	-0.277	2.203	-9.468	0.263557	0.16861	-0.31711
42.254674	-85.638342	-0.292	2.117	-9.447	0.130691	0.115074	-0.058538
42.254674	-85.638342	-0.285	2.167	-9.479	-0.449427	0.149993	0.016034
42.254673	-85.638342	-0.259	2.222	-9.488	-0.405981	0.172627	0.057492
42.254673	-85.638342	-0.261	2.225	-9.464	0.051971	0.122994	-0.091574
42.254673	-85.638342	-0.291	2.148	-9.486	-0.072411	0.166668	-0.126475
42.254673	-85.638342	-0.293	2.157	-9.483	-0.309353	0.149326	0.06892
42.254673	-85.638342	-0.256	2.199	-9.478	-0.362268	0.133763	0.033398
42.254673	-85.638342	-0.268	2.202	-9.471	-0.03131	0.144641	-0.080705
42.254673	-85.638342	-0.266	2.166	-9.48	0.146567	0.198701	-0.052612
42.254674	-85.638343	-0.301	2.13	-9.484	-0.151282	0.151103	-0.104146
42.254674	-85.638343	-0.299	2.17	-9.446	-0.300521	0.124541	0.001541
42.254674	-85.638343	-0.24	2.24	-9.498	-0.13183	0.171557	-0.019361
42.254674	-85.638343	-0.275	2.169	-9.467	-0.137413	0.099676	-0.093272
42.254674	-85.638343	-0.25	2.156	-9.477	-0.269513	0.118131	0.029832
42.254674	-85.638343	-0.198	2.274	-9.477	0.148202	0.052894	-0.439156
42.254674	-85.638343	-0.44	2.277	-9.454	-1.245748	0.149627	-0.31558
42.254674	-85.638343	-0.264	2.261	-9.503	-0.799571	0.103601	0.780035
42.254674	-85.638343	-0.195	2.266	-9.468	0.189635	0.167049	-0.330238
42.254674	-85.638343	-0.335	2.147	-9.453	0.648845	0.168789	-0.309158
42.254674	-85.638343	-0.274	2.066	-9.521	-0.475716	0.112288	0.037844
42.254674	-85.638344	-0.308	2.296	-9.437	-0.902636	0.16796	0.338994
42.254674	-85.638344	-0.192	2.252	-9.475	0.01585	0.169751	-0.006201
42.254673	-85.638344	-0.315	2.201	-9.442	0.469679	0.17576	-0.476343
42.254673	-85.638344	-0.3	2.121	-9.509	-0.103721	0.203175	0.081211
42.254673	-85.638344	-0.278	2.174	-9.486	-0.848609	0.144374	0.090796
42.254673	-85.638344	-0.243	2.288	-9.447	-0.305311	0.165562	0.08664
42.254673	-85.638344	-0.248	2.216	-9.484	0.307667	0.162702	-0.30418
42.254673	-85.638344	-0.325	2.122	-9.447	0.015004	0.187792	-0.058061
42.254673	-85.638343	-0.276	2.095	-9.502	-1.9987	0.069214	0.835035
42.254673	-85.638344	-0.195	2.378	-9.444	-0.207554	0.309129	0.061027
42.254673	-85.638344	-0.192	2.267	-9.494	0.979989	0.13272	-0.285026
42.254673	-85.638344	-0.406	2.082	-9.441	0.099928	0.171407	-0.456034
42.254673	-85.638344	-0.272	2.241	-9.48	-0.546975	0.112653	0.29127
42.254673	-85.638344	-0.269	2.181	-9.474	-0.806734	0.135659	0.239707
42.254673	-85.638344	-0.205	2.309	-9.458	0.053303	0.16651	-0.10837
42.254673	-85.638344	-0.265	2.142	-9.492	0.298342	0.179163	-0.342689
42.254673	-85.638344	-0.337	2.151	-9.458	-0.266351	0.115811	0.031261
42.254673	-85.638344	-0.218	2.225	-9.46	-0.416268	0.146512	0.013278
42.254673	-85.638344	-0.272	2.263	-9.475	-0.22674	0.159513	-0.228748

