Final Report

Bicyclist Longitudinal Motion Modeling

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16. Abstract
Bike is a promising, human-powered, and emission-free transportation mode that is being increasingly advocated as a sustainable mode of transportation due to its significant positive impacts on congestion and the environment. Cities in the United States have experienced a rapid increase in bicycle ridership over the past decade. However, despite the growing popularity of bicycles for short-distance commuting and even for mid-distance recreational trips, researchers have generally ignored the investigation of bicycle traffic flow dynamics. Due to the shared space and frequent interactions among heterogeneous road users, bicycle flow dynamics should be evaluated to determine the tendency of lateral dispersion and its effects on traffic efficiency and safety. Therefore, this research effort proposes to model bicyclist longitudinal motion while accounting for bicycle interactions using vehicular traffic flow techniques. From the comparison of different states of motion for these two transport modes, we assumed there is no major difference between vehicular and bicyclist traffic characteristics. The study revamps the Fadhloun-Rakha car-following model previously developed by the research team to make it representative of bicycle traffic flow dynamics. The possibility of capturing cyclists' behaviors through revamping certain aspects of existing car-following models is investigated. Accordingly, 33 participants were recruited to ride the bike simulator and drive the car simulator simultaneously. The participants were recruited to operate a bike-simulator in order to test the proposed model under realistic traffic conditions and verify the output of the proposed model formulation remains valid when bicyclists are operating under realistic traffic conditions. Both simulators were integrated together, and each participant could inform about the location of another participant in the simulation interval. Six scenarios based on the initial position of the bike and car were developed. Based on the collected data, the Fadhloun-Rakha model was validated to ensure the development of a good descriptor for speed and acceleration and deceleration behaviors. A reliable sample including 100 model parameters values was selected. Root Mean Square Error (RMSE) for the mentioned sample was obtained, and the smallest RMSE in each scenario was identified. Using the obtained RMSEs, the speed and acceleration trajectories for the smallest RMSE in each scenario were drawn. Eventually, the optimal values of the model parameters (a,b,d) in each scenario were specified.

17. Key Words: Longitudinal motion, Bicyclists, Bicycle traffic flow dynamics, Bike Simulator (BS.), Traffic efficiency and safety

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ABSTRACT

Bike is a promising, human-powered and emission-free transportation mode that is being increasingly advocated as a sustainable mode of transportation due to its significant positive impacts on congestion and the environment. Cities in the United States have experienced a rapid increase in bicycle ridership over the past decade. However, despite the growing popularity of bicycles for short-distance commuting and even for mid-distance recreational trips, researchers have generally ignored the investigation of bicycle traffic flow dynamics. Due to the shared space and frequent interactions among heterogeneous road users, bicycle flow dynamics should be evaluated to determine the tendency of lateral dispersion and its effects on traffic efficiency and safety. Therefore, this research effort proposes to model bicyclist longitudinal motion while accounting for bicycle interactions using vehicular traffic flow techniques. From the comparison of different states of motion for these two transport modes, we assumed there is no major difference between vehicular and bicyclist traffic characteristics. The study revamps the Fadhloun-Rakha car-following model (1) previously developed by the research team to make it representative of bicycle traffic flow dynamics. The possibility of capturing cyclists' behaviors by revamping certain aspects of existing car-following models is investigated. Accordingly, 33 participants were recruited to ride the bike simulator and drive the car simulator simultaneously. The participants were recruited to operate a bike-simulator in order to test the proposed model under realistic traffic conditions and verify that the output of the proposed model formulation remains valid when bicyclists are operating under realistic traffic conditions. Both simulators were integrated together, and each participant was aware of the location of another participant in the simulation interval. Six scenarios based on the initial position of the bike and car were developed. Based on the collected data, the Fadhloun-Rakha model was validated to develop a good descriptor for speed, acceleration and deceleration behaviors. It means that, driver's variability, perception and control inaccuracies and errors are captured. Furthermore, speed and acceleration profiles that are consistent with empirical data are drawn to validate FR model under driving simulation environment. A reliable sample including 100 model parameters values was selected. Root Mean Square Error (RMSE) for the mentioned sample was obtained, and the smallest RMSE in each scenario was identified. Using the obtained RMSEs, the speed and acceleration trajectories for the smallest RMSE in each scenario were drawn. Eventually, the optimal values of the model parameters (a,b,d) in each scenario were specified.

