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Effect of Cycling Skills on Bicycle Safety and Comfort Associated with Bicycle Infrastructure and Environment

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16. Abstract

This study seeks to improve the methodology for determining the relationship between cycling dynamic performance and roadway environment characteristics across different bicyclists' skill levels. To achieve the goal of this study, an Instrumented Probe Bicycle (IPB) equipped with various sensors was built. A naturalistic field experiment, including intersections, roundabout, alignment changes, and different road surface conditions, was conducted. Two self-reported questionnaires were used in order to obtain each participant's skill level as well as perception on the level of cycling comfortability. The Cycling Comfortability Index (CCI) was derived from the probabilistic outcome of an Ordered Probit Model, which describes the relationship between bicycle dynamics and level of comfortability. Fault Tree Analysis (FTA), a technique widely used to measure the risk of a fault event occurrence in a system, was employed to integrate mobility and comfortability. The estimation results showed that the probability of a fault event occurrence is related to the bicyclist's experience level, incline of the roadway, and quality of the road surface. It was also found that cycling comfort level is significantly affected by the average y-axis acceleration and the mean absolute deviation of the z-axis velocity. The results of this study have practical implications for improving bicyclist perceptions on comfortability and for increasing safety for cyclists.

17. Key Words Instrumented Probe Bicycle, Cycling environment, Cycling skill level, Cycling Comfortability Index	**18. Distribution Statement** No restrictions.

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Chapter 1 Introduction

1.1 Research Problem

Bicycling is a fantastic form of transportation, which is used by a very small percentage of the population in North America. The modern transportation infrastructure has been designed as an automobile-centered system that, for the most part, considers bicycling and walking traffic as secondary. The use of a bicycle varies within a country as well as between countries. Many people use a bicycle to transport themselves and their goods; this is common and documented internationally. Others use bicycles for the purposes of entertainment or sports.

There are many benefits of riding a bicycle compared with driving; these include improved health and air quality as well as a reduction in congestion among other benefits. The use of a bicycle also contributes to minimization of climate change and improvement of health, according to human factor Human factors/ergonomics (HF/E) professionals (Ayres, 2014). The presence of these many benefits do not diminish the fact that the dominant mode of transportation in most cities across North America (NA) are motor vehicles. The presence of such a large amount of vehicles is causing concerns about the safety and comfort of cycling. Therefore, the best tool for planners and engineers to identify areas of deteriorating bicycle infrastructure is through bicyclists indicating adverse safety and comfort. Bicycle equipped with the monitoring equipment is an important research tool (Mohanty, 2014).

Recent increases in population densities and social sentiments toward sustainability have raised a strong push towards the promotion of cycling. More individuals consider cycling as a transportation alternative, but many are deterred when faced with the challenges of mobility and comfort. In other words, the numerous benefits of using bicycles do not outweigh cyclists' concerns with safety and comfort. Therefore, a reliable method for planners and engineers to identify poor cycling infrastructure is through bicyclists who complain about their safety and comfort. Objectively assessing rider behavior is necessary to lay a foundation of knowledge for quantifying these perceptions. Recent interest in this field has led to the design and build of the so-called instrument probe bicycle (IPB). These tools allow researchers to log data pertaining to specific aspects of cycling. However, because this area of research is in its infancy, these bicycles have taken a rudimentary form, leaving much room for improvement. Bearing this in mind, the goals of this research were two-fold. First and foremost, this study aimed to evaluate a rider's control scheme with respect to their feelings of general comfortability while riding. Secondly, this study aimed to build upon the previous IPB work by the design and manufacture of another iteration in the instrumented bicycle family.

It is a well-known fact that cyclists with stores of experience are quite confident on a bicycle, as they have developed a good sense of control over the machine. However, as any cyclist can recount, when first learning how to ride, there was a point when they simply could not balance on a bike. It was foreign and unsteady task, but suddenly it all became easier, even to the point of feeling natural. This skill becomes part of a person's inherent abilities. In other words, while many people *can* ride a bicycle, most of them do not actually know *how* they do it. Taking a basic look at the physical machine shows that the key to maintaining stability on a bicycle is being able to appropriately steering the front wheel into the direction of bicycle lean. As a moving bicycle tends to fall toward one side or the other, a simple angular displacement of the front wheel drives the frame to rotate in the opposite direction, and therefore, back toward an upright position. Make those corrections in a fast enough sequence, and they become nothing more than small, quick deviations about a fairly stable equilibrium. However, a question arises, is the bicycle always unstable? As many riders can attest, when riding a bike at a certain speed, it feels as if the machine itself wants not to tip over, but to maintain its trajectory. This is easy to imagine if one pictures a person casually riding with no hands on the handlebar. In such a case there is no steering input yet, even in the presence of mild disturbance, the bicycle seems to stay upright on its own. So the question presents itself, is this phenomenon truly happening, and if so, what causes it? Beyond the simple physical observations mentioned above, there has been extensive work done in modeling the dynamics of a bicycle, which will later be discussed in some detail.

Regardless of any measure of self-stability, a rider is the component in the system that imparts a true stability, and each rider has a slightly different array of skills. By recording and analyzing these skills in a transportation setting, it was hypothesized that common trends could be found for bikers of different "levels" of experience. These trends could then be analyzed with respect to the perception of comfort. An experiment was designed to collect the necessary data to make these assessments. A public road-based route was selected as the control course for testing.

In this way, the most naturalistic form of data could be collected. Surveys were prepared to collect necessary rider information, and administered during the testing procedure. Concurrently, an instrumented probe bicycle was designed and built, to gather the dynamic test data.

1.2 Research Objectives

The ultimate goal of this research is developing a method to determine the bike-ability of bicycle environment in terms of safety and comfort using an Instrumented Probe Bicycle (IPB). However, there are differences in the IPB measurements by the level of cycling skills. Therefore, there are needs for investigating the effect of different level of cycling skills on bicycle safety and comfort associated with bicycle infrastructure and environment by means of IPB in determining the bike-ability.

1.3 Research Scope and Overview

There are several studies that focused on infrastructure influence on riding performance and cycling safety which using different kinds of bicycles, including Instrumented Probe Bicycle. The focus of this research is to analyze the effect of cycling experience on riders' comfortable. Moreover, effects of road infrastructure and environment including road surface quality condition on biking is determined. To accomplish the objectives of this research, the following tasks will be performed:

Task 1: Literature Review

Task 2: Instrumented Probe Bicycle

Task 3: Data Collection

Task 4: Data Analysis

Chapter 2 Literature Review

2.1 Overview

Oja et al. (2014) found that cycling regularly reduces relevant disease risk factors, such as cardiovascular problems, cancer, and obesity in middle-aged and elderly men and women. It was also found that walking and cycling minimize the cost associated with traffic crashes and congestion. Carbon emission from transportation can be reduced if cycling or walking are frequently used (Wierda & Brookhuis, 1991).

2.2 Skill Level

Cycling requires complex skills, including perceptual-motor ability and cognitive tasks (Wierda & Brookhuis, 1991). As the ability to perform motor skills (e.g. pedaling, braking, and steering) is based on a rider’s experience, determining the impact of rider’s skill level on their performance is crucial. Stinson and Bhat (Stinson & Bhat, 2005) examined various bicycle route preferences across different experience levels in bicycle commuting. They found that experienced bicyclists are more susceptible to time-related factors and less responsive to changes in conflicts with vehicle traffic. Similarly, Fonda et al. (Fonda et. al. 2017) believed that lateral deviation and steering angle motions for experienced bicyclists are more than those for the beginners. Likewise, Cain et al. (Cain et. al. 2015) reported that more experienced riders steer in the direction of the roll, whereas less skilled riders perform additional steering motions that are unrelated to the roll of the bicycle. They also illustrated that experienced bicyclists exhibit a higher correlation between the lateral position of center pressure and the center of mass, comparatively. The importance of skill level also led to the development of studies that focus on vulnerable road users (Zeuwts et. al. 2016, Linus et. al. 2015). For example, Zeuwts et al. (2016) employed multiple regression analyses to determine factors that affect children’s cycling skills. They found that younger children have less ability to cycle straight between lines and often miscalculate stopping time. Furthermore, basic cycling skills are related to children’s physical and mental maturation. The main purpose of these studies were to investigate the relationship between skill level and cycling performance. However, they lacked in their evaluation of the cycling environment and road infrastructure.

2.3 Infrastructure-related Factors

While there has been a rising call for the use of bicycles in recent decades, some infrastructure-related weaknesses still threaten bicycle systems. For instance, Reynolds et al. (2009) showed that multilane roundabouts, among two main infrastructure categories (Harris et. al. 2013, Wang et. al. 2015), can significantly reduce bicyclist safety, while the presence of on-road bike lanes and off-road bike paths lead to the lowest risk (Teschke et. al. 2012). Allen-Munley et al. (2004) found that grades affect bicycle injury severity, as steep roads cause speeding when moving downslope and maneuvering problems when going upslope. Some studies have focused on pavement types and conditions in order to capture significant relationships with bicyclist safety. For example, Koike et al. (2003) found that straightaways should be smooth and even, but uneven surfaces could prevent crash risk at intersections. Kang and Fricker (2013) adopted a mixed logit model to evaluate bicyclist facility preferences and demonstrated that road fundamental class, traffic signal, sidewalk width, and one-way street configurations are statistically significant for choosing on-street versus off-street segments. Other factors affecting the use of bicycles include signage, stops, humps, traffic volume, and curbs. Accordingly, cycling environments should be improved to increase the use of bicycles.

The other existing approach to the analysis of roadway infrastructure and facility deals with the Level of Service (LOS) for bicycle traffic flow and attempts to measure indicators for representative characteristics of flow (Dixon, 1996 and Petritsch et. al. 2007). Harkey et al. (1998) adopted the Bicycle Compatibility Index (BCI) by using riders' perception of a presented video about existing or proposed facilities. Davis (1995) demonstrated the Bicycle Safety Index Rating (BSIR) in which some important facilities, such as slope and marking, were not considered. Jensen (2007) employed a cumulative logit regression model to describe bicyclist satisfaction in various rural landscape scenarios and then calculated the level of service. None of these studies, which were developed for off-line analysis based on rider perception, were linked to the actual rider responses and performances during the experiments. Several studies examined bicyclists' perceptions on riding comfortability and measured favorable paths for riding on different route. For instance, Li et al. (2012) adopted an Ordered Probit model and a Factor Analysis (FA) to analyze the psychological perception of comfort on physically separated bicycle paths. Joo et al.

(2013) proposed a novel methodology to monitor the cycling environment and our study attempts to improve the methodology. They employed a Fault Tree Analysis (FTA) technique (Dhillon, 2016) to integrate safety and mobility, and then calculated the probability of a fault event.

2.4 Instrumented Probe Bicycle (IPB)

In this study, we developed an operational Instrumented Probe Bicycle (IPB) that was designed, built, and tested before being used. The IPB is a completely mobile system capable of collecting a variety of empirical data. There have been several different IPBs created around the world. It is the intent of this section to hold a brief review of these technologies to establish a baseline for the design proposed in this study, as well as provide a reference for understanding the improvements that have been made. Each study aimed at addressing its own issues, and the bikes were therefore constructed to fit the purpose. This led to a diverse population of IPB technology, yet, there were still many common pieces of hardware used. Sensors ranged from simple accelerometers and gyroscopes to full inertial measurement units (IMU’s), to pedal force sensors, to steering angle and torque sensors. Video camera usage was also popular. Research groups mounted these cameras in all sorts of orientations, on both the bicycle and the rider. They were used to either record the rider’s field of vision or rider motion. Therefore, this diversity with the magnitude of the available literature, has led to a spilled into two parts as shown below:

2.4.1 Literature review around the world

Many researchers in the various countries of the world were interested in studying the bikes as well as riders and the circumstances surrounding them. These efforts and activities were varied depending on the vision and methodology researchers.

In 2007, Ian Walker submitted study, which employed a camera and sensors to study the effects of riding position, helmet use, vehicle type and apparent gender on drivers overtaking bicyclists (Walker, 2007). Followed by Johnson et al. - 2010, in Melbourne, Australia, where they used a helmet-mounted video camera to study the naturalistic driving behavior of bicyclists and tried to identify the risk factors affecting that (Johnson et al. 2010). Gehlert et al. (2012) used a data acquisition system to record the speed and video data from numerous bicyclist groups, namely pedelec, e-bike and traditional bicycles. Also, Zhang, et al. (2012) employed an instrumented bicycle system to research the dynamic interactions between the cyclist and the bicycle.

In 2013, a number of important research included within this area. Vanwalleghem, at al. concerned with the vibrational comfort evaluation of the cyclist when cycling a rough surface, by assessing the hand–arm and seat interface of the cyclist with the bicycle (Vanwalleghem et al. 2013). Twisk, et al. studied the safety of e-bikes for the elderly. Measures were taken on heart rate, mental workload, and geographical position (GPS), balance and riding speed. They found that both age groups rode significantly faster on an e-bike than on a conventional bike (Twisk et al. 2013). Joo, et al. studied the bicycle maneuvering which is affected by environmental factors such as heavy vehicle volume, surface conditions, grade, crossings, humps, and curbs. This study has been found that bicycle–pedestrian shared road sections are safer and more comfortable than bicycle–car shared road sections. Joo & Oh (2013) and Yamanaka & Sanada (2013) developed the IPB, which can automatically measure and record speed, braking, steering, lateral distance, and vibration using electric sensors. In addition, apparent traffic density in front of a bicycle can be checked by the video recorder.

Dozza and Fernandez (2014) attempted to provide a platform for collecting field data from bicycles and show how such data can support the development of intelligent systems by offering novel insights into bicycle dynamics and bicyclist behavior. Table 2-1 summarizes information about recent studies that benefited some applications of IPB around the world.

Table 2-1: Summary of recent studies that use IPB around the world

Researcher	year	Country	Title	Tools/Instrument utilized with Probe Bicycle studies	Results
Ian Walker	2007	United Kingdom	Drivers overtaking bicyclists: Objective data on the effects of riding position, helmet use, vehicle type and apparent gender	• Massa M-5000/95 (Ultrasonic distance sensor) • Video Camera • laser (to assist cyclist with maintaining fixed distance from the edge of pavement)	• Overtaking motorists pass closer to a bicyclist when the rider wears a helmet, rides away from the edge of the road, is male, or when the vehicle concerned is a bus or heavy goods vehicle.
Johnson, et al.	2010	Australia	The application of a naturalistic driving method to investigate on-road cyclist behavior: A feasibility study	• Oregon Scientific ATC3K Action Camera (Helmet Mounted Camera) • survey	• Investigate the behavior of on-road commuter cyclists and their interactions with other road users in urban areas. • This study contributed to the provision of information for researchers in the field of identifying near-collision rates being advanced studies at that time.
Zhang, et al	2012	Taiwan	Rider/Bicycle Pose Estimation with IMU/Seat Force Measurements	• 8 Bonica cameras from Vicon Inc. (motion capture) • Inertial Measurement Unit - Motion Sense Inc. • Handlebar force/torque sensor • Seat force/torque sensor • pedal force sensor • EEG sensor. • EMG sensor • eye tracking sensor • Compact RIO– National Instruments Inc. (controls pneumatic actuators that support the bicycle frame)	• This study presented an instrumented bicycle system to study the dynamic interactions between the human rider and the bicycle. • A dynamics model was presented to capture the energetic interactions between the rider and the bicycle. • Experimental results were presented to demonstrate the capability of the pose estimation development.

Researcher	year	Country	Title	Tools/Instrument utilized with Probe Bicycle studies	Results
Gehlert, et al.	2012	Germany	The German Pedelec Naturalistic Cycling Study – Study Design and First Experiences	• ACME FlyCamOne eco V2 (front and back camera). • SM Modellbau GPS-Logger (GPS). • SM Modellbau Uilog2 (Wheel Sensor and Altimeter)	• Used a data acquisition system to record the speed and video data of different bicyclist categories, namely pedelec, e-bike and traditional bicycles.
Yamanaka, et al.	2013	Japan	Evaluation Models for Cyclists' Perception Using Probe Bicycle System	• SHARP GP2Y0A02YK0F (PSD distance sensor – lateral distance sensor) • MicroStone MA3-04AD (Vibration Sensor) • Race Technology DL1 • (Data logger and GPS) • Speed sensor • Braking sensor – displacement sensor • Steering sensor – string sensor. • Video camera • Microphone	• This study developed the Probe Bicycle System which can provide real-time data of cycling conditions and evaluate cyclists' comfort by using LOS index functions. • The authors developed evaluation models using the measurement of braking, vertical vibration, speed, steering and so on.
Vanwalleghem, et al.	2013	Belgium	Sensor design for outdoor racing bicycle field testing for human vibration comfort evaluation	• A Bruel and Kjaer type 4507 IEPE (integrated electronic piezoelectric) accelerometer fulfills these aspects. • Electrodynamic shaker, type LDS V406. • Polytec vibrometer controller OFV-5000. • National Instruments DAQ. (Acquired all sensor output signals)	• This study is concerned with the vibrational comfort evaluation of the cyclist when cycling a rough surface. • High acceleration levels do not necessarily correspond to high absorbed power values because a high or low contact force may change this.