Table 4: IMU Data

Mobile App Data

latitude	longitude	Accel_x	Acce_y	Acce_z	gyro_x	gyro_y	gyro_z
42.25480439	-85.63831956	2.25012085	9.108259277	2.845732269	0.02034442	0.013852699	-0.004366253
42.25480439	-85.63831956	2.243384857	9.086105347	2.857857056	0.01071656	0.014892397	-3.89E-05
42.25480439	-85.63831956	2.221530304	9.07757309	2.851719818	0.005349758	0.013843111	-0.002145176
42.25480439	-85.63831956	2.249671783	9.09044632	2.887645111	0.009640643	0.012771455	-0.001103614
42.25480439	-85.63831956	2.230661316	9.113947449	2.875071259	0.011779694	0.010649715	-0.002186722

42.25480439	-85.63831956	2.134561157	8.768914948	2.970722351	0.016053535	0.015988288	-0.005406217
42.25480439	-85.63831956	2.199226685	8.989256744	2.850222931	-0.019259981	0.015917181	0.007607852
42.25480439	-85.63831956	2.246977386	9.130862274	2.865042114	0.029980802	0.006416088	-0.006567888
42.25480439	-85.63831956	2.238894196	9.099577332	2.860701141	0.00749307	0.011714713	-0.002160623
42.25480439	-85.63831956	2.251468048	9.087602234	2.868484955	0.006425675	0.012772254	-0.001085238
42.25480439	-85.63831956	2.231110382	9.091494141	2.850671997	0.008568987	0.011707789	-0.001099087
42.25480439	-85.63831956	2.022893372	9.718839569	1.770667877	0.002147573	0.005312474	0.0010634
42.25480439	-85.63831956	2.456840973	8.638536072	4.164938965	-0.025643046	-0.075652683	0.019251459
42.25480439	-85.63831956	1.912722473	9.078770599	3.860921173	0.23248118	-0.03931678	-0.018470886
42.25480439	-85.63831956	2.149530029	9.419761505	2.315983887	0.487671667	-0.13428324	0.014094247
42.25480439	-85.63831956	1.783690796	9.344468079	1.930984497	0.556342874	-0.222739869	0.03492283
42.25480439	-85.63831956	2.533780975	9.001680908	-0.081280975	0.63468029	-0.259099475	0.061112889
42.25480439	-85.63831956	2.543510742	9.535770264	-1.581161957	0.500680677	-0.183460374	0.051315386
42.25480439	-85.63831956	2.39980957	9.86852829	-0.092058563	0.315088176	-0.054372162	0.003455984
42.25480439	-85.63831956	2.37990097	9.358987885	1.232686615	0.047191215	-0.003263438	0.009334646
42.25480144	-85.63826898	2.294877777	9.41332489	0.130378876	0.340922969	-0.106691027	0.032057535
42.25480144	-85.63826898	2.863545227	8.910370789	-2.851420441	0.544554658	-0.128046916	0.035132421
42.25480144	-85.63826898	3.637136536	9.072932739	-3.668421478	0.439592022	-0.118538632	0.050694337
42.25480144	-85.63826898	2.798131256	9.482930145	-1.685494995	0.269049578	-0.04697976	0.014407169
42.25480144	-85.63826898	2.566862183	9.060807953	-2.819387054	0.316223748	-0.043832968	0.019480757
42.25480144	-85.63826898	2.637814636	9.428742828	-2.238744507	0.221930801	-0.057660633	0.023201992
42.25480144	-85.63826898	2.574047241	8.642128601	-0.265547791	-0.011749867	-0.052189702	0.009598033
42.25480144	-85.63826898	2.464774475	9.411229248	-2.83046402	0.177980121	-0.038478949	0.020278906
42.25480144	-85.63826898	2.826721802	8.42343338	-3.960613861	0.343015148	-0.068310082	0.019290874
42.25480144	-85.63826898	2.77073822	8.649163971	-3.136427765	0.177830984	0.013886787	-0.017010941
42.25480144	-85.63826898	2.489473114	9.10676239	-2.756966858	0.241011818	0.14374412	-0.028921663
42.25480144	-85.63826898	2.031575317	8.222401428	-2.029928741	0.16810512	0.077851656	-0.037145505
42.25480144	-85.63826898	5.036726074	10.21101608	-4.649780731	0.129627768	0.001098288	-0.011416173
42.25480144	-85.63826898	-0.528700562	9.856104126	-2.146835632	-0.198260625	-0.039309589	6.39E-06
42.25480144	-85.63826898	3.906725922	8.82834137	-1.721719666	-0.131941523	0.275791104	-0.030862575
42.25480144	-85.63826898	1.955383759	8.391549683	-3.613485718	-0.095321992	-0.085177479	0.014296914
42.25480144	-85.63826898	2.987637177	9.336235199	-3.768712921	0.017253023	-0.137418047	0.026387399
42.25480144	-85.63826898	4.485123138	7.031927032	-4.202810211	-0.016062057	0.045733134	0.003363572
42.25480144	-85.63826898	0.708476715	11.60746216	-0.912502441	0.184757333	0.187140862	-0.160929232
42.25480144	-85.63826898	2.4325914	8.330177307	-4.108656006	-0.077210366	-0.326528317	-0.01286147