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1. INTRODUCTION

The last decade has seen cycling emerge as a sustainable mode of transportation with growing popularity among both users and governments. As cities have invested in non-motorized transportation infrastructure, bicycling has become a meaningful alternative mode of transportation for those commuting to activities such as school, work, shopping, and recreation (Pucher and Buehler, 2016). Bikes improve other modes of transportation by reducing traffic congestion, emissions, pollution, and delays in central downtown areas. They also connect more people to public transportation and provide a low-cost mode of transportation that requires minimal federal investment. For these reasons, the popularity of bike commuting, bike-sharing systems, and electric bikes in general has increased the desirability of safe and efficient bicycle infrastructure like protected bike lanes. According to one questionnaire exploring bicycle usage patterns in the United States, 47% of Americans say they would be more likely to ride a bike if pathways were physically separated from motor vehicles, 52.4% of Americans worry about being hit by a motor vehicle when riding a bicycle, and only 0.6% percent of American employees include biking in their commute to work (People for bikes participation study, 2016).

Despite the urgent need to develop models and planning techniques for bicycle traffic operation, traffic researchers have neglected the traffic flow dynamics of bicycles relative to vehicular traffic flow. The observed gap between vehicular and bicycle traffic flow dynamic models can be justified by the scarcity of naturalistic and experimental cycling data. Using two naturalistic cycling datasets in this study is one of the important, heuristically-added values of this research.

Our research aims to provide a comprehensive investigation of the traffic flow dynamics of bicycles. The research will develop a model that captures the characteristics of the longitudinal motion of bicyclists while accounting for their interactions and the variability of their behavior. It is worth mentioning that this study hypothesizes that there are significant similarities between car-following behavior and bicycle-following behavior and therefore applies vehicular traffic flow modeling techniques that more effectively simulate bicyclists' behavior. This approach is based on the assumption that there are significant similarities between the traffic flow dynamics of bicycles and cars. The assumption is partly justified by the fact that existing cycling data comes from single-file ring-road experiments in which overtaking was not allowed. The research group's previous study (Fadhloun and Rakha, 2020) presented the performance of a new car-following model using a naturalistic driving dataset. The proposed model is able to explicitly model the driver throttle and brake pedal input while allowing for shorter than steady-state following distances when following faster leading vehicles. Upon completion, the performance of this model will be assessed by comparing its predictive power with that of models specifically designed for bicyclist behavior simulation. To achieve this goal, the research team will recruit participants to operate a Bike Simulator (BS) under realistic traffic conditions. The interactions between bicyclists and cars are investigated through the BS. The collected simulator data is used to further investigation and confirm the validity of the proposed model.

1.1. Problem Statement

There is growing interest in bicycle riding for short-distance commuting, recreation, and fitness purposes. Bicycles are also increasingly recognized as an environmentally conscious form of urban transportation (Liu et al, 2013). Despite the growing popularity of bicycles as a sustainable transport mode, researchers have generally ignored investigations of its traffic flow dynamics. Evaluation of its traffic flow dynamics can be performed by examining bicycle interactions using vehicular traffic flow techniques. Accordingly, the Fadhloun-Rakha (FR) acceleration-based car-following model previously developed by the research team will be used to determine bicycle traffic flow dynamics. The FR car-following model uses very similar collision-avoidance strategies to ensure safe following distances between vehicles. It can capture vehicle dynamics, the human-in-the-loop, and the randomness associated with human driving behavior in the form of a seamless structure. Assuming no major differences between vehicular and bicyclist traffic characteristics, the FR car-following model (as a vehicular traffic flow modeling technique) is considered the basic model. Our research will then attempt to revamp the bicyclist longitudinal motion in the form of the FR car-following model and simulate bicyclist behavior. Bicyclist longitudinal motion is achieved through the re-parameterization of vehicle-related input variables along with the potential integration of necessary new parameters such as the characteristics and fundamentals of the bicycle/bicyclist system. As the last step, adequacy of the proposed formulation as a descriptor of bicycle longitudinal motion is assessed by estimating its quality of fit using an experimental collected dataset.