Researcher	year	Country	Title	Tools/Instrument utilized with Probe Bicycle studies	Results
Joo, & Oh.	2013	Korea	A novel method to monitor bicycling environments	• GPS • Accelerometer • gyro sensor • questionnaire survey	• This study proposed a novel monitoring method that can be used for evaluating bicycle performance regarding safety and mobility. • This study has been found that bicycle–pedestrian shared road sections are safer and more comfortable environments, compared to bicycle–car shared road sections.
Twisk, et al.	2013	Netherlands	Preliminary results from a field experiment on e-bike safety: Speed choice and the mental workload for middle-aged and elderly cyclists.	• Speedometer • potentiometer (steering sensor) • GPS • GoPro 3 Silver video camera ProMove 3D (Inertial Measurement Unit)	• Studied the safety of electrical-assist versus traditional pedal-power-only bicycles for elderly users, by conducting a field study utilizing IPBs. • The data collected from the IPB • showed that riders rode faster on electrical assist bicycles, with no significant difference for • Metal workload between bicycle types.
Dozza, & Fernandez	2014	Sweden	Understanding bicycle dynamics and cyclist behavior from naturalistic field data	• GoPro Hero, Hero2 video camera, Phidget IMU 1056. • (Inertial Measurement Unit), Phidgets GPS 1040. • Flexiforce resistive force sensor (Brake force sensor).	• This study presents a platform for collecting field data from bicycles and shows how such data can support the development of intelligent systems by offering novel insights into bicycle dynamics and bicyclist behavior.

2.4.2 Literature review in North America (NA)

With so many of the benefits of using the bicycling, which vary between the economic and the environment, but the motor vehicles remain the dominant mode of transportation in many cities across North America (NA), caused largely by concerns over the safety and comfort of cycling (Mohanty et al. 2014).

Charlton et al. (2011) tried to show the clear viability of smartphone-based GPS data collection. In 2013, Farrell et al. studied the relationship between traffic emissions and cyclists' exposure to air pollution across a variety of cycling facilities within the Island of Montreal.

In 2014, a number of important research included within this area. Mohanty et al. (2014) provided an effective summary of most of the currently instrumented probe bicycle technology. In addition, it provided a wonderful chronology of that development in those studies and techniques used. Lee et al. (2014) developed a method of ranking biker comfortability using various metrics. Their theory was that perception of safety is tantamount in a rider's decision whether or not to venture into the transportation environment. Hamann, et al. (2014) presented a study to describe the methods of natural riding bikes that allow for the examination of the risks cyclist study, including factors such as route selection, and use of infrastructure specific bike, rider, and errors. Table 2-2 provides brief information of recent studies mostly about the application of IPB in North America.

Table 2-2: Summary of recent studies that use IPB in North America

Researcher	year	Country	Title	Tools/Instrument utilized with Probe Bicycle studies	Results
Charlton	2011	USA	Bicycle Route Choice Data Collection using GPS-Enabled Smartphones	• Smartphone and associated applications	• This study showed a bias toward frequent cyclists, and toward male users (even more than cycling is already male-dominated in the region's most recent household travel survey). • A bicycle route choice model developed using the data revealed sensitivity to slope, presence of bike lanes and bike route designations, trip purpose, and gender.
Farrell, et al	2012	Canada	Measuring Cyclists' Exposure to Traffic Emissions Across Urban Cycling Facilities	• Air pollution monitors (TSI Condensation Particle Counter, Black Carbon Micro aethalometer, TSI Dust • The track, Harvard Impactor). • GPS. • Go-Pro Video Camera. • Holter monitors (on cyclists)	• This study seeks to examine the relationship between traffic emissions and cyclists' exposure to 2 air pollution across a variety of cycling facilities within the Island of Montreal. • Preliminary results show a significant correlation between cyclists' exposure to ultrafine particulate matter (UFP) and measured traffic volumes ($p<0.05$), but the even stronger correlation between exposure and the volume of trucks ($p<0.01$), indicating that vehicle composition may be an instrumental component of traffic data collection.
Mohanty, et all	2014	USA	A Global Review of Current Instrumented Probe Bicycle (IPB) Technology and Research	• survey	• Provided the majority of research on the subject of the Instrumented Probe Bicycle (IPB).

Researcher	year	Country	Title	Tools/Instrument utilized with Probe Bicycle studies	Results
Lee, et al	2014	Canada	Using Instrumented Probe Bicycles to Develop Bicycle Safety and Comfort Prediction Models	• Microsoft Kinect Sensor • Front Facing Camera • Handlebar Potentiometer • Hall effect sensor • 3DM GX3 -45 (GPS-Aided Inertial Navigation System)	• In this paper, an ordinal logit regression model is proposed as a potential Bicycle Comfort and Safety Prediction Model (BCSPM) to predict a cyclist's perceived safety and comfort quantitatively. • The analysis yielded observations comparable to research studied in the other research. Similar to Yamanaka, Joo and Yao's study the amount of open space in front of the cyclist, the path type, and the cycling speed, were found to be significant factors for a cyclist's sense of safety and comfort. Other significant variables revealed in this study include traffic volumes and speeds as well as cyclists experience and fitness.
Hamann, et al	2014	USA	A naturalistic study of child and adult bicycling behaviors and risk exposure	• GPS. • Camera. • survey	• 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. • This study tried to provide evidence for the variations in risk exposure and behaviors among cyclists of different ages and characteristics.

Chapter 3 Building Instrumented Probe Bicycle

3.1 Introduction

To meet the specific needs of this study, an instrument probe bicycle was designed and built. It was capable of measuring a range of dynamic data, not only with respect to the bicycle but also with respect to the rider. The basic framework of the bicycle was influenced by several of the previous IPB bicycles mentioned in the previous chapter. Many refinements and improvements to this framework were designed into the bicycle used in this study. These were done with the hope of pushing IPB tools to become more standardized units; such that general research efforts can become more comparable.

3.2 Bicycle geometry

The IPB used in this study was built around a Jamis Coda Sport frame, and consisted of an array of sensors coupled with a mobile data acquisition system. The Jamis Coda Sport is a popular commuter bicycle. It has been selected because of its average size and robust steel frame.

The size of a bicycle is defined by its' seat tube length. It is the primary dimensional aspect of the bicycle because it directly relates to a person's height. It allows the rider to feel that their body size “fits” with the bicycle in a comfortable way. Due to the naturalistic nature of this study, it would have been ideal to have several of IPBs in stock to meet the needs of the variously sized participants, but given timeframe and budget constraints, this was highly infeasible. The Coda Sport was the only truly ideal for a small number of people, but its' average nature made it at least practically suitable for all bike trial participants. This aspect was one limitation of the study that was noted as such, and given no further consideration.

3.3 Data Acquisition System

The data acquisition system for the bike was designed to be compact, and robust in capability. Unlike other studies that generate IPBs for testing in lab environments, this IPB was attempted to be used in real transportation environment. Therefore, the system had to be robust enough to handle and number of situations that a participant rider would impose on it. Furthermore, compactness was paramount, as it was desirable to make the bike look and feel as normal as possible for the participant riders. The goal was to have the bicycle systems set up in a way that would not interfere in any way with a rider's natural motions.

The system is generally comprised of two main constituents, an array of sensors and a station for data logging. The sensor array consisted of five individual sensors, each selected for specific aims, and a video camera. A list and general description of these sensors is provided below in Table 3-1. The data logging station was located in the aft portion of the bicycle. A small metal case was bolted to a cargo rack, which was in turn attached to the bicycle; these can be seen in Figure 3-1. The foam-insulated case housed a small laptop and NI DAQ. Also, the case provided a platform for the rider position sensor, which will be discussed in following sections.

Table 3-1: IPB sensor array

Sensor	Component(s)	Function
Front Wheel RPM	Bourns Optical Encoder	Measure the angular velocity of the front wheel
Rear Wheel RPM	Bourns Optical Encoder	Measure the angular velocity of the rear wheel
Inertial Measurement Unit/GPS	SBG Ellipse miniature IMU/GNSS	Measure bicycle linear accelerations, angular velocities, and GPS position
Steering Angle	Honeywell Hall-Effect Potentiometer, 180˚ of travel	Measure the angular displacement of the handle bar
Rider Position	2x Honeywell Hall-Effect Potentiometers, 90˚ of travel, combined with universal joint	Measure the lean and pitch angles of the rider, relative to the bicycle
Video Camera	Sony ActionCam	Capture snapshots of environment in front of bicycle

Figure 3-1: Instrumented probe bicycle

Each of the sensors was mounted to the bicycle via a custom bracket. The brackets were designed and machined to be low-profile and very durable. The goal was to enable the sensors to preform without inhibiting the rider in any way. A close up of each sensor is shown in Figure 3-2. In all, there was only minimal modification made to the bicycle itself. Two friction wheels were attached by tapping threaded holes in the hubs of each wheel, otherwise, the original bicycle was left untouched.

Figure 3-2: Close up view of each of the sensors used on the IPB: Steering Angle (top left), Rider Position and GPS Antenna (top right), IMU (bottom left), Wheel RPM (bottom right).

3.4 Sensors

3.4.1 Internal Measurement Unit

The inertial measurement unit (IMU) was in some ways the principle sensor used in this study. The unit itself houses eleven individual sensors: three single axis accelerometers, one for each of the coordinate axes, three rate gyros, three magnetometers, a barometric pressure sensor and a temperature sensor. For this study, only the three accelerometers and rate gyros were used to collect data. Both the accelerometers and gyros sensors are industrial grade, high-performance MEMS technology. Coupled with the onboard Extended Kalman Filter, the unit was able to generate accurate and consistently output. The GPS/GNSS aided the IMU in measurement estimation and correction, thereby reducing error over time. The selling company, SBG Systems, supplies an external software package with their IMU units that made for easy and consistent data logging. It is also possible to use various other software packages to interface with the raw data outputs of the unit, but none of those options was explored for this study. It was convenient to use the provided software because of the user interfaces. For example, the program included routines to account for and correct mounting orientations. By inputting the lever arms and misalignment angles between the unit and the bike's center of gravity, the sensor could be mounted in any way, and still output correct data.

Seen above in Figure 3-1 and Figure 3-2, the IMU was mounted to the bicycle on the seat tube, and located directly under the frame member between the seat tube and the head tube. High-precision, rigid mounting helped isolate the sensors from secondary vibrations, improving output accuracy and long term reliability. This mounting location tucked the unit up into the frame of the bicycle, which kept it out of the way of interfering with the rider, as well as protected it from any impact in the event of a crash or the bicycle falling over.

3.4.2 Rider position sensors

The rider positon sensor consists of an aluminum universal joint that had been specially modified to accept the sensing shafts of two potentiometers as the pivot axes of the joint. Each potentiometer provided information on the angular displacement along a given axis. The rotational motion caused by a rider's longitudinal motion was labeled as rider pitch, which the rotation motion from lateral rider movements was labeled as rider lean. The sensor was aligned in such a way that each axis of the sensor corresponded with these pitching and leaning motions. The universal joint was welded to an angle bracket and affixed to the bicycle's data acquisition box.

In order to gather motion data from a rider, a "sensing rod" was used to tether the rider to the sensor. The sensing rod consisted of two small carbon fiber tubes, one of larger diameter and one of smaller. The larger tube was anchored to the open end of the universal joint, while the smaller tube was attached to the rider via a small piece of Velcro. These smaller tube telescoped inside the larger tube. The Velcro tip attached to an adjustable chest harness worn by the rider. The design of this system was three-fold. Primarily, the system needed to be able to track the motion of the rider effectively. Second, the system needed to be adjustable for riders of all different sizes.

Third, the system needed to be attached to the rider safely, so, in the instance of a crash the rider would be able to separate from the bicycle. Overall, the system provided a safe, lightweight, low-profile interface for tracking a rider's motion.

3.4.3 Wheel RPM sensors

The wheel RPM sensors used optical encoders and were both mounted in a same way. An aluminum disk was mounted to the hub of the bicycle wheel, while a bracket attached the encoder to the bicycle frame, as seen in Figure 3-2. a rubber coated driven disk was placed in contact with the aluminum disk, as a pick up to the rotational motion. The aluminum disk was given a mild knurl to increase the friction at the contacting surfaces. Despite carefully machining and mounting, very small eccentricity was still present. To account for this, a spring and pivot arm assembly was designed to keep smooth, constant contact between the aluminum disk and the friction wheel. This subsystem was designed to improve the accuracy and durability. With continuous sensing available, the resolution and accuracy of the wheel RPM was greatly increased over previous IPB models, which use much simpler magnetic pick-ups.

3.4.4 Steering angle

The steering angle sensor was constructed from a potentiometer and friction disk, similar to those used on the encoders, that contacted the steering column. It was mounted to the bicycle by an aluminum bracket that allowed the sensor to sit directly adjacent to the steering column, in an orientation that was perpendicular to the column. This allowed the sensor to be tight to the bike, out of the way of the rider's legs, and make good contact with the steering column. The sensor's bracket assembly also used a spring and pivot arm system to generate better contact pressure with the steering column.

3.4.5 Data acquisition box

The data acquisition system consisted of three components, a National Instruments USB-6210 DAQ, a small ASUS laptop, and a foam-padded rigid container to house the system. All potentiometers and encoders were wired into the DAQ, which was then plugged into the computer. A LabVIEW program was created to read and adjust the raw data signals to attain the desired outputs, i.e. converting encoder pulses to wheel RPM. This program was also responsible for logging all the data recorded by these sensors. The IMU was connected directly to the laptop via a RS-232 to USB cable, where the SBG recording software was used to initialize the internal sensors and log all of the requested data. Because the system was running two different programs for data acquisition, this introduced the need for synchronization. This process for overcoming this is discussed in a later section of this report.

3.5 Sensor calibration

Sensor calibration was important to ensure the data being collected could be trusted as accurate. To this end, simple procedures were used to assess the general condition of each sensor. The IMU was factory calibrated prior to being purchased, and all testing was complete during a time period where the initial calibration was still valid, so not recalibration was necessary. Calibration records accompanied the purchased unit. However, when mounted, the location and orientation of the sensor relative to the center of gravity of the IPB system was required for correct data collection. A digital angle gauge was used to measure the offset angle between the sensor plate and the ground plane. There was negligible misalignment of the other two orientation angles. The longitudinal linear offset distances were approximated by balancing the bicycle on a metal rod and measuring with a tape measure. The vertical direction was approximated in the same way, although less accurately, and there was negligible lateral offset. While these methods were very much approximating, they were deemed acceptable, because of the onboard estimation software in the IMU it is able to compensate for the error in misalignment arms of up to 5 centimeters.

Both encoders were calibrated during steady state angular velocity conditions by manually counting wheel RPM, using a spoke marker and a stopwatch. The manual calculations were compared with the computer measured RPM and found to be ± 3 RPM in accuracy, this test was repeated multiple times for each wheel, for angular velocities ranging from 10 to 80 RPM, with consistent results. In reality, the accuracy was much better, but it was difficult to maintain a perfectly constant wheel RPM from manual pedaling during the measuring period.

For the steering angle sensor, a digital angle gauge with an accuracy of 0.1˚ was used to verify the output readings. The potentiometer used for steering angle had a rotational range of 180˚ ± 2˚, and output linearity of ± 4% across the range. It was found that most of the deviation from linear behavior occurred near the extrema of the range. So, the sensing shaft was set at about 90˚ and the voltage measurement zeroed in LabVIEW, thereby setting this point as the equilibrium zero. Once this was completed, multiple trials were run to evaluate the ratio of voltage output to angle. The relationship was found to be about 45 mV per degree. Further calibration trials were then run in a range of ± 45˚ from the equilibrium point, as this was assumed to encompass the entire operational range, and it was found that the measured output was within ± 1˚ of the angle gauge.