Table 5: Mobile App Data

Risks Reported Through the Mobile Application

RiskId	RiskType	UserId	Date	Lat	Lng	RiskValue	Place_id	Highway
Potholes	1	website	2016-10-03 14:09:51:20	42.2526776	-85.6413993	5	1.23E+08	NA
Potholes	1	website	2016-10-24 14:53:43:530	42.2544253	-85.6384959	4	1.21E+08	NA
Pavement cracking	1	0C655A66-	2016-10-05 00:32:02:286	42.2882625	-85.62614322	5	1.28E+08	tertiary
Pavement rutting	1	040232C8-	2016-12-26 17:21:27:277	42.0298935	-88.21408513	5	6.88E+07	tertiary
Curbside auto parking	3	B71847EB-	2016-11-13 06:57:39:394	42.1895460	-85.56821823	3	1.76E+08	NA

High-speed traffic	2	website	2016-10-07 15:34:47:627	42.2548554	-85.63666821	5	1.25E+08	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:34:28:361	42.2794843	-85.6502288	4	1.27E+09	NA
High-speed traffic	2	05C99074-	2016-10-26 13:42:45:94	42.2747684	-85.59070587	4	1.25E+08	NA
High-speed traffic	2	website	2016-09-21 02:24:54:00	42.2541883	-85.61885834	5	1.27E+09	NA
Lack of dedicated bicycle lane	1	B71847EB-	2016-11-05 19:22:09:547	42.2595048	-85.56217931	4	1.76E+08	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:24:39:484	42.2794858	-85.6502321	4	1.27E+09	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:24:39:484	42.2794858	-85.6502321	4	1.27E+09	NA
Curbside auto parking	3	05C99074-	2016-10-26 13:43:02:515	42.2925483	-85.57285309	4	1.76E+08	NA
Unpruned trees and overgrowing vegetation (blocking bike lane)	3	website	2016-12-20 18:06:42:963	42.2899241	-85.6274831	4	6.51E+07	residential
High-speed traffic	2	website	2016-09-21 02:24:54:00	42.2541883	-85.61885834	5	1.27E+09	NA
Potholes	1	05C99074-	2016-10-26 13:42:34:31	42.2988018	-85.60053349	3	1.76E+08	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:24:39:484	42.2794858	-85.6502321	4	1.27E+09	NA
Lack of dedicated bicycle lane	1	05C99074-	2016-10-26 13:42:19:764	42.2836273	-85.61452389	4	1.14E+08	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:34:28:361	42.2794843	-85.6502288	4	1.27E+09	NA
High-speed traffic	2	website	2016-09-21 02:38:03:687	42.2794836	-85.6502352	5	1.27E+09	NA
High-speed traffic	2	website	2016-09-21 02:24:54:00	42.2541883	-85.61885834	5	1.27E+09	NA
Lack of dedicated bicycle lane	1	website	2016-09-21 02:24:39:484	42.2794858	-85.6502321	4	1.27E+09	NA
Lack of dedicated bicycle lane	1	B71847EB-	2016-11-13 06:58:29:401	42.1589498	-85.56890488	4	1.76E+08	NA
Potholes	1	EFB5FCD1-	2016-10-03 16:57:12:168	42.2581195	-85.64592088	3	1.76E+08	NA
Aggressive driver behavior	2	website	2016-10-03 14:10:30:323	42.2561577	-85.68975449	5	1.76E+08	NA

Table 6:Reported risks