1.2. Goal

This research models bicyclist longitudinal motion while accounting for interactions with other vehicles using vehicular traffic flow techniques. There is a need for methods that provide a better understanding of bicyclists' behavior and preferences on currently unavailable and unknown bicycle facilities. Different survey methods have been used to study bicyclists' behavior, experiences, and preferences, all ranging from verbally described facilities to surveys including images and videos (Nazemi et al, 2021). Bicyclist longitudinal motion has not been modeled in previous studies. The main achievement of this research is the modeling of bicyclist longitudinal motion while accounting for bicycle interactions using vehicular traffic flow techniques. The second achievement is revamping an appropriate car-following model previously developed by the research team to make it representative of bicycle traffic flow dynamics. The third achievement is using an accurate, naturalistic dataset to develop a good descriptor for bicycle speed, acceleration, and deceleration behavior. Finally, the last achievement is using the BS to provide a realistic environment for bicyclists (Jiang et al, 2017). The BS determines the bicyclist's behavior under different scenarios, and the interaction of the car-following model with bicyclists and the proximity of the behavior of car drivers and bicyclists appear through the BS.

2. LITERATURE REVIEW

Our research is multi-faceted, covering "bicyclist's behavior and bike flow dynamics," "bicycle interactions using vehicular traffic flow techniques," "BS applications studies," and "usage of car-following models for bicyclists." These topics are addressed in this section.

2.1. Bicyclist's behavior and bike flow dynamics

(Gavrilidou et al, 2019) defined the cyclist's operational level in terms of decision-making factors, arguing that it consists of two intertwined processes, a mental one and a physical one. They also argued that it consists of two intertwined processes, a mental and a physical process. The mental process refers to path choices made within a route and the physical process refers to the bicycle control dynamics through pedaling and steering. A novel two-layer framework was proposed where each layer captured the tasks of one of the processes within the operational level. A discrete choice theory was proposed to model each layer, and mathematical models were estimated for the two layers using cyclist trajectory data collected at a signalized intersection in Amsterdam, the Netherlands.

Unsafe bicyclist-overtaking behavior based on social or psychological factors was studied by (Goddard, 2020). Their research explored the impact of implicit and explicit attitudes on drivers' behavior in interactions with bicyclists. In a driving simulator, various objective measures of safety (e.g., speed, passing distance, crash occurrence) were collected in an overtaking scenario. Participants' self-reported attitudes about driving and bicyclists were collected via a survey instrument and an online test of subconscious attitudes called an "Implicit Association Test." The results provided potential avenues for infrastructure and education interventions to improve pedestrian and bicyclist safety. One of the best models to determine bicyclist's behavior is cellular automata. A cellular automaton consists of a regular grid of cells, each in one of a finite number of states.

An improved multi-value cellular automata that modeled heterogeneous bicycle traffic flow by taking the higher maximum speed of electric bicycles was developed by (Jin et al, 2015). The study proposed an improved multi-value cellular automata (MCA) model that introduces the maximum speeds of two and three cells(s) for Regular Bicycles (RBS) or Electric Bicycles (EBS). The numerical simulation results and fundamental diagrams for bicycle traffic were analyzed and discussed. Three parameters consisting of the slowdown probability, the percentage of EBS, and the number of bicycle lanes were analyzed in both the deterministic and stochastic cases. The results determined that the proposed model matches the field bicycle data better than previous models. Understanding bicyclist's behaviors on real-world roads has been a pertinent topic in transportation research for some time, but the modeling and simulation of heterogeneous bicycle traffic flow is becoming increasingly important for bicycle path planning, management, and operation.

Investigating bicycle flow dynamics on wide roads by using a wide track model was proposed by (Guo et al, 2019). By studying the weight density of the radial locations of cyclists, their research argued that bicycle flow rates remain nearly constant across a wide range of densities. This behavior arises from the formation of additional lanes with the increase of global density. The extra lanes prevent the longitudinal density from increasing as quickly as in a single-file bicycle flow. When the density is larger than 0.5 bicycles/m2, the flow rate begins to decrease, and stop-and-go traffic emerges (Guo et al, 2019).