The digital angle gauge was also used in calibration of the rider position sensor. Both potentiometers used in this sensor were the same as was used in the steering angle sensor, with the exception that their rotational ranges were only 90˚. In order to attain accurate measurements, each potentiometer was checked individually. The sensor's two degrees of freedom allow for some complex motions, so for calibration purposes the two arms of the universal joint were kept in-plane with each other as the potentiometers was checked. The same procedure as for the steering angle potentiometer was followed, including the nominal zeroing point being at half of the travel range. The testing range was ± 30˚ around the equilibrium point. The results of this showed an accuracy of ± 0.5 degrees for each potentiometer.

3.6 Summary

Now that the entire system has been described in some detail, it seemed necessary to present a concise summary of certain accuracy characteristic of the sensors used for data collection. This summary is shown in Table 3-2. Additionally, in Figure 3-3 sensors, and their position on the bicycle are represented.

Table 3-2: Overview of certain accuracy properties of each sensor used

Sensor	Accuracy Information
IMU Outputs	Velocity: Horizontal/Vertical – 0.05 m/s Attitude: Roll/Pitch – 0.2˚ Yaw – 0.4˚
IMU GPS	Position: ± 2 m (Latitude and Longitude)
Optical Encoders	Resolution: 64 pulses per revolution Wheel RPM: ± 3 rev/s
Potentiometer	Resolution: 45 mV/˚ Steering Angle: ± 1˚ Rider Position Angles: ± 0.5˚

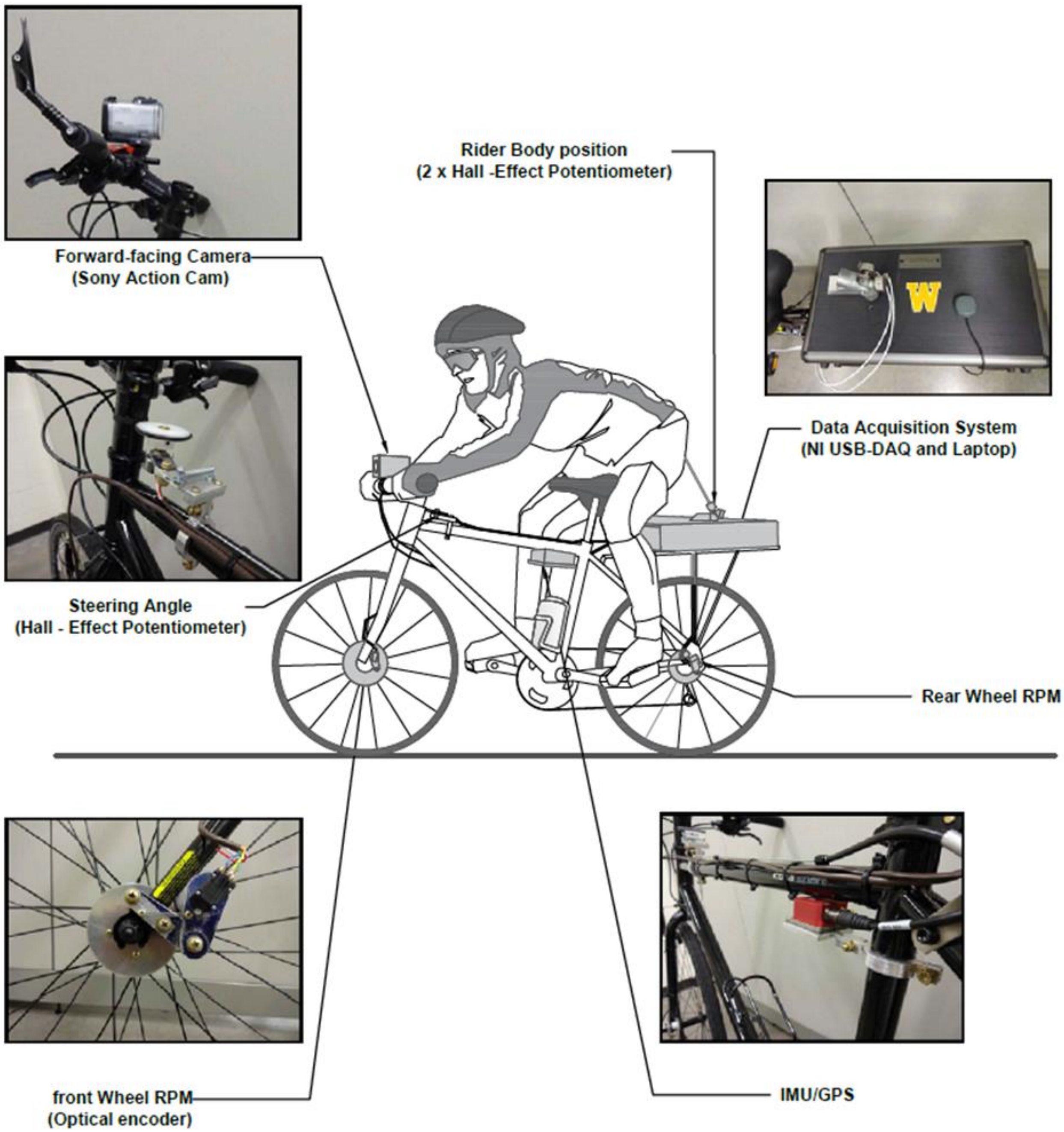

Figure 3-3: Sensors and their position on the bicycle

Chapter 4 Data collection

4.1 Overview

The field experiment was organized on a fixed route (Figure 4-1) near the Main Campus of Western Michigan University, Kalamazoo, U.S. during the summer. The route was approximately 0.85 mile (1.4 Kilometers), and included a different range of surface conditions, roadway environments (e.g. roundabout and signalized intersections), and alignment changes. The main purpose of the field experiment was to organize a dataset, which included not only bicycle speed, but also the positioning of the bicycle. The study subjects were recruited through campus e-mails, announcements in class, and announcement board postings in WMU's campus. In addition, the research team contacted members of local bicyclist clubs for participation. Thereafter, potential participants were asked to sign up through an on-line schedule to determine their preferred day among one week and three time categories (9:30 a.m.-11:30 a.m., 1:30 p.m.-3:30 p.m. and 5:00 p.m.-7:00 p.m.).

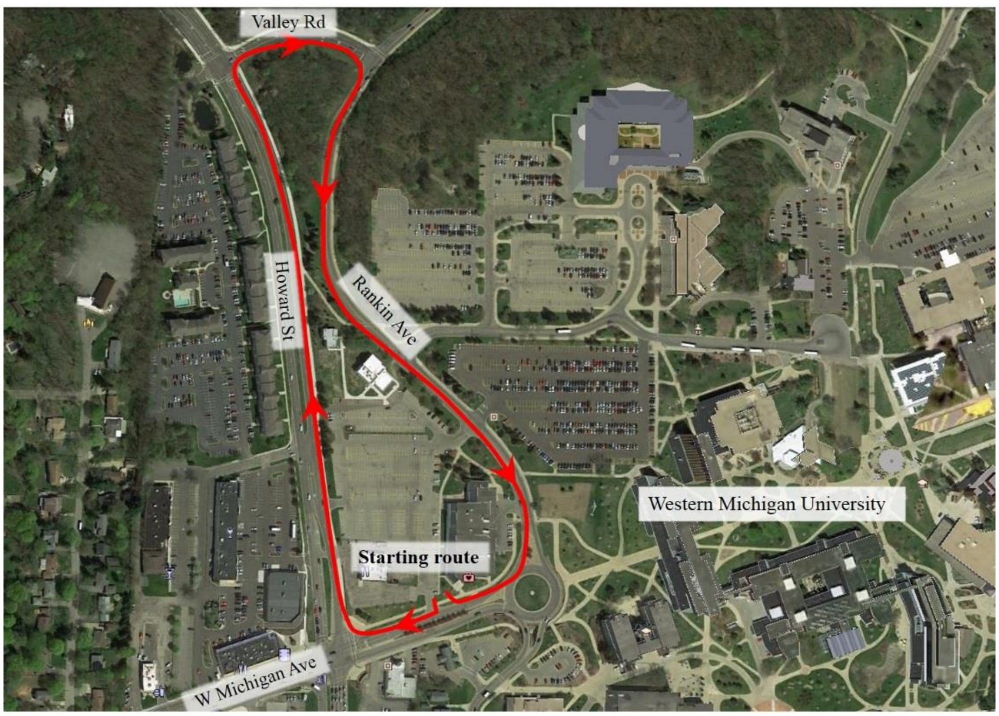

Figure 4-1: Experiment site

Two surveys were taken to observe the effect of various levels of cycling skill on bicycle dynamics and their perception of comfort during the experiment. Respondents were given the questionnaires before and after the field experiment. The survey was including two different questionnaires, which each rider may to respond before and after completing the field experiment. It was intended to observe the effect of different levels of cycling and skills on bicycle, also their perception of safety, comfort, and confidence associated with infrastructure and environment. Each respondent was asked with two different questionnaires before and after field experiment. Pre-survey questionnaire was including two parts, the first part contained some personal questions, i.e. gender, age (less than 16, 16-24, 25-35, 35-49, 50-64, more than 65), height, weight, cycling frequency, primary purpose of cycling, mileage riding each week and skill level classification. The second part in the pre-survey was implemented to determine sense of confidence to ride in different facilities (i.e. roadway with dedicated roadway, roadway with shoulder, sidewalk with pedestrian). A rating system in a scale of 1 to 5 (1=least confident, 5= most confident) was used. The post-survey questionnaire was applied for finding comfort perception of riders about infrastructure and environmental characteristic. Thus, they were asked for determining the level of comfort (1= very uncomfortable, 5= very comfortable) at each segment. Additionally, in three segments, there were two choices, roadway and sidewalk, for riding, and each respondent chose the preferred way which rode during the field experiment.

After the analysis of pre and post-survey, this chapter also presents details on data collection in experiment field. Data collected at this study included two main categories;

- field experiment data by sensors,
- environment and infrastructure characteristics

4.2 Pre-survey

Sixty participants (16 females, 44 males) in five age groups performed the experiment. After processing the data, statistics were estimated from respondents. Descriptive statistics and t-test were the main methods to classify perception of participants and the strength of their performances. A sample of 60 riders was examined and Figure 4-2 presents the number of participants per age group and gender.

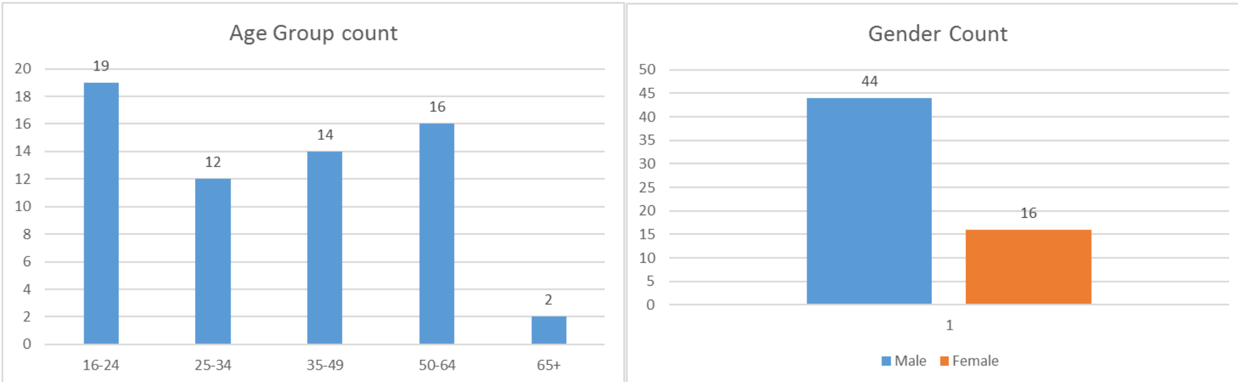

Figure 4-2: Number of participants per age group and gender

4.2.1 Weight and height distribution

To identify physical characteristic of individual participants, Body Mass Index (BMI) was implemented. The body mass index (BMI) or Quetelet index is a value derived from the mass (weight) and height of an individual. The BMI is defined as the body mass divided by the square of the body height multiple by 703 - The 703 is to convert the index from the original metric version of the formula, resulting from mass in pounds and height in inches. The BMI is an attempt to quantify the amount of tissue mass (muscle, fat, and bone) in an individual, and then categorize that person as underweight, normal weight, overweight, or obese based on that value. However, there is some debate about where on the BMI scale the dividing lines between categories should be placed. Recommended BMI ranges by Centers for Disease Control and Prevention (CDC) are underweight: under 18.5, normal weight: 18.5 to 25, overweight: 25 to 30, obese: over 30. Figure 4-3 demonstrates average BMI per age and also BMI range distribution among the respondents.

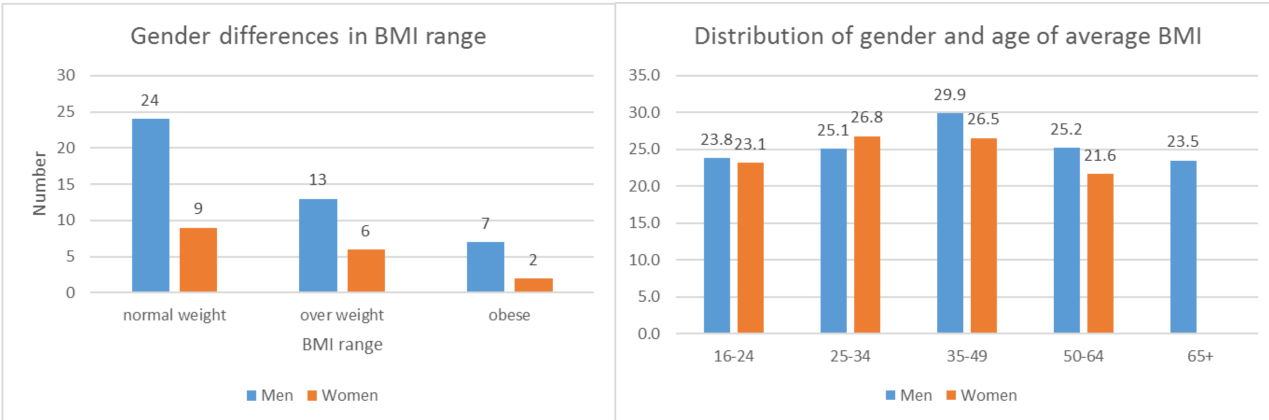

Figure 4-3: Average BMI per age group and BMI range

4.2.2 Skill level

As it is discussed previously, one of the objectives of this report is to assess the effect of skill level on the biking behavior. To achieve this important variable, this question was asked and bicyclist's perception about their skill level was obtained. According to the previous studies, three different skill levels (beginner, intermediate and experienced) were defined. Figure 4-4 presents the frequency and percentage of participants' skill level.

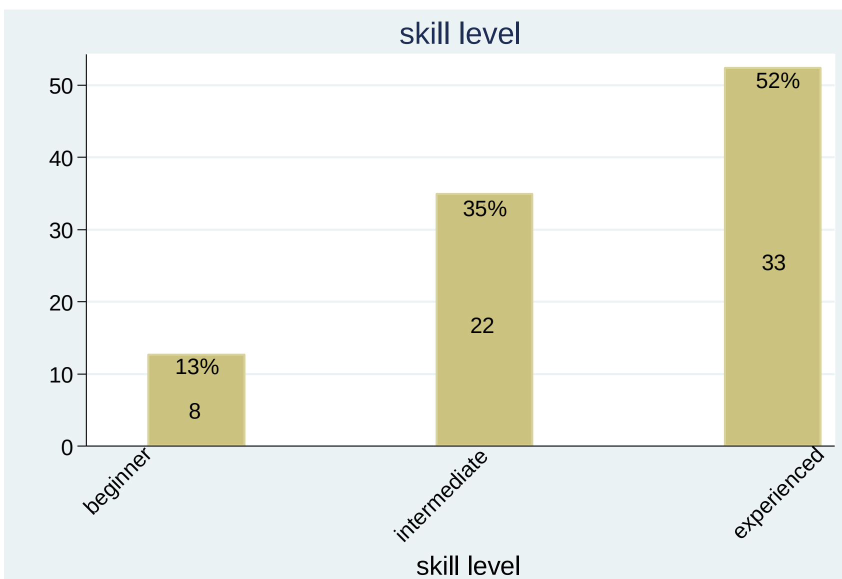

Figure 4-4: Frequency and percentage of participants' skill level

It can be understood that more than 50 percent of respondents believed they are experienced in biking. In this study, due to inadequacy of sample size for beginner and intermediate riders, these two groups are considered as a new accumulative group.

Additionally, Figure 4-5 shows the skill levels differences based on the gender, which the difference was not statically significant.