Studies on bicyclist's behaviors at signalized intersections based on real-world data were conducted by (Twaddle, 2017). Behavioral models were calibrated and validated in a microscopic traffic simulation. Video data were collected at four intersections that differed from one another in their geometry and traffic volume. Automated video analysis was used to extract trajectories, which quantify the spatial progression of road users in a subset of the video data. Distortion in the trajectory data resulting from a wide-angle lens was corrected, and the maneuver (right turn, left turn or traveling straight across the intersection) of each bicyclist was identified. The resulting behavioral models were integrated with the microscopic traffic simulation software SUMO to evaluate the overall ability of the models to realistically simulate bicycle traffic. Results indicated that the proposed integrated modeling approach is capable of realistically simulating the flexible behavior of bicyclists at signalized intersections.

As the number of bicyclists in urban areas continues to increase, the need to realistically model the movement and interactions of bicyclists in mixed urban traffic is rapidly gaining importance. In response to this need, (Twaddle et al, 2014) modeled and evaluated bicyclist behavior on "uninfluenced operational and tactical behavior" and "influenced operational and tactical behavior" levels. The ability to model bicyclist behavior on each of these levels was evaluated based on the results of an extensive literature review. The results of the assessment indicated that it is possible to model the majority of bicyclist's behaviors on an "uninfluenced operational and tactical behavior" level. It is worth mentioning that the uninfluenced and influenced tactical behaviors of bicyclists are important for accurate modeling as bicycle behavior is less constrained by road markings and traffic regulations.

Some studies have evaluated complex patterns of bicycling behavior, such as those conducted by (Thigpen et al, 2019) and (Thigpen, 2019). They considered the readiness for bicycling. The added-value of a categorization of bicyclists based on the stages of change feature of the Trans theoretical Model (TTM) was presented and examined how this new categorization can contribute unique insights for practice through novel behavioral information. Spatial statistical techniques were conducted using survey data from a sample of 2398 individuals from three medium-sized Canadian cities were presented. The results suggested that categorizing people as a function of readiness for change allows for populations to be characterized by their likelihood of being beneficially impacted by policies that support bicycling.

Another study was conducted by (Chuang, 2013) that scrutinized how motorized vehicle-related factors, road-related factors, and bicyclist-related factors influenced motorists' decisions about initial passing distances and bicyclists' behaviors after the motorists started to pass. A quasi-naturalistic riding method was used for thirty-four participating bicyclists riding an instrumented bicycle in real traffic.

Another study included 1,380 incidents of left-side passing by motorists. It revealed the main factors influencing motorists' initial passing distance and bicyclists' positions (lateral distance from the passing motorists), wheel angle, and speed control behaviors while the motorists passed. They also found that bicyclists avoided road surface hazards and reduced initial passing distances that the motorists had chosen (Piatkowski et al, 2017). Furthermore, the presence of behavioral norms while riding a bicycle in mixed-traffic conditions was examined. They studied car and bicycle on-street interactions by asking bicyclists to consider how they would respond when driving a car while encountering a bicyclist behaving in ways that might be perceived as reckless, rude, and/or illegal.

The behavior of bicyclists when they were biking and using instrumental devices such as mobiles, MP3 players etc. was studied by (Nygårdhs et al, 2018). The aims of this study were to explore how cyclists adapt when texting and listening to music in a complex urban environment and whether they compensate sufficiently to maintain safe traffic behavior. Forty-one cyclists participated in a semi-controlled study, using their own bikes and smartphones in real traffic. They were equipped with eye-tracking glasses and traveled two laps, completing a total of 6 km divided into six segments. The results showed that listening to music while cycling did not affect workload, speed, SMS interaction or attention.

This section examined studies evaluating bicyclist path choice behaviors (path planning, management, and operation), bicycle control dynamics, bicyclist overtaking behaviors in different real-world segments such intersections, and the adaptation of cyclist's behaviors when they are not limited to a certain set of behaviors. To the best of the authors' knowledge, simulations bicyclist longitudinal motions along specific segments were not performed in prior studies. This research proposes the bicyclist longitudinal motion while accounting for bicycle interactions using vehicular traffic flow techniques and considers the behavioral and physical aspects of bike motion on different roads.

2.2. Bicycle interactions using vehicular traffic flow techniques

There is a need to better understand bicyclists' interactions with vehicles and to build models and to evaluate multimodal transportation infrastructure with respect to cycling safety, accessibility, and other aspects. This section reviews the previous studies in terms of bicyclists and other road user's interaction under different traffic conditions based on traffic flow techniques.

A framework for modeling the bicyclist's comfort zone and interactions was provided by (Lee et al, 2020). Unlike the driver's comfort zone, little was previously known about that of the cyclist. They modeled the braking and steering maneuvers of cyclists by using obstacle avoidance data. Their results determined that when cyclists avoid obstacles by braking, they kept a constant rate of deceleration; as their speed increased, they started to break earlier, farther from the obstacle, while maintaining a nearly constant time to collision zone. When cyclists avoid obstacles by steering, they maintain a constant distance from the object, independent of speed. Overall, the higher the speed, the more the steering maneuvers were temporally delayed compared to braking maneuvers.

Another way to address cyclist's interactions with their surrounding environment is to construct bike-friendly environments. Bike-friendly environments can be evaluated in such a way whether associations between environmental characteristics and cycling are context-specific. Furthermore, bike-friendly environments may improve natural environment characteristics' contribution to cycling duration. The viability of constructing bike-friendly environments to increase the use of bicycles as a significant transportation mode was investigated by (Joo and Oh, 2013). Evaluating the performance of bicycling environments remains a significant technical challenge for researchers, and this study proposed a novel method of doing so that evaluates bicycle performance in terms of safety and mobility. An Instrumented Probe Bicycle (IPB) equipped with a Global Positioning Systems (GPS) receiver, accelerometer, and gyro sensor was used to develop the proposed method. The IPB provides useful bicycle maneuvering data for identifying longitudinal, lateral, and vertical maneuverings of the bicycle, which are affected by environmental factors such as heavy vehicle volume, surface conditions, grade, crossings, humps, and curbs.

Another way to monitor the interaction of bicyclists and motorized vehicles was explored by utilizing video data (Twaddle et al, 2014) collected at three busy urban intersections in Munich, Germany. In order to analyze the interaction of bicyclists and motorized vehicles through traffic flow techniques, large volumes of motor vehicles, bicycles, and pedestrians at intersections were tracked. The trajectories of cars, bicycles, or pedestrians were monitored. Then, their interaction was classified based on their dynamic characteristics. A classified structure for the maneuvers of different road users (as important interactions between cyclists and other vehicles) was also presented.

(Luo et al, 2013)proposed a cellular automata model to simulate heterogeneous traffic on urban roads. In the proposed model, the researchers adopted a novel occupancy rule to capture the complex interactions between cars and bicycles and consider the variable lateral distances of mixed vehicular traffic. Researchers devised fundamental diagrams under different bicycle densities before discussing the bicycles' spilling behavior. They then modeled the interference transformation from friction state to block state to reflect the interference of a bicycle on a car. Their results indicated that the constant and fixed occupancy rule adopted in the study might lead to overestimation of car flux in heterogeneous traffic flows with different bicycle densities.

The relevant factors impacting lateral spacing between bicycles and vehicles in mixed urban traffic (passing distance, PD) and their resulting effect on a bicyclists' comfort were examined based on a study of six sites performed by(Apasnore et al, 2017). The average distance of bicycles from the curb and parked vehicles, motor vehicle speed, lane width, and bicycle position from adjacent curb edge line, whiles inversely correlated to ambient traffic density and bicycle speed and Ambient Traffic Density (ATD), were found to be the most important factors to a Bicyclists' Comfort Perception (BCP).

The interaction of bicyclists and motor vehicle drivers was studied by (Klieger and Savage, 2020) and (Silva et al, 2019). They evaluated how well unprotected bicycle lanes function as dedicated travel lanes for bicyclists. Two types of bicycle lanes were included in this study, including on-street bicycle lanes demarcated with painted lines on the vehicular roadway and bicycle lanes at-grade with, and immediately adjacent to, the pedestrian sidewalk. More specifically, the research focused on how people behave and interact on street segments with these facilities in place.

2.3. BS Applications Studies

Various types of vehicle simulators – such as automobile, bicycle, flight, tank and ship simulators – have been developed and widely used for testing the design evaluation of environments, training for driving, entertainment, and so on (Guiso, 1995). Even though many studies have been conducted regarding various driving simulators, few are related to two-wheeled, human-powered simulators like a BS. A BS consists of a stationary bike, a monitor, analyzing software, and a VR-Design platform. It visualizes biking behavior on different roads in a realistic environment. A BS also includes of a frame, clamp to hold the bicycle securely, a roller that presses up against the rear wheel, and a mechanism that provides resistance when the pedals are turned (Curtis, 2014).