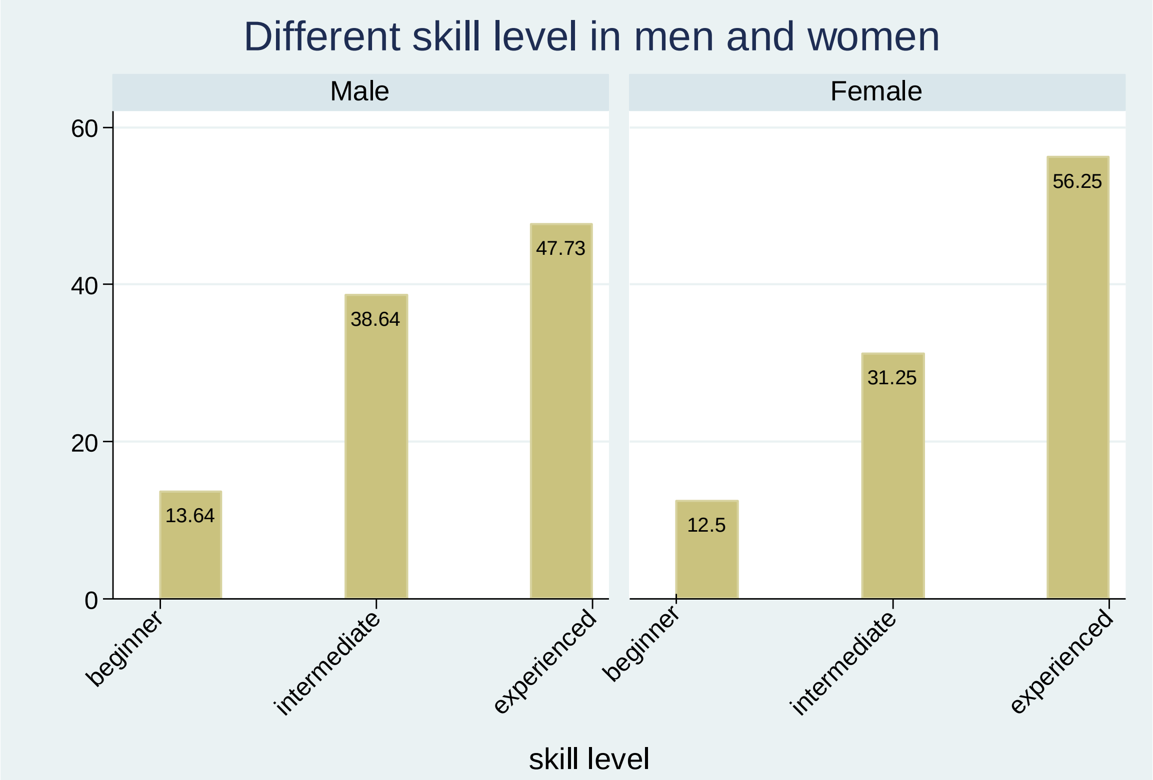

Figure 4-5: Frequency percent of skill level per gender

4.2.3 Biking frequency

To determine biking frequency, participants were asked to identify which answer (every day, several times a week, several times a month and very rarely) could best describe their bicycling repetition (See Figure 4-6). It can be found that almost half of participants use bicycle several times in a week

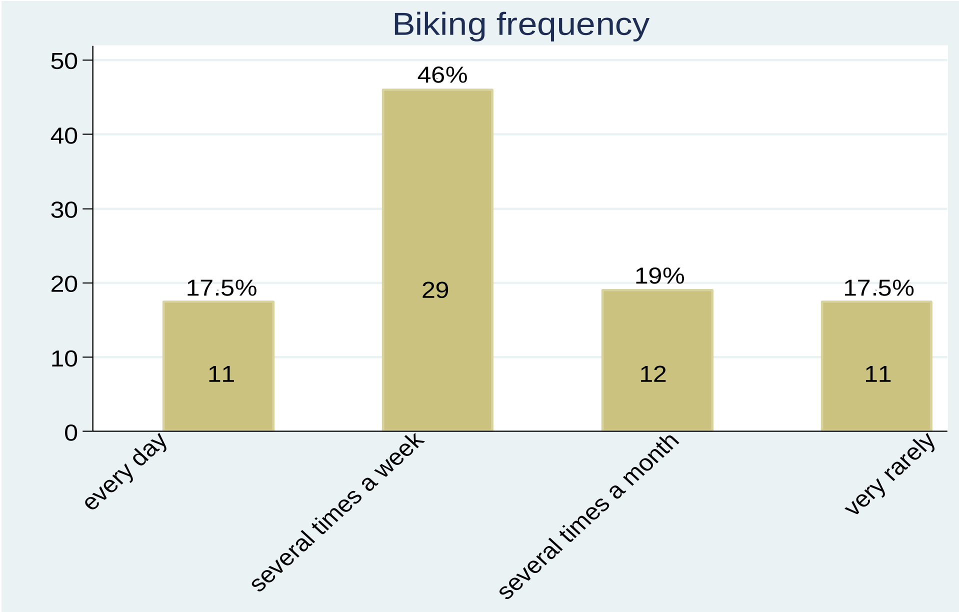

Figure 4-6: Responds for biking frequency question

Figure 4-7 shows that women reported biking frequency several times in a week and several times a month more than men did. However, t-value indicates that gender difference is not statistically significant

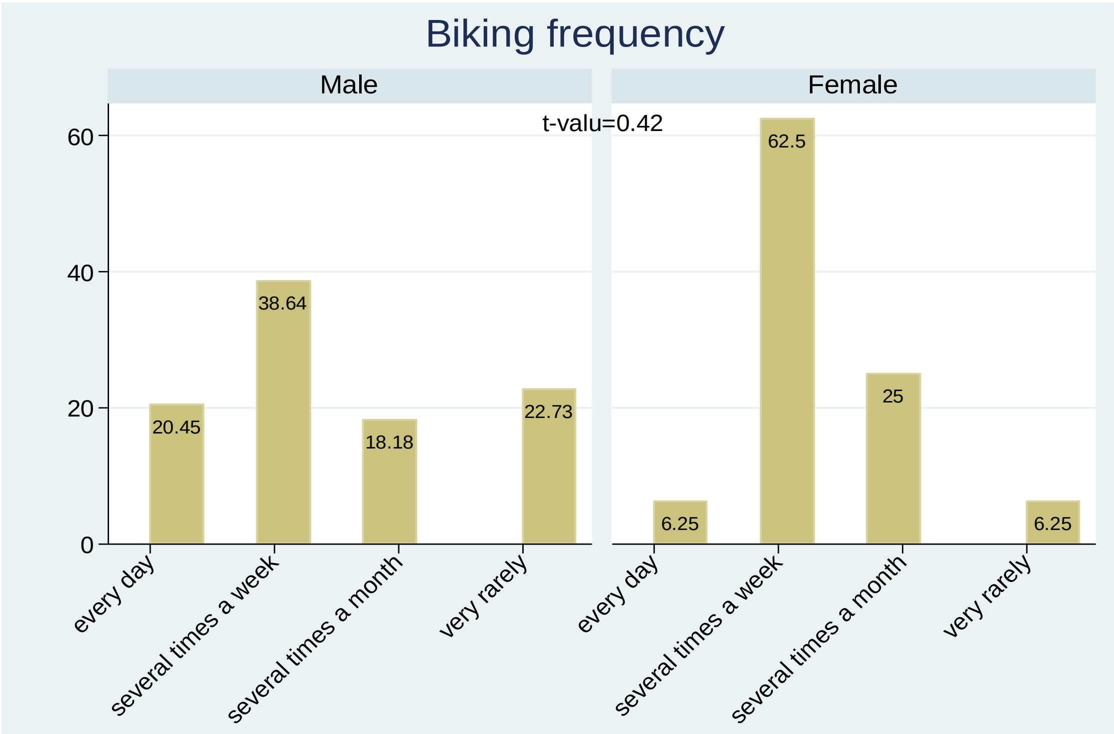

Figure 4-7: Gender difference for biking frequency

Figure 4-8 presents the distribution of biking frequency versus skill levels. It could be interpreted that as skill level increases, frequency of biking also increases. Although, there is no statistically significant differences observed among the levels.

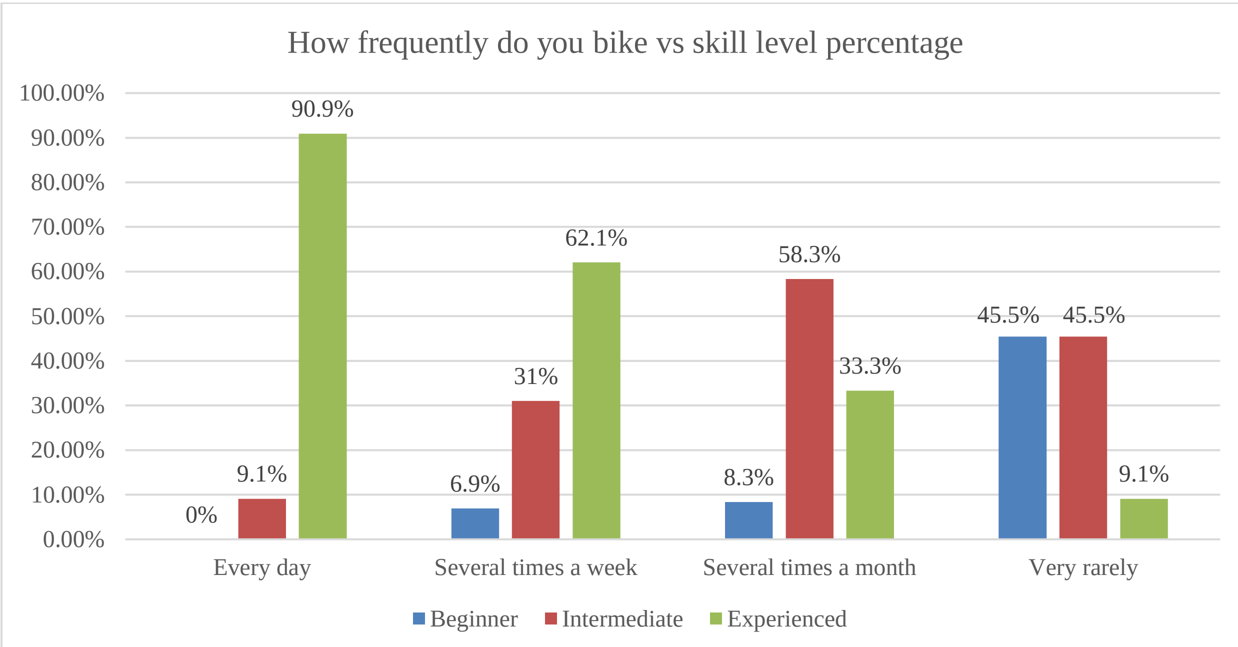

Figure 4-8: Biking frequency based on skill levels

4.2.4 Biking primary purpose

Participants were asked to answer the primary bicycling purpose among four main groups (exercise and health, recreation, commuting errands/ shopping). They could answer more than one choice. As it is shown in Figure 4-9 presents, exercise and recreation are the main purposes of biking, also choosing bicycle mode for shopping assigns almost 5 percent of trips.

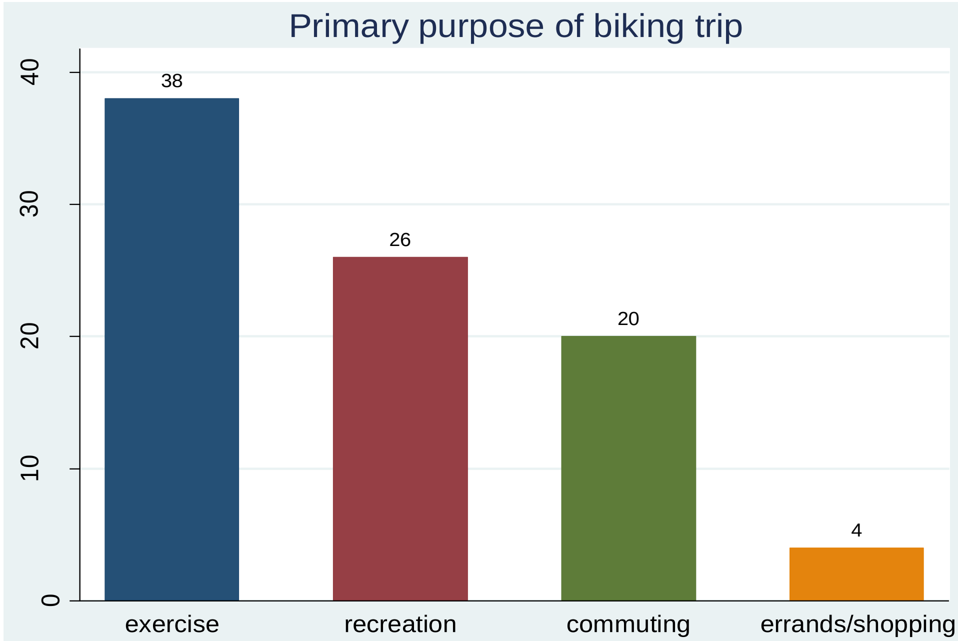

Figure 4-9: Primary purpose of biking trip

4.2.5 Biking per week

To obtain additional information about biking experience, participants were asked to indicate their mileage biking per week. Four choices (less than 5 miles, 5 to 15 miles, 15 to 30 miles and more than 30 miles) were considered. Figure 4-10 shows that intermediate and experienced riders' responds are statistically. In the other words, skillful riders reported more frequency riding in a week.

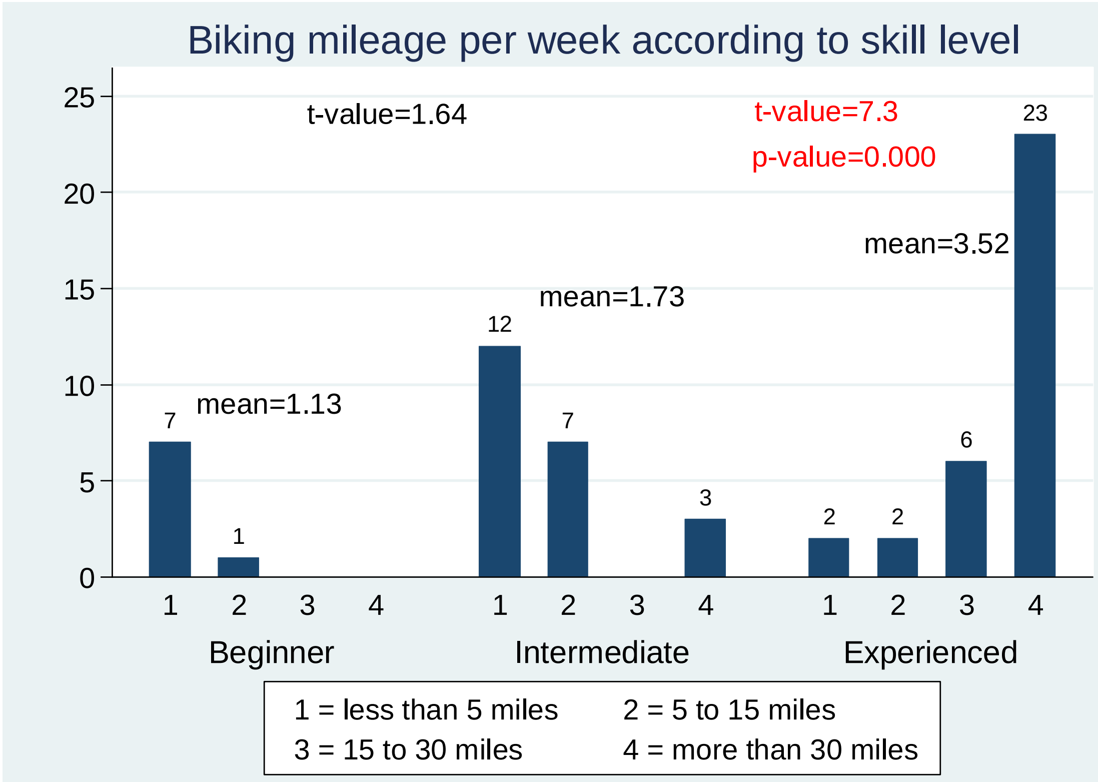

Figure 4-10: Weekly biking versus skill levels

4.2.1 Cycling confidence level

This part was examined to find the relationship between roadway environment and rider's confidence level. To achieve this purpose, participants were asked to rank their confidence level (1= least confidence and 5= most confidence) in a variety of road conditions (roadway with dedicated bike lane, roadway with sharrow, roadway with shoulder, roadway without bike lane, sharrow and shoulder, sidewalk with pedestrian and sidewalk without pedestrian). Figure 4-11 presents confidence level for each road type.

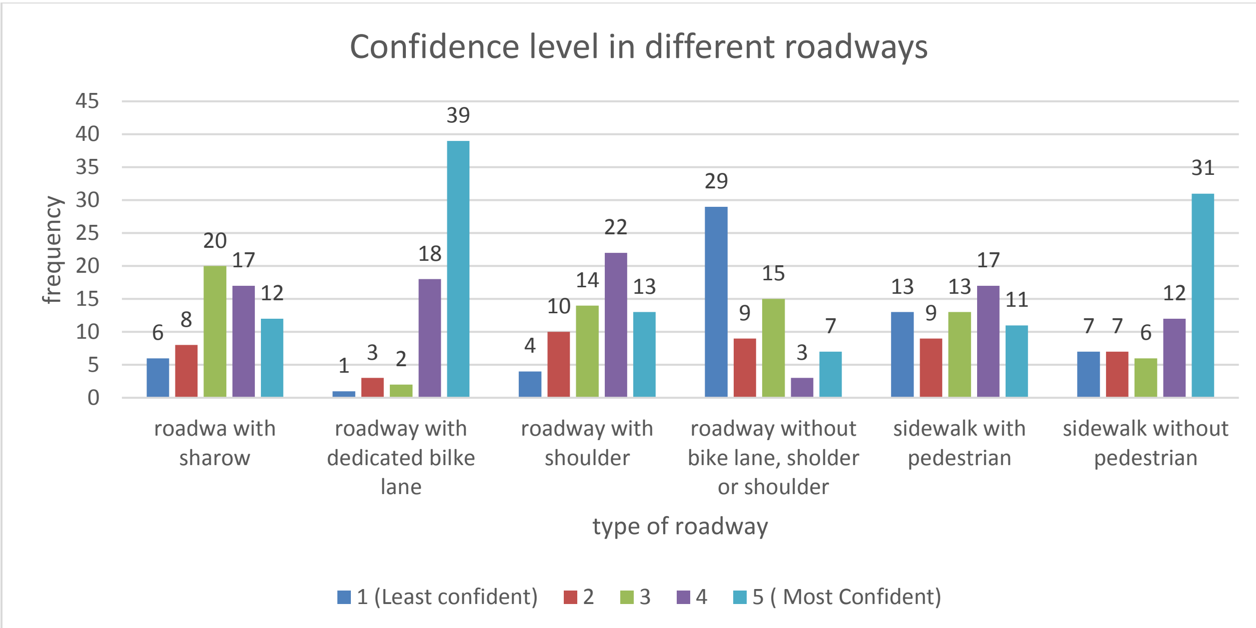

Figure 4-11: Confidence level in different road types

4.3 Analysis of post-survey data

In the post-survey section, participants were asked to determine their comfortability (1= very uncomfortable and 5= very comfortable) at each segment after completing the field experiment. Additionally, participants were asked to their chosen way (roadway or sidewalk) in each segment during the experiment. Figure 4-12 shows that the most comfortable segment is segment A1 (mean=4.86) and the most uncomfortable segment is segment D1 (mean=3.92).

Furthermore, there were two available riding way in three segments (A1, B1 and B2). Figure 4-13 indicates that nearly 30% of participants preferred riding in sidewalk instead of roadway.

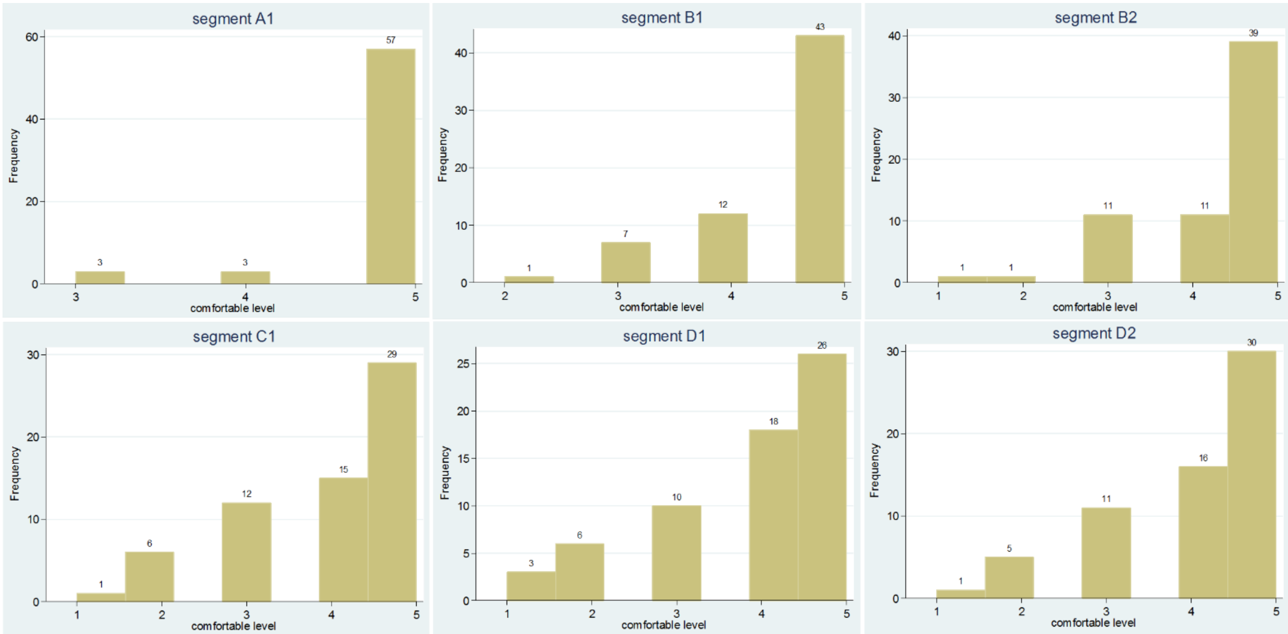

Figure 4-12: Comfortable level for segments

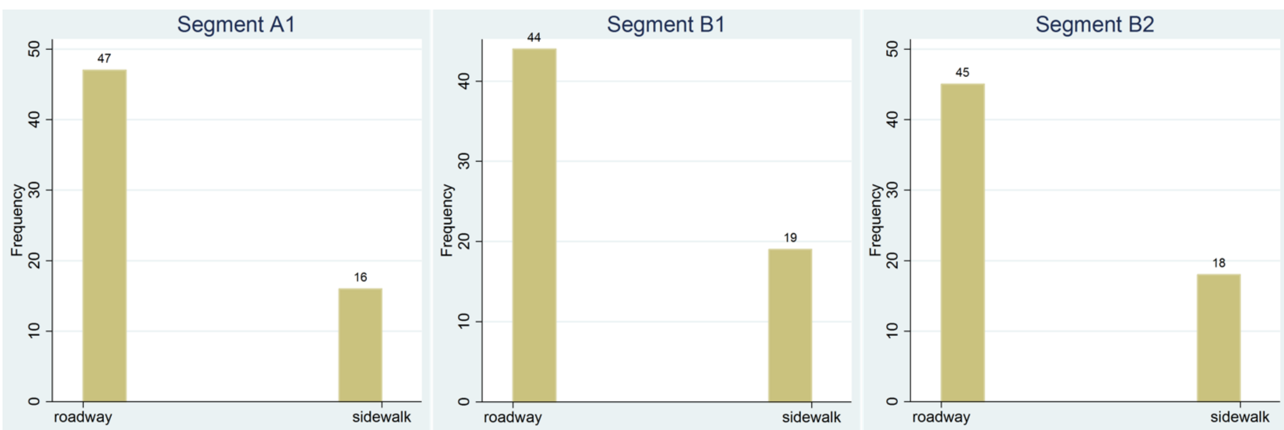

Figure 4-13: Participants chosen way (roadway or sidewalk) for segments

4.4 Field experiment data

An instrumented probe bicycle was designed and constructed to collect necessary motions of a human-bicycle dynamic system. IPB was including six different sensors which are able to measure and record the data. Table 4.1 indicates descriptive analysis for variables were measured or calculated in the field experiment.

Table 4-1: Descriptive analysis for field experiment data

Variable	Average				Standard Deviation	Min	Max
	Inexperienced	Experienced	Total	t-value			
xacc	1.245	1.151	1.195	10.573	1.643	0	40.912
yacc	0.636	0.607	0.621	8.576	0.618	0	25.702
zacc	9.829	9.825	9.827	0.354	2.240	0	30.511
xvel	5.077	5.281	5.186	17.307	2.181	0	13.468
yvel	0.080	0.068	0.074	34.069	0.070	0	1.602
zvel	0.064	0.068	0.066	7.064	0.084	0	1.762
roll (°)	0.000	0.285	0.152	13.659	3.875	-42.901	31.175
pitch (°)	0.332	0.39	5.713	18.767	1.863	-7.959	9.238
yaw (°)	13.345	12.531	12.913	1.275	61.172	-52.937	134.505
str_ang	8.182	7.096	10.269	19.262	10.619	-60.56	69.242
rd_pitch	24.904	18.608	21.635	18.290	19.307	-43.244	56.059

xacc: X-axis Acceleration (m/s^2), yacc: Y-axis Acceleration (m/s^2), zacc: Z-axis Acceleration (m/s^2), xvel: X-axis Velocity (m/s), yvel: Y-axis Velocity (m/s), zvel: Z-axis Velocity (m/s), Roll (°), Pitch (°), Yaw (°), str_ang: Steering Angle (°), rd_pitch: Rider Pitch (°).

The pairwise mean comparison method with taking advantage of t-value was used. For a confidence level of 95%, t-value should be more than 1.96 and for rejecting the null hypothesis and statistically significant difference being proved. Figure 4-14 presents standard deviation Y-velocity variable categorized by skill level. It is shown that difference between beginner and intermediate riders is not significant; however, lateral speed for intermediate riders is more than experienced. In other words, by increasing the skill level from intermediate to experienced, zigzag maneuvering will be decreased.

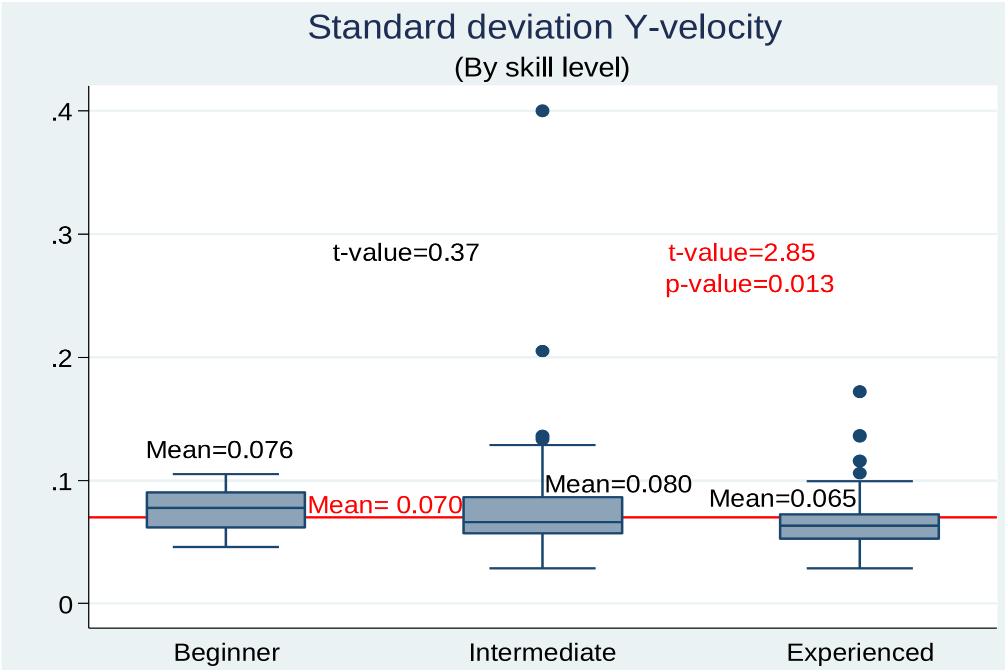

Figure 4-14: Skill level by Standard deviation Y-velocity

The other variable, which measured significant differences in skill level categories, is mean absolute error of steering angle. Figure 4-15 presents distribution and statistical analysis for each group differences. As it is shown, experienced riders moved the bicycle's steer less than beginners and intermediates in the field experiment, and this difference is statistically significant.

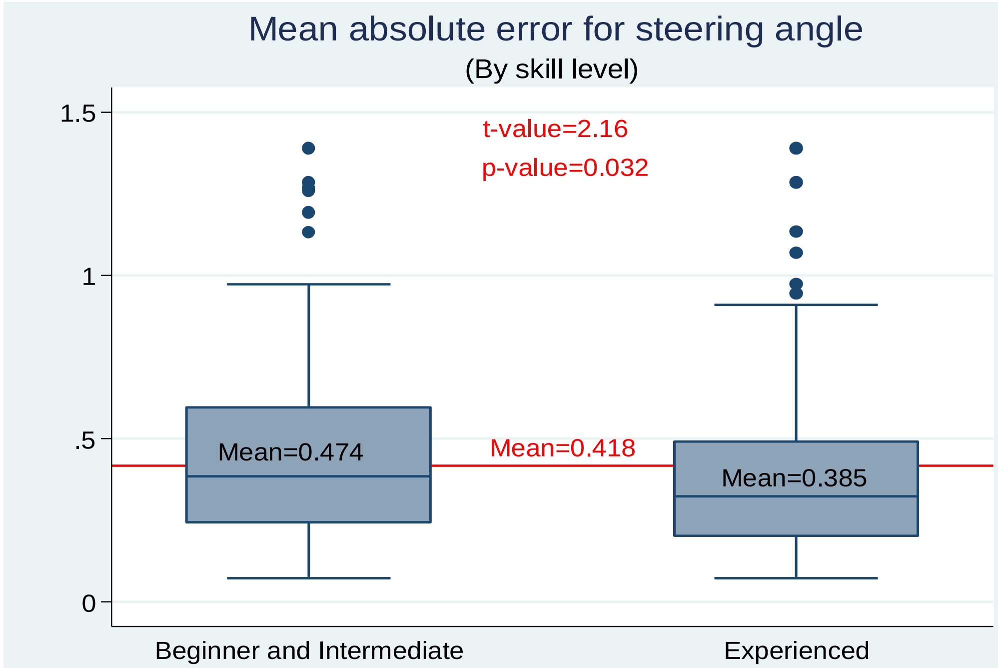

Figure 4-15: Mean absolute error for Y-velocity categorized by skill level

4.5 Environment and infrastructure characteristics

To obtain bicycle safety and comfort associated with bicycle infrastructure and environment, two main variables were measured during and after field experiment. To achieve environment and infrastructure characteristics, road surface condition and traffic flow status during the field experiment in each segment were established.

4.5.1 Roadway surface condition

One of the other crucial variables that should be considered, is roadway condition. To determine this variable, the Pavement Surface and Evaluation Rating System (PASER) is used. PASER method is applied by MDOT to measure road distress. The PASER scale is a 1-10 rating system for road pavement condition developed by the University of Wisconsin-Madison Transportation Information Center. Table 4.2 shows how the rating system works.

Table 4-2: Rating system evaluated by MDOT

Surface rating	Visible distress	General condition
10 Excellent	None.	New construction.
9 Excellent	None.	Recent overlay. Like new.
8 Very Good	No longitudinal cracks except reflection of paving joints. Occasional transverse cracks, widely spaced (40’ or greater). All cracks sealed or tight (open less than 1⁄4”).	Recent sealcoat or new cold mix. Little or no maintenance required.
7 Good	Very slight or no raveling, surface shows some traffic wear. Longitudinal cracks (open 1⁄4”) due to reflection or paving joints. Transverse cracks (open 1⁄4”) spaced 10’ or more apart, little or slight crack raveling. No patching or very few patches in excellent condition.	First signs of aging. Maintain with routine crack filling.
6 Good	Slight raveling (loss of fines) and traffic wear. Longitudinal cracks (open 1⁄4”– 1⁄2”), some spaced less than 10’. First sign of block cracking. Sight to moderate flushing or polishing. Occasional patching in good condition.	Shows signs of aging. Sound structural condition. Could extend life with sealcoat.
5 Fair	Moderate to severe raveling (loss of fine and coarse aggregate). Longitudinal and transverse cracks (open 1⁄ 2”) show first signs of slight raveling and secondary cracks. First signs of longitudinal cracks near pavement edge. Block cracking up to 50% of surface. Extensive to severe flushing or polishing. Some patching or edge wedging in good condition.	Surface aging. Sound structural condition. Needs sealcoat or thin non-structural overlay (less than 2”)
4 Fair	Severe surface raveling. Multiple longitudinal and transverse cracking with slight raveling. Longitudinal cracking in wheel path. Block cracking (over 50% of surface). Patching in fair condition. Slight rutting or distortions (1⁄2” deep or less).	Significant aging and first signs of need for strengthening. Would benefit from a structural overlay (2” or more).
3 Poor	Closely spaced longitudinal and transverse cracks often showing raveling and crack erosion. Severe block cracking. Some alligator cracking (less than 25% of surface). Patches in	Needs patching and repair prior to major overlay. Milling and removal of deterioration extends

	fair to poor condition. Moderate rutting or distortion (1" or 2" deep). Occasional potholes.	the life of overlay.
2 Very Poor	Alligator cracking (over 25% of surface). Severe distortions (over 2" deep). Extensive patching in poor condition. Potholes.	Severe deterioration. Needs reconstruction with extensive base repair. Pulverization of old pavement is effective.
1 Failed	Severe distress with extensive loss of surface integrity.	Failed. Needs total reconstruction.