For bicycle dynamics calculation and real-time simulation, it is necessary to identify the control inputs from both the rider and the virtual environment (Shin and Lee, 2002). The virtual environments, such as the ground configuration and condition, can be generated and provided by a visual system. The steering, pedaling and braking torques can be measured directly by using torque sensors attached to the corresponding components. Given the significant application of BSs in previously published studies and the utility of applying simulators as an alternative to real bicycles, this study was designed to synthesize the lessons learned from existing studies that quantified the application of BSs. We implemented a scoping review to identify, screen, and review the existing literature on BS applications. The results of which we hope can assist researchers, policy makers, and practitioners with the selection of appropriate evaluation methods based on their objectives. This study can be a starting point for other researchers to explore more frequent objectives when applying BSs and present new studies with additional innovations.

After reviewing the literature, five approaches were identified: application of a BS to suggest a mathematical dynamic model for bicycle stability, incorporation of a BS with virtual reality (VR) technology, application of a BS in safety promotion studies, installing special sensors on the BS to measure specific datasets, and the application of a BS in medicine, psychology, sports management, and other branches of science.

2.4. Applications of BS in Modeling Bicycle Stability

A simulator is designed to create a virtual model of a real-life situation for the purpose of instruction or experiment in a laboratory environment. Studies that generate different prototypes for a bicycle product using a systematic concept generation method, describe the use of an instrumented bicycle and its computational model, and provide mathematical models for bicycle stability are reviewed in this section. Methods for data collection, analysis, modeling, and simulation of performance parameters by BSs were developed or evaluated are also discussed. BS is and efficient way to scrutinize the interaction of bicyclists with other road users in a real-world simulation environment. Hereupon, this section reviews the interaction of bike and motorized vehicles in terms of bike stability, and lateral and longitudinal movements. The degree-of-freedom (DOF) of BS affects its stability. The higher the DOF of the BS, the more it can obtain acceptable results regarding the participant's behavior during interaction with motor vehicles. Hereupon, this section reviews previous studies in terms of conceptual designing of the BSs.

Scholars e.g., (Abagnale et al, 2016), (Arunachalam and Rajesh, 2014), (Beckmann et al, 2015), (Dahmen et al, 2011), (Escalona et al, 2018), and (Englund et al, 2016) proposed a series of new dynamic models and mathematical equations that use a BS for bike stability. A new dynamic model consisting of an electrical motor in the central position that, by means of a bevel gear, transmits the torque to the central hub to investigate the tracking errors was proposed by (Abagnale et al,2016). (Arunachalam & Rajesh, 2014) suggested a mathematical equation for investigating the stability of foldable bicycles. A method of mixed reality extended by modern industrial technologies to allow natural interaction with virtual prototypes of the BSs was proposed by (Beckmann-Dobrev et al, 2015). A mathematical model was implemented by (Dahmen et al, 2011) for simulating rides on real courses, providing similar quality measures when comparing field and simulator measurements. (Escalona et al, 2018) proposed the mathematical equations to generate a simple computer graphics animation of bicycle riding. In another study, a mathematical model was suggested by (He et al (a), 2005) to investigate the bicyclist's stability and vibration behavior. A new dynamic model was suggested by (He et al (b), 2005) for BSs consisting of motion generation, and force reaction, dynamics simulation, and visual/audio systems. In addition to previous studies, a new rehabilitation training system (consisting of a dynamic model) was developed by (Jeong et al, 2005) to improve equilibrium sense control by combining virtual reality technology with a fixed exercise bicycle. A new dynamic model to validate the integrated power-assisted BS was proposed by (Kakutani & Furusho, 2004). They suggested an integrated prototype that was able to investigate power-assisted bicycle. (Kim et al, 2017) developed a heuristic dynamic model to evaluate the user experience of virtual systems. They modeled the user experience of virtual bikes by VR technology. In another research project, (Kooijman et al, 2008) suggested a model study to consider many physical aspects of a real bicycle such as the flexibility of the frame and wheels, play in the bearings, and precise tire characteristics. One of the first proposed BSs was introduced by (Kwon et al, 2001) KAIST Interactive BS (Korean BS) consists of a bicycle, a Stewart platform, magnetorheological handle, pedal, resistance system to generate motion feelings, real-time visual simulator, and a projection system, sub-controllers, and an integrating control network. A dynamic model that couples the bicycle roll and steer in a realistic manner was proposed by (Lee et al, 2017) and it also allowed studying the effect of balance on the rider's higher-level cognitive decisions. (Schwab & Recuero, 2013) described and used a BS prototype that can help understand the synergy among the parts intervening in the active stabilization process in cycling. An affordable BS prototype with proper longitudinal and lateral stability (Snapika et al, 2018) that simulates the form of indoor cycling was presented. To increase the efficiency of BSs, new methods were proposed by the following researchers. In all reviewed methods, a particular structure or architecture is presented that can increase the efficiency of the BS. This issue is clearly discussed in studies such as (Englund et al, 2016): (Ginters et al, 2014): (Jamin et al, 2019(. (Shin and Lee, 2002) proposed the control inputs from the rider as well as the virtual environments for the calculation of bicycle dynamics in a bicycle simulator. The impression of geometry and road surface characteristics – such as radius of curvature, road adhesion, and unevenness of road profile – was simulated by (Shoman & Imine, 2020), based on which a dynamic model was developed. Finally, a 6-degrees-of-freedom (DOF) platform that is controlled by linear actuators and a microcontroller was proposed by (Yap et al, 2016), who successfully formulated the kinematics equation. The aforementioned studies propose different physical concepts of the BS. In each of these studies, the degree of freedom and dynamic features of a BS have been changed to suggest the new structure for the BS.