An important aspect of PASER is the use of visual inspection to evaluate pavement surface conditions instead of measuring each distress. We employed the PASER method to categorize the route into separate segments. Table 4-3 illustrates distress types, overall conditions, and distress rank allocated for each segment.

Table 4-3: Applying PASER method to rank segments

Segments	Segment Length (m)	Road (Sidewalk) Distress Rank	Distress Types	Overall surface condition
Segment A1	190	6 (Sidewalk 9)	Crashes in concrete road gutter. Low edge cracking. Very low transverse	Good
Segment B1	260	8 (Sidewalk 9)	Very low edge cracking.	Good
Segment B2	290	8 (Sidewalk 9)	Very low edge cracking	Very Good
Segment C1	160	3 (No sidewalk)	High block cracking. Moderate patch and potholes. High edge cracking. Transverse and longitudinal cracking.	Poor
Segment D1	270	8 (No sidewalk)	Very Low raveling. Very Low transverse Cracking	Very Good
Segment D2	190	7 (No sidewalk)	Very ow raveling. Very low transverse cracking	Good

The primary method of data classification was based on each segment's attributes (e.g. roadway alignment, surface condition) and presence of intersections or roundabouts. The goal of the segmenting algorithm was to define homogenous segments, which were connected together without conflicts. First, we plotted longitude and latitude points extracted from IMU in a coordinate system (see Figure 4-16).

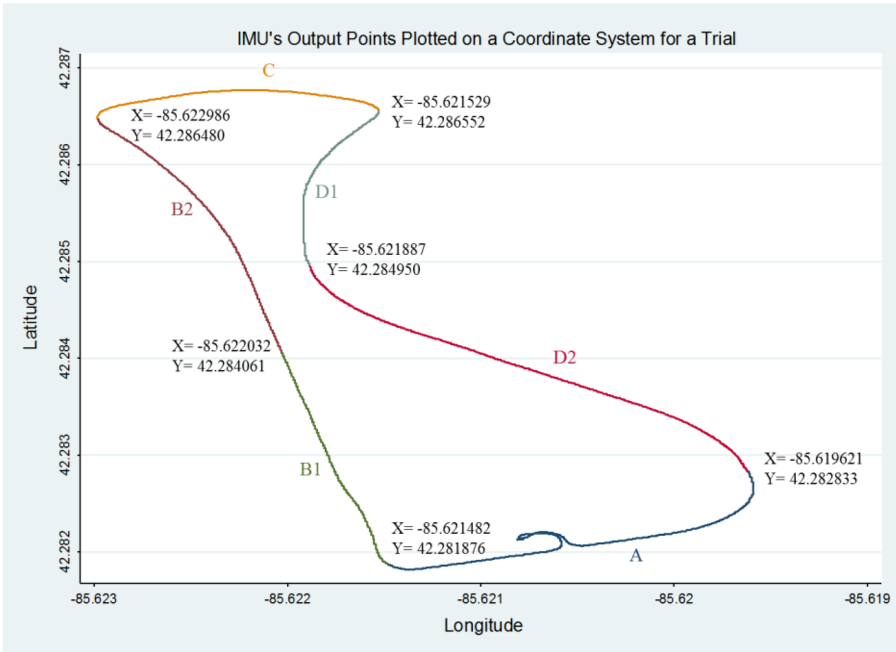

Figure 4-16: Trajectory of a sample trial

Thereafter, existing roadway environment facilities and infrastructures as well as alignment changes were considered. The next step was to allocate each environment characteristic to each segment, which was obtained from the PASER method. For example, intersections at both sides of segment C were allocated to this segment, and the segment's beginning and ending points were established. The final step was to categorize all the points of the trials to specific segments without any conflicts between one other. Figure 4-17 demonstrates the procedure of the segmenting algorithm in this study.

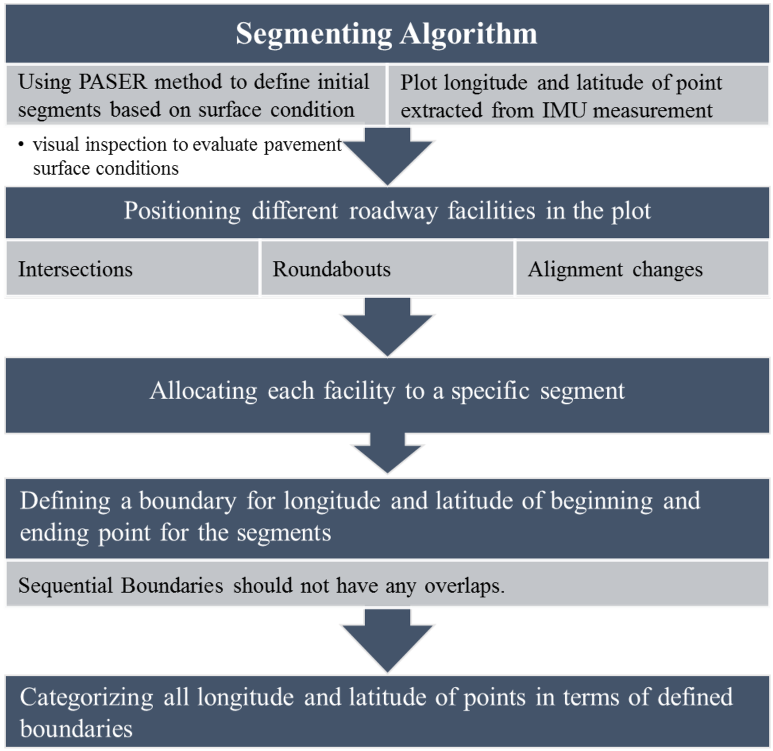

Figure 4-17: Segmentation algorithm procedure

Once the segmentation process was completed and the dataset was stratified into particular groups, we analyzed the impacts of environment characteristics on cycling performances as shown in Figure 4-18. The speed profile provides substantial information about bicyclist performance in diverse riding situations. Steady cycling occurs more at uphill and good surface conditions (D1 and D2) with an approximate average speed. Figure 4.b shows that some cycling environments, such as poor surface conditions (principally segment C), have negative impacts on riding performance and high fluctuation of Z-axis acceleration. The last graph of Figure 4-18 clarifies that the local maximums of bicycle rolling profile appeared at the neighborhood of curbs and intersections, in which bicyclists were required to change their direction immediately.

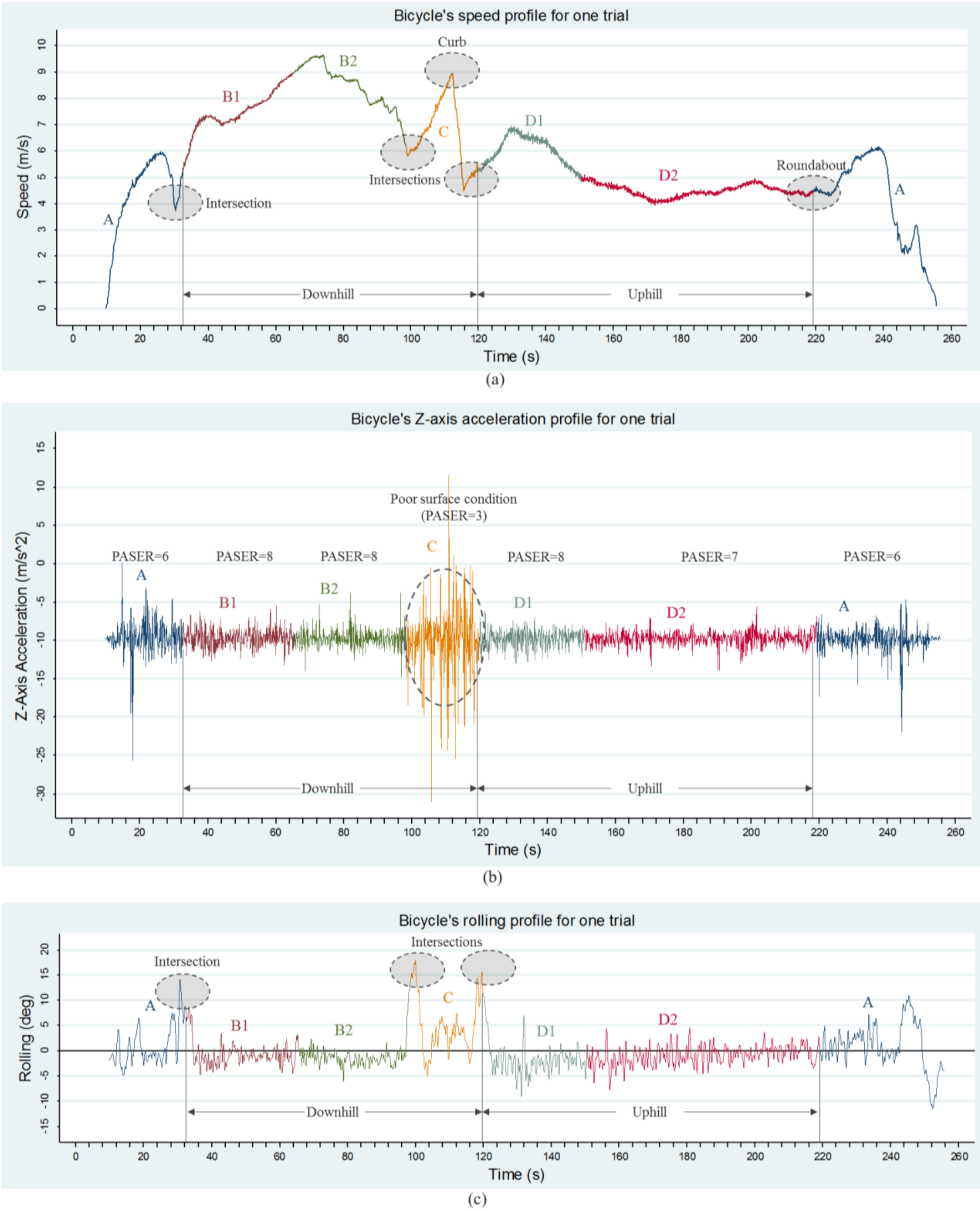

Figure 4-18: Examples of data collected profiles: (a) bicycle speed, (b) z-axis acceleration, and (c) rolling

Figure 4-19 presents X-acceleration for each roadway segment separately. Due to different road surface conditions and score rating, each segment is significantly different from the others. It is shown that participants rode with more acceleration in segments with better surface pavement quality. On the other hand, segment B1 and B2 seem to not comply with this rule and acceleration in these segments became lower. Roadway pavement quality of these segments are excellent, however, segments B1 and B2 are uphill (with almost 4% average slope) and it is difficult for riders to accelerate on the up-hill segments. So, decreasing the acceleration at these segments might be reasonable because of existing slope.

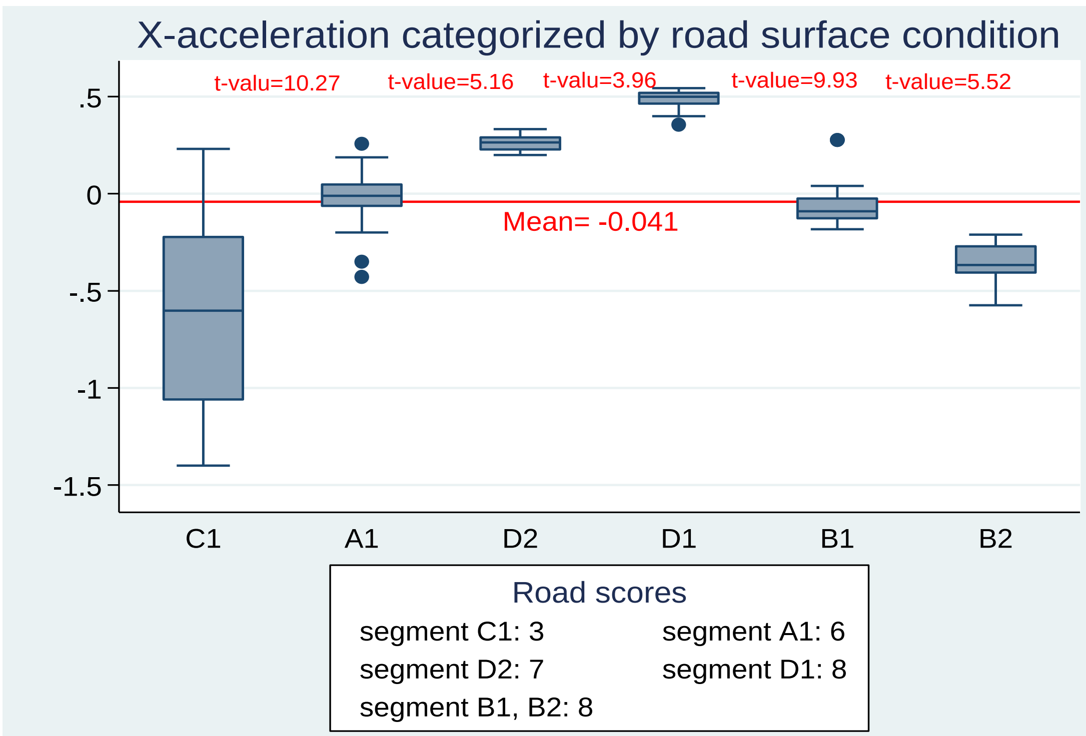

Figure 4-19: X-acceleration for each segment sort by road score

Figure 4-20 shows the relationship between road scores and mean absolute error for Y-acceleration. It is shown that participants at segment C1 (road score=3), had maximum lateral acceleration. Moreover, at the segments A1 (road score=6) and D2 (road score=7) by increasing the road scores, MAE for lateral acceleration is decreased. On the other hand, statistical differences among D2 (road score=7), D1, B1 and B2 (road score=8) segments are not significant. This could be interpreted by the fact that road score differences for these segments are not highly noteworthy. In addition, the pavement quality of these segments is similar.

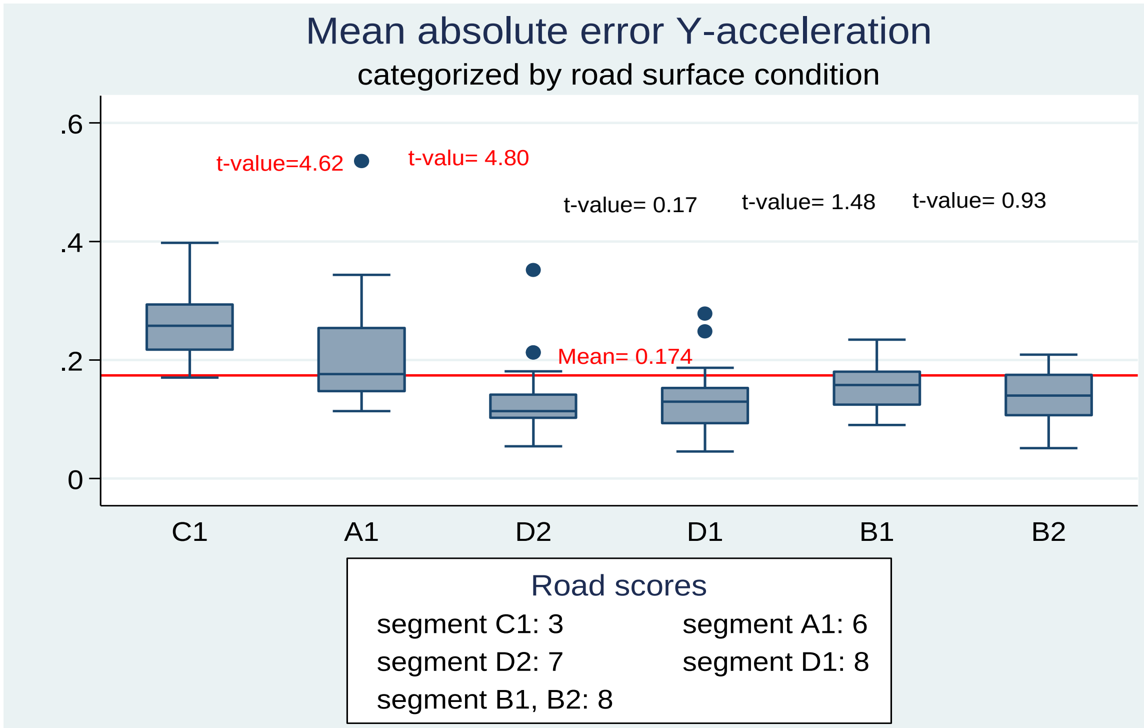

Figure 4-20: Standard deviation Y-velocity categorized by skill level

4.5.2 Traffic condition

To evaluate traffic condition in rider's behavior, number of vehicles that passed through at each segment were counted. As the field experiment was located at WMU on campus, light traffic flowed and this variable is not varied enough through the experiment Table 4-4 and Figure 4-21 present descriptive analysis and the number of vehicles counted respectively. It is shown that more than half of counted vehicle were zero.

Table 4-4: Descriptive analysis for traffic condition

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Number of vehicles	192	0.8333	1.343331	0	7

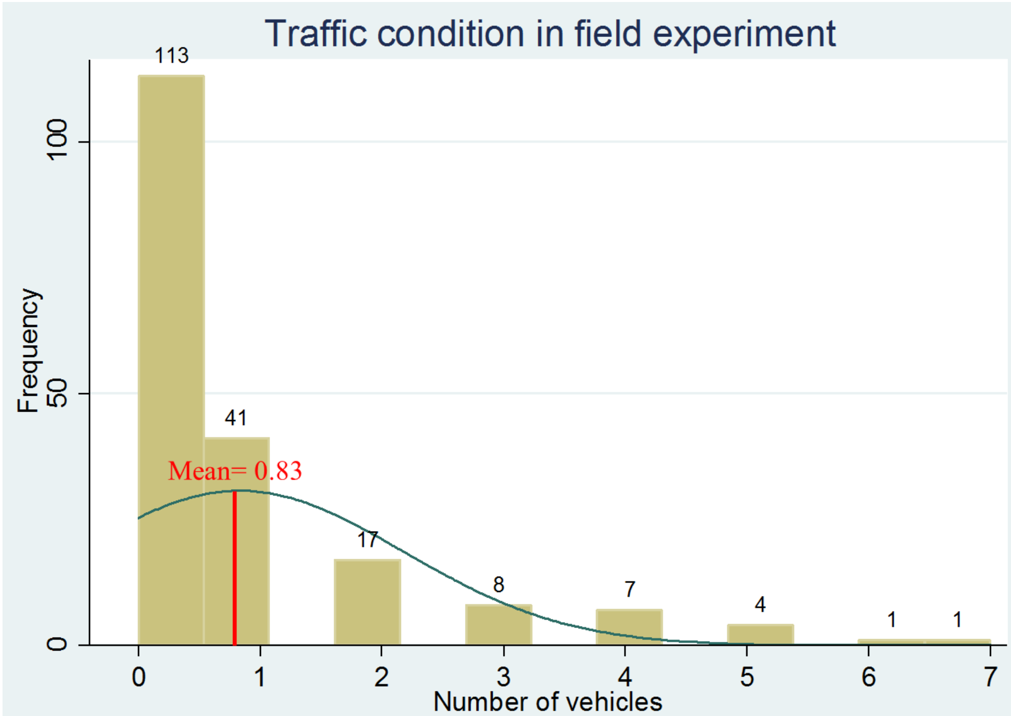

Figure 4-21: Number of counted vehicles at each segment

Chapter 5 Data analysis

5.1 Introduction

This chapter presents functions, which are prediction models used to estimate key parameters under specific conditions. Data collection, as described in Chapter 3 and 4, involved pre-survey questionnaire, field experiment data collected by sensors, post-survey questionnaire and measured infrastructure and environment characteristics. This chapter focuses evaluating the cycling environments by using an equipped bicycle as the primary goals of the study. We examined two facets of performances: mobility and comfortability. Mobility refers to the quality of movement from origin to destination and assumes that any enhancement in travel speed benefits the system. The second performance measure, comfort, is defined as the probability that bicycle travel provides a comfortable situation for the bicyclist. By distinguishing between experienced and inexperienced bicyclists, this study develops a Cycling Comfort Index (CCI) using an Ordered Probit Model.

5.2 Modeling approach

To develop appropriate models, three different models depend on the type of independent variables were used:

- Logistic regression, and
- Ordered Probit regression.

In statistical modeling, regression analysis is a statistical process for estimating the relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps one understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables – that is, the average value of the dependent variable when the independent variables are fixed. In all cases, the estimation target is a function of the independent variables called the regression function. In regression analysis, it is also of interest to characterize the variation of the dependent variable around the regression function which can be described by a probability distribution. A related but distinct approach is necessary condition analysis (NCA), which estimates the maximum (rather than average) value of the dependent variable for a given value of the independent variable (ceiling line rather than central line) in order to identify what value of the independent variable is necessary but not sufficient for a given value of the dependent variable. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables.

5.2.1 Logistic regression model

In statistics, logistic regression, or logit regression, or logit model (Freedman, 2009) is a regression model where the dependent variable is categorical. In this case, binary dependent variables—that is, where it can take only two values— are determined. Logistic regression was developed by statistician David Cox in 1958 (Cox, 1958; and Walker & Duncan, 1967). The binary logistic model is used to estimate the probability of a binary response based on one or more predictor (or independent) variables.

Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution. Logistic regression can be seen as a special case of the generalized linear model and thus analogous to linear regression. The model of logistic regression, however, is based on quite different assumptions (about the relationship between dependent and independent variables) from those of linear regression. Thus, it treats the same set of problems as Logit regression using similar techniques, with the latter using a cumulative normal distribution curve instead. Equivalently, in the latent variable interpretations of these two methods, the first assumes a standard logistic distribution of errors and the second a standard normal distribution of errors (Rodriguez, 2008). In particular, the key differences of these two models can be seen in the following two features of logistic regression. First, the conditional distribution y|x is a Bernoulli distribution rather than a Gaussian distribution, because the dependent variable is binary. Second, the predicted values are probabilities and are therefore restricted to (0,1) through the logistic distribution function because logistic regression predicts the probability of particular outcomes.

The particular model used by logistic regression, which distinguishes it from standard linear regression and from other types of regression analysis used for binary-valued outcomes, is the way the probability of a particular outcome is linked to the linear predictor function:

$$logit\ (E[Y_i|\boldsymbol{X}_i]) = logit(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta.\boldsymbol{X}_i \qquad (5\text{-}1)$$

In logistic regression, the regression coefficients (β) represent the change in the logit for each unit change in the predictor. Given that the logit is not intuitive, researchers are likely to focus on a predictor's effect on the exponential function of the regression coefficient – the odds ratio. In linear regression, the significance of a regression coefficient is assessed by computing a t-test. In logistic regression, there are several different tests designed to assess the significance of an individual predictor, most notably the likelihood ratio test and the Wald statistic. In logistic regression analysis, deviance is used in lieu of sum of squares calculations (Cohen et al., 2013). Deviance is analogous to the sum of squares calculations in linear regression (Hosmer et al., 2004) and is a measure of the lack of fit to the data in a logistic regression model (Cohen et al., 2013). When a "saturated" model is available (a model with a theoretically perfect fit), deviance is calculated by comparing a given model with the saturated model (Hosmer et al., 2004). This computation gives the likelihood-ratio test:

$$D_{null} - D_{fitted} = -2\ ln\frac{likelihood\ of\ the\ null\ model}{likelihood\ of\ the\ fitted\ model} \qquad (5\text{-}2)$$

If the model deviance is significantly smaller than the null deviance, then one can conclude that the predictor or set of predictors significantly improved model fit.

In linear regression the squared multiple correlation, R^2 is used to assess goodness of fit as it represents the proportion of variance in the criterion that is explained by the predictors:

$$R^2 = \frac{D_{null} - D_{fitted}}{D_{null}} \qquad (5\text{-}3)$$

5.2.2 Ordered Probit model

In statistics, a probit model is a type of regression where the dependent variable can only take two values. A probit model is a popular specification for an ordinal (Bliss & Chester, 1934) or a binary response model. As such it treats the same set of problems as does logistic regression using similar techniques. The probit model, which employs a probit link function, is most often estimated using the standard maximum likelihood procedure, such an estimation being called a probit regression. For the logit model, the errors are assumed to follow the standard logistic distribution while for the probit, the errors are assumed to follow a Normal distribution

$$\Pr(Y = 1|X) = \Phi(X^T\beta) \tag{5-4}$$

It is possible to motivate the probit model as a latent variable model. Suppose there exists an auxiliary random variable:

$$Y^* = X^T\beta + \varepsilon \tag{5-5}$$

where y^* is the exact but unobserved dependent variable; **x** is the vector of independent variables, and β is the vector of regression coefficients which we wish to estimate. Further suppose that while we cannot observe y^*, we instead can only observe the categories of response:

$$y = \begin{cases} 0 \quad\quad if \;\; y^* \le 0, \\ 1 \;\; if \;\; 0 \le y^* \le \mu_1, \\ 2 \; if \;\; \mu_1 \le y^* \le \mu_2 \\ . \\ . \\ N \quad if \; \mu_{N-1} < y^*. \end{cases} \tag{5-6}$$

In statistics, ordered probit is a generalization of the popular probit analysis to the case of more than two outcomes of an ordinal dependent variable. Similarly, the popular logit method also has a counterpart ordered logit.

$$y = \begin{cases} 0 \quad\quad if \;\; y^* \le 0, \\ 1 \;\; if \;\; 0 \le y^* \le \mu_1, \\ 2 \; if \;\; \mu_1 \le y^* \le \mu_2 \\ . \\ . \\ N \quad if \; \mu_{N-1} < y^*. \end{cases} \tag{5-7}$$

5.3 Model development

After generating two new variables with PCA method, model development with new data set began. Models were developed for three variables: road choice (roadway or sidewalk), skill level (beginner and intermediate or experienced) and comfort factor.

5.3.1 Road choice

Participants chose a specific path to ride the bicycle during their field experiment, after that they stated their selected path at each segment in post-survey. As there were two paths available (roadway and sidewalk), the *logistic regression* model was selected. Therefore, the dependent variable is choosing the road and it is binary (0=sidewalk, 1=roadway). Additionally, due to lack of sidewalk in C1, D1, and D2 segments, the model focused on three A1, B1, and B2 segments, which contains available roadway and sidewalk for biking. All variables were entered into the model and irrelevant variables were removed one by one. Note that, 95% confidence was assumed and variables with the p-value less than 0.05 were considered. While Table 5-1 shows model characteristics, Table 5-2 represents coefficient, p-value, and other attributes of independent variables in the model.

Table 5-1: Road choice model summary

Number of observation	99
LR chi2(5)	41.97
Prob > chi2	0.0000
Pseudo R2	0.3682
Log likelihood	-36.02

Table 5-2: Variables in road choice logit model

Variable	Coefficient	Std. Err.	Z	P>|Z|	[95% Conf. Interval]	
Number of vehicles	-0.4079843	0.190021	-2.15	0.032	-0.7804178	-0.035551
Standard deviation Y-velocity	49.34238	15.81947	3.12	0.002	80.34797	18.33678
Standard deviation Z-distance	5.860177	2.452463	2.39	0.017	1.053438	10.66692
mile_per_week	0.939106	0.3219807	2.92	0.004	0.308039	1.57018
Biking frequency	2.2895	0.6352336	3.60	0.000	1.044465	3.534535
Constant	-3.619908	1.946478	-1.86	0.063	-7.434936	0.195119

The results can be interpreted from the table are below:

- Number of vehicles that are passing while participants cycling affects their decision to choose a root. Clearly, when the number of vehicles passing increase participants go for sidewalks.
- The standard deviation of Y-velocity has a positive impact on choosing roadway. It means that riders who have more speed for zig-zag maneuvering, tend to ride in the roadway.
- The standard deviation of Z-distance covered by riders has a positive impact selecting the way they want to ride. This variable is correlated with road surface condition, and because road condition in roadways is less than sidewalks, riders experienced more Z-distance in the roadways.
- By increasing bicycling mileage, riders experience will be increased (they are correlated), so they prefer to choose roadways for riding.
- The frequency of riding is similar to riders experiment and has a positive impact on road choice. It means that riders who reported more bicycling in a period of time, tend to choose roadway instead of sidewalk.

5.3.2 Skill level

To estimate skill level of riders based on their personal characteristics (i.e. age, gender, biking frequency, etc.) and biking performance (data obtained from the field experiment), *ordered probit regression* model was examined. The dependent variable -skill level- that participants checked in the pre-survey had three discrete levels (1=beginner, 2=intermediate, and 3=experienced). At the first step, correlated variables were removed, and then all other variables entered into the model. At the last step, insignificant (p-value more than 0.05) and irrelevant variables were removed. Table 5-3 represents model summary, and Table 5-4 shows all variables that remained in the model. Moreover, Table 5-4 indicates positive or negative impacts of each variable on the dependent variable, coefficients, and p-values. Note that, as the age variable is a discrete variable, it is recommended that each should be considered separately to find the significant values.

Table 5-3: Skill level model summary

Number of observation	198
LR chi2(3)	167.13
Prob > chi2	0.000
Pseudo R2	0.5151
Log likelihood	-78.6623

Table 5-4: Variables in skill level ordered probit model

Variables	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
Mean absolute error steering angle	-1.018867	0.4163946	-2.45	0.014	-1.834986	-0.20275
Mile per week	1.373023	0.2082242	6.59	0.000	0.9649113	1.781135
Standard deviation Y-velocity	-6.768832	3.18706	-2.12	0.034	-13.01535	-0.52231
age						
3	0.9456482	0.3684566	2.57	0.010	0.2234865	1.66781
4	1.620991	0.585008	2.77	0.006	2.767586	0.4744
5	0.7296803	0.3879142	1.88	0.060	-0.0306176	1.489978
6	3.244866	597.5198	0.01	0.996	-1167.872	1174.362
/cut1	-0.1407129	0.4195646			-0.9630444	0.681619
/cut2	2.327352	0.4460408			1.453128	3.201576

The results can be interpreted from the table are below:

- The variable of mean absolute error (MAE) of steering angle has a negative impact on skill level. It means that by increasing the skill level, riders move less the steering and have better control on the bike. In the same manner, amateur riders perform more changes in the angle of steering.
- By increasing bicycling mileage, riders experience will be increased. It is an obvious fact; the model also strongly confirms it.
- The standard deviation of Y-velocity has a negative impact on riders' skill level. It means that riders who have more speed for zig-zag maneuvering, have less riding experience.
- Two levels of age variable (3= age between 25 and 34, and 4= age between 35 and 49) are statistically significant in the model and the other levels could be denied.

Therefore, by increasing the participants' age -between 25 and 49- their riding experience will be increased. At the other age groups, these changes are negligible.

5.4 Fault Tree Analysis (FTA)

FTA is a systematic method widely used in evaluating the reliability of engineering systems and for analyzing risk. Key elements of the FTA include events (inputs) and gates (outputs). The analysis explains the relationship of events that induce unfavorable outcomes and employs a tree structure with "and", "or", etc. symbols to understand the functional relationship of a system (Dhillon, 2016). In this study, FTA was employed to develop the performance measures used for recognizing the probability of fault event occurrence.

As mentioned before, our effort is to improve the method of cycling performance measures. To meet the purpose of this study, we considered comfortability and mobility of cycling performance as the inputs for the FTA. The comfort measurement was an aspect that had been newly added. To evaluate the system performance, an appropriate threshold for individual performance measurement was defined and applied. In addition, the calculation of each skill level category (experienced, or inexperienced) was run separately to find out the impact of cycling skill level. Details for each concept are depicted in the following sections.

5.4.1 Mobility Performance Measure

Mobility represents how fast one could travel from an origin to a destination. In this study, bicycle speed is being used to measure the mobility performance of the bicycle environment system. The equipped IPB was able to detect the bicycle speed 10 times per second. Joo *et al.* (2013) suggested an appropriate bicycle speed as the speed in which the bicycle is moving faster than the average speed of pedestrian (3.1 mph = 1.4 m/s). Therefore, this study defines the threshold of bicycle speed to be equal to 1.4 m/s. In other words, a cycling system with less speed than the threshold cannot be presumed to be an efficient cycling mobility performance.