After reviewing the aforementioned studies, we conclude that a BS can be used to model the physical motions of the human body. Therefore, spatial geometric equations have been defined to model the stability of bicyclists. To sum up, the first application of the BS is limited to the process of presenting such models or mathematical equations.

2.5. Incorporation of BS with Virtual Reality (VR) Technology

Virtual reality (VR) refers to a computer-generated simulation in which a person can interact with an artificial three-dimensional environment using electronic devices with a screen or gloves fitted with sensors (Mitchell, 2020). VR can be a 360-degree immersive experience, where computer-generated graphics help create things as close to reality as possible. Many researchers have attempted to integrate BSs with the VR technology to gain more realistic data. VR's most immediately recognizable component is the Head-mounted Display (HMD), which can be applied to simulate the performance of bike riders in different situations.

VR technology was used by (Bogacz et al, 2020) to contribute to a better understanding of the implications of the choice of the experimental setup by comparing the cycling behavior between two groups of participants. The first group controlled the maneuvers using a keyboard and the other group rode an instrumented bicycle. Some studies examined unique applications of a BS&VRT (Bottone et al, 2015): (Carraro et al, 1998): (Kikuchi, 2011): (Kakutani, 2004): (Katsigiannis et al, 2019): (Al-Kefagy, 2019): (Padmini et al, 2019): (Schulzyk et al, 2009(. The two degree of freedom (2-DOF) mechanism on a dynamic platform driven by changing the cable length and its application to VR for bicyclists in virtual environments was presented by (Chen et al, 2007) Their prototype could interact between the bicycle and VR system and integrate exercise with entertainment. (Dahmen & Saupe, 2009) concentrated on the simulation of endurance sports with an emphasis on competitive cycling with BS&VRT. The goal of Gao et al.'s work was to provide a simulator system that enables race bikers to improve their performance in training (Gao et al, 2005(. In another study, (Hernández–Melgarejo et al, 2020) integrated physical VR and control behavior systems to compose a virtual bicycle simulator. They designed and implemented a VR bicycle system based on a functional-based mechatronic design approach. An immersive bicycle simulation platform and VR technology for several applications in the areas of biomechanics, sports, traffic education, road safety, and entertainment was proposed by (Herpers et al, 2009) Their prototype consists of special immersive visualization systems to simulate biking in a real-world environment. All the aforementioned studies were tested in a laboratory environment.