Participants conducted the experiment based on their personal ability to ride the bicycle. For this reason, the study assumed the perceived bicyclist' skill level as a parameter of dividing system performance calculations into experienced and inexperienced users. The probability that a particular segment fails to support a user with a specified skill level is defined as the first

performance measurement failure. The normal distribution was employed to evaluate the probability of system failure (the bicycle speed less than 1.4 m/s) from a mobility performance perspective. The probability density function calculation was used to determine the failure ratio for experienced bicyclists in segment D2 as shown below, and for other segments as presented in

Table 5-5.

Experienced: $\Pr(\text{speed} < 1.4) = \int_0^{1.4} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx = \int_0^{1.4} \frac{1}{1.168\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-4.321}{1.168})^2} dx = 0.0062$ (5-8)

Where:

x = bicycle speed on x-axis;

μ = average speed on segment D2;

σ = standard deviation of speed on segment D2.

Table 5-5: Probability of a Fault Event Occurrence Performance Measures

Segment	Skill level	Average speed (μ)	S.D. of speed (σ)	Pr(speed<1.4)	Pr(COM≤2)	Φ
A	Experienced	4.0527	1.6620	0.0552	0.07733	0.1283
	Inexperienced	3.8444	1.7274	0.0785	0.08514	0.1570
B1	Experienced	6.9368	1.7491	0.0008	0.0507	0.0515
	Inexperienced	6.5973	1.4265	0.0001	0.0575	0.0576
B2	Experienced	8.6567	1.8332	3.8E-06	0.0392	0.0392
	Inexperienced	7.8212	1.8349	0.0002	0.0465	0.0467
C	Experienced	6.7284	2.0275	0.0043	0.0804	0.0844
	Inexperienced	5.9951	2.1207	0.0151	0.0914	0.1051
D1	Experienced	4.1449	1.1256	0.0074	0.1109	0.1175
	Inexperienced	4.6644	1.0409	0.0009	0.0994	0.1002
D2	Experienced	4.3210	1.1680	0.0062	0.0934	0.0990

Inexperienced	4.0530	1.2272	0.0153	0.1048	0.1185

Since the start and end point of the route was in A segment, the mobility failure ratio was highest in this part of the route. Furthermore, on segments with PASER ≤ 6, the mobility failure ratio for inexperienced bicyclists was greater than that for experienced bicyclists. When interpreting this data, it appears that the poor surface conditions impacted the inexperienced riders more than the experienced riders.

5.4.2 Comfort Performance Measure

Comfortability is an attribute of any transportation system component (roadway or vehicle for example) that may vary according to its specification. Comfort had long been considered a parameter not only to define disaggregated behavioral choice modeling (Algers et. al. 1975), but also to describe the service quality of transportation systems (Litman, 2008). This study concentrated on bicyclist comfort perceptions on different roadway segments and deals with a scale of five choices. Regarding comfort performance measurement, an Ordered Probit Model approach was used to address the stratification of perceived comfort level. The model expresses the relationship of discrete dependent variable with independent variables. As mentioned previously, the dependent variable achieved from the post-survey and independent variables consisted of the parameters derived from IPB sensors as well as the PASER rating. This study considered the ordered comfort level in a 5-level scale (1=very uncomfortable, and 5=very comfortable), so the model should have at most 4 cut-off points. Table 5-6 presents the significant variables that remained in the model.

Table 5-6: Ordered Probit Model for bicyclists' perceived comfort level

Variable	Coefficient	Std. Err.	P value	95% Confidence Interval	
str_ang	-0.0059	0.0003	0.000	-0.0064	-0.0053
yaw	-0.0009	2.63E-05	0.000	-0.0010	-0.0009
xvel	0.0741	0.0015	0.000	0.0712	0.0769
paser	0.0062	0.0022	0.005	0.0019	0.0104
mad_zvel	-2.659	0.0810	0.000	-2.8178	-2.5004
mean_yacc	-0.918	0.0419	0.000	-1.0003	-0.8362

cut-off 1	-2.112	0.0196	-2.1500	-2.0732
cut-off2	-1.288	0.0181	-1.3238	-1.2529
cut-off3	-0.533	0.0177	-0.5674	-0.4982
cut-off4	0.222	0.0176	0.1876	0.2566
Pseudo R2	0.0178			

str_ang: Steering Angle, xvel: X-axis velocity, paser: PASER rating for surface condition, mad_zvel: Mean Absolute Deviation of Z-axis velocity, mean_yacc:Mean of Y-axis acceleration

5.4.3 Developing Cycling Comfortability Index (CCI)

The bicycle dynamic movements as well as the road surface condition rating (PASER) estimate the comfortability level of the bicyclists. The probabilistic outcome of the proposed Ordered Probit Model was considered to develop the Cycling Comfortability Index (CCI), which is a range of continuous numbers between 0 and 1. Thus, there are j=1,2,…,5 indices which represents the probability of falling comfort level of individual observations into a specific category ($Pr_{(COM=j)}$). CCI is defined as when a bicyclist perceives the bicycling system (including roadway, environment attributes, bicycle, etc.) as natural (j=3), comfortable (j=4), or very comfortable (j=5) ($Pr_{(COM\geq 3)}$):

$$CCI_t = \sum_{j=1}^{3} Pr(COM_t = j) \tag{5-9}$$

Where

CCI_t = Cycling Comfortability Index for observation time of t;

j = number of ordered comfort categories; and

Pr (COM_t) = the probability of comfort level for observation time of t.

While the CCI represents the probability of system comfortability, this study desires to find out the system failure in terms of bicyclists' perceived comfortability. To establish the failure ratio, $Pr_{(COM\leq 2)}$=1- CCI had to be evaluated first. Then, $Pr_{(COM\leq 2)}$ needed to be calculated for each segment by skill level. The method for calculating the failure ratio for comfortability performance is shown below. The results by segment and skill level are illustrated on column 6 in Table 5-5.

$$\Pr(COM_i \leq 2) = \frac{\int_t (1-CCI_t)\, dt}{T_i} = \frac{\int_t [\Pr(COM_t=1)+\Pr(COM_t=2)]dt}{T_i} \tag{5-10}$$

Where

i = segment name, which includes A, B1, B2, C, D1, and D2; and

T_i = total bicycling time on segment i.

Probability Evaluation of Fault Tree

Once the probabilities of initial events were evaluated, the objective event probability could then be calculated. Since this study examined the OR gate fault event as the final fault event, the occurrence probability was given by (Dhillon, 1999):

$$\Phi = 1 - \prod_{m=1}^{m}[1 - \Pr(A_m)] \tag{5-11}$$

Where

Φ= occurrence probability of the OR gate output fault event;

m= number of OR gate input fault event; and

Pr (A_m) = occurrence probability of fault event A_m.

Eventually, the occurrence probability of the output fault event of this study was derived from Equation (5-11), which is Φ=1-[(1-Pr (Speed<1.4)) (1-Pr (COM≤ 2))]. Column 7 in Table 5-5 indicates Φ for the segments divided by skill level. It can be comprehended that in all segments – except D1- the fault event ratio was greater for inexperienced bicyclists than experienced ones. The highest fault event ratio occurred at segments A and C, where their PASER ratings were equal or less than 6. It should be noticed that the high value of the fault event ratio in the aforementioned segments might be related to the impact of existing intersections. Moreover, the effect of roadway alignment could be explained by the results in Table 5-5. Fault event ratios were higher on uphill segments (D1 and D2) than downhill segments (B1, B2, and C). Generally, bicyclists feel less comfortable on the uphill segments due to the speed reduction and increased energy consumption. This effect could be intensified dramatically when the uphill distance increases.

5.5 Conclusion

The objective of this study was to find the relationship between cycling performance and roadway environment attributes. To evaluate the effect of cycling skills and the characteristics of roadway infrastructure, a naturalistic field experiment was conducted with 50 participants using an Instrumented Probe Bicycle (IPB). The roadway included three intersections, one roundabout, and alignment changes. In addition to measuring the cycling performance by IPB, the authors were also interested in making a comparison between skill and comfort level. Two self-reported questionnaires were developed to determine the experience level and the comfortability level of participants. After the data collection phase, a segmentation process was developed based on the environment characteristics and road surface conditions. A two-gate FTA was also applied to determine the impact of environmental attributes on the bicyclist's performance. Two crucial performance measures were chosen: mobility and comfort. To evaluate the probability of fault event occurrence in the mobility performance, the bicycle speed distribution was assumed to be normally distributed. The fault event threshold was defined as the average pedestrian walking speed (1.4 m/s). The analysis of the fault event in the second OR gate, comfort performance, was quite complex. An Ordered Probit Model was developed to describe the relationship between the bicycle's dynamic movements and bicyclists' perceived comfort level. The probabilistic outcomes of the proposed model were used as the Cycling Comfortability Index (CCI). The fault event occurrence for comfortability performance was established by $Pr_{(COM\leq 2)}$ = 1- CCI. In the end, the overall probability of fault event occurrence was calculated separately by segments and the two skill levels.

We found that the probability of a fault event occurrence, derived from the level of comfort and mobility, was strongly related to the bicyclist's level of experience. The fact that inexperienced bicyclists had higher failure ratio implies that their levels of mobility and comfortability are lower. The difference was more prominent in segments A and C where the surface quality was not good. Moreover, the quality of road surface had a significant impact on the speed as well as the comfortability index. This means that the probabilities of a fault event occurrence in segments B1 and B2, downhill with good and very good surface conditions, were the lowest among all other segments. Regardless of the bicyclist's skill level, cycling at intersections and uphill roadways could possibly increase the risk. The Ordered Probit Model showed that cycling comfortability was significantly affected by the average Y-axis acceleration and the mean absolute deviation of Z-axis velocity. Steering movements and Z-axis angular movements (yawing) also affected cycling comfortability.

The IPB developed in this study turned out to be very useful in collecting cycling maneuver data and in analyzing bicycle safety associated with bicycle infrastructure. Although the data we collected was sufficient for our purposes, it would be a good idea to add more sensors for measuring braking performance, bicyclist's head movements and other conditions, such as weather, road lighting, emissions, and various roadway features for further IPB studies. This research employed scientific research instruments and analysis techniques to shed light on the importance of bicycle safety and comfortability.

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Appendix

Appendix 1: Poster sample

Appendix 2: Consent Form

Western Michigan University
Department of Civil and Construction Engineering

Principal Investigator: Jun-Seok Oh, Ph.D., P.E.
Co-Principal Investigator: Valerian Kwigizile, Ph.D., P.E.
Student Investigator: Fadi Abdallah Alhomaidat

Title of Study: Effect of Cycling Skills On Bicycle Safety and Comfort Associated with Bicycle Infrastructure and Environment.

You have been invited to participate in an experiment for a research project, *"Effect of Cycling Skills On Bicycle Safety and Comfort Associated with Bicycle Infrastructure and Environment*" funded by the U.S. Department of Transportation through the Transportation Research Center for Livable Communities (TRCLC) at Western Michigan University. This consent document will explain the purpose of this research project and will go over all of the time commitments, the procedures used in the study, and the risks and benefits of participating in this research project. Please read this consent form carefully and completely and please ask any questions if you need more clarification.

What are we trying to find out in this study?

The purpose of this experiment is to collect bicycle movement data using an instrumented bicycle equipped with various sensors. This experiment is expected to take approximately 15 minutes including an introduction, a pre-survey on your bicycle experience, bicycle riding in a given site, and a post-survey on your comfortableness measures. While you are riding, motion sensors and a video camera mounted on the bicycle will collect positions of the bicycle and body, speed, acceleration, angles, and surrounding traffic conditions. However, no identifiable personal information will be collected in this experiment. The data collected will be used for understanding bicycle dynamics associated with the bicycle skill levels as well as bicycle infrastructure conditions.

Who can participate in this study?

Anyone who can ride a bicycle for a mile can participate in this study.

Where will this study take place?

This study will take place at Western Michigan University's main campus near Howard Street and W. Michigan Avenue. The 0.9-mile route starts from W. Michigan Ave and ends at the same location through Howard St, Valley Rd, and Rankin Ave. Subjects may ride either on sidewalk or travel lane by their choice.

What is the time commitment for participating in this study?

The whole process is expected to take approximately 15 minutes, including an introduction, a pre-survey, a field experiment, and a post survey.

What will you be asked to do if you choose to participate in this study?

In this study, you will be asked to participate in a pre-survey, a ride along a 0.9-mile route, and a post-survey. In the pre-survey, you will be asked to tell us about your bicycle skill and your comfortableness on bicycle infrastructure. In the ride experiment, all you need to do is riding the instrumented bicycle along the 0.9-mile route. Sensors will collect bicycle and body dynamics while you are riding. In the post-survey, you will be asked to your perception on safety and comfortableness on each segment of the route.

What information is being measured during the study?

In the bicycle experiment, we will measure bicycle's GPS position, x, y, z accelerations, steering angle, body angel against bicycle, surrounding traffic conditions from snapshot images taken by the front-view video camera.

What are the risks of participating in this study and how will these risks be minimized?

There are no risks other than the normal risk that bicyclists may face. The possible risks that may lead to injury include falling from the bicycle and colliding with other vehicles. In order to avoid possible risks, we suggest you use most comfortable infrastructure, such as sidewalk, bicycle lane, or travel lane. The research team will prepare a first aid kit in order to provide basic first aid in case of injury. There is no cost to you in this experiment other than their time commitment. The research team will provide beverage for your rest after riding the bicycle.

What are the benefits of participating in this study?

There is no benefit to you in participating in this study. However, this study is expected to improve bicycle environment in general.

Are there any costs associated with participating in this study?

There are no costs associated with participating.

Is there any compensation for participating in this study?

There is no compensation to you in participating in this study. However, this research team will provide beverage for your rest after bicycling.

Who will have access to the information collected during this study?

The data collected will be analyzed only by the research team members. No others will have access to the data collected. The results of the study are expected to be disseminated on an aggregate basis through a report to US Department of Transportation as well as possible journal/conference publications.

What if you want to stop participating in this study?

You can choose to stop participating in the study at anytime for any reason. You will not suffer any prejudice or penalty by your decision to stop your participation. You will experience NO consequences either academically or personally if you choose to withdraw from this study. The investigator can also decide to stop your participation in the study without your consent.

Should you have any questions prior to or during the study, you can contact the primary investigator, Dr. Jun-Seok Oh at (269) 276-3216 or jun.oh@wmich.edu. You may also contact the Chair, Human Subjects Institutional Review Board at 269-387-8293 or the Vice President for Research at 269-387-8298 if questions arise during the course of the study.

This consent document has been approved for use for one year by the Human Subjects Institutional Review Board (HSIRB) as indicated by the stamped date and signature of the board chair in the upper right corner. Do not participate in this study if the stamped date is older than one year.

I have read this informed consent document. The risks and benefits have been explained to me. I agree to take part in this study.

Please Print Your Name

Participant's signature　　　　　　　　　　Date

Appendix 3: Pre-survey form

Gender Male_____ Female______

AGE >16 _____ 16-24 _____ 25-34_____ 35-49 _____ 50-64 _____ 65+ _____

What is your home ZIP CODE? ____

What is your height? _____ feet _____inches

What is your weight? _____ pounds

How frequently do you bike?

a. Every day
b. Several times a week
c. Several times a month
d. Very rarely

What is the primary purpose of bike trips?

a. Exercise and health
b. Recreation
c. Commuting(Work/School)
d. Errands/Shopping

How many miles do you ride a week?

a. Less than 5 miles
b. 5 - 15miles
c. 15-30 miles
d. More than 30

How would you classify yourself as a biker?

a. Beginner
b. Intermediate
c. Experienced

Rank your cycling confidence level on scale of 1 to 5? when you ride in the following facilities

		1 (least confident)	2	3	4	5 (most confident)
Roadway with dedicated bike lane		❑	❑	❑	❑	❑
Roadway with shared lane pavement marking (sharrow)		❑	❑	❑	❑	❑
Roadway with shoulder		❑	❑	❑	❑	❑
Roadway without bike lane, sharrow and shoulder		❑	❑	❑	❑	❑
Sidewalk with pedestrian		❑	❑	❑	❑	❑
Sidewalk without pedestrian		❑	❑	❑	❑	❑

Appendix 4: Post-survey form

Please circle 1) how comfortable you were when riding at each segment and intersection, and 2) where you rode the bicycle, on road or sidewalk?

1 Very uncomfortable	2 Uncomfortable	3 Neutral	4 Comfortable	5 Very Comfortable