The following studies are instances of new integrated systems that have been suggested to promote the performance of BS&VRT. Studies like (Horne et al, 2018): (Jia et al, 2006) proposed new techniques to improve the performance of a BS&VRT. A calibration procedure was proposed by Horne et al. that uses general equations and techniques to calibrate speed measurements and improve the consistency of experimental data. (Jia et al, 2006) evaluated the role of the human-computer interaction system as the key technology of a virtual bicycle simulator.

Researchers, e.g., (Keler et al, 2020) and (Nazemi et al, 2018)_ used BS&VRT to evaluate novel traffic control strategies on existing transport infrastructure depicted in VR environments. In addition, (Nazemi et al, 2018) used BS&VRT to evaluate the effects of environmental properties and road infrastructure design on cyclists' perceived safety. This study investigated the combination of immersive VR and an instrumented cycling simulator for in-depth behavioral studies of cyclists. Researchers, e.g., (Ouden, 2011) used a BS for physical rehabilitation purposes. BS&VRT has been used to train children and help them get used to being on a bicycle. Children's cycling has been studied less than adult cycling. Therefore, additional studies should be conducted because children have been considered as one of the groups for whom education can positively affect their behavior in adulthood.

An example of a well-done study regarding the bicyclists' behavior on different pavements was performed by (Rakhmatov et al, 2018) They designed a data-collection bike that captures the vibrations induced at the handlebar and the cycling velocity for different tire pressures. The level of tire pressure, the weight of bicyclists, and the role of pavement in the reaction of bicyclists was investigated. By studying the behavior of cyclists, (Schramka et al, 2017) investigated how different street design configurations and traffic levels impact perceived cycling stress levels, cognitive reactions, and mobility behavior. The role of environmental elements to investigate how cyclists adapt their behavior (e.g., speed, safety, gaps, steering, etc.) was evaluated by (Shoman & Imine, 2021) They adjusted their riding practices as they interacted with other road users and anticipated risks in hazardous riding situations. In another study, (Ullmann et al, 2020) used the integration of BS&VRT to provide rare qualitative factors (such as stress, perception of time, and attractiveness of the environment). They utilized an audiovisual VR bicycle simulator to allow the user to ride in a virtual urban environment. The aforementioned studies were conducted with adult cyclists. Finally, the exercise and entertainment purposes of a BS&VRT were studied by (Tang et al, 2018) and (Yap et al, 2018) who investigated the entertainment role of BSs.

Overall, the number of studies regarding incorporating VR and BSs has risen in recent decades, reflecting increasing interest by researchers. Incorporating VR and BS provides a fairly realistic environment for the participants of the research, and they can efficiently adapt to the simulated environment when riding a BS. Riding a BS which is integrated with VR technology may improve the BS participant's understanding regarding the simulated environment and it effects positively on the bicyclist's behavior in interaction time intervals with other motorized vehicles.

2.6. Application of BS in Safety Promotion Studies

The popularity of biking has drawn researchers' attention to finding methods for protecting bicyclists on public roads. Bicyclists (and pedestrians) are frequently classified as "vulnerable road users." The biking community, however, is not comfortable regarding the safety of these two groups (Cynecki, 2012). Bicyclists are susceptible to serious injuries, and special attention should be paid to the safety of this group (Ragland, 2012). The elevated risk of injury to bicyclists when they encounter motor vehicles makes it important to identify and implement strategies to protect cyclists on the road. There is some evidence that bicycling has increased in recent years (Jacobsen et al, 2009). However, even with widespread encouragement, many will be deterred from biking if they do not feel safe.

When a crash occurs between a vehicle and a bike, it is the cyclist who is most likely to be injured. By law, bicycles on the roadway are vehicles with the same rights and responsibilities as motorized vehicles. Over 1,000 people were killed in bicycle crashes in 2018 and over 300,000 ended up in the emergency room. In the U.S. in 2017, over eight times more men were killed in bicycle crashes than women (Grover, 2020). One notable application of BSs is in safety promotion studies. Researchers have studied the interaction of bicycles with other vehicle types, plans to increase bicyclist's safety, and the most hazardous situations for bicyclists. Different cyclist's behaviors and cyclist-enhanced safety schemes can be evaluated when they interact with the road and other vehicle types. "The role of bicyclists under different conditions" and "the role of the road and its characteristics" are two critical properties involved in increasing or decreasing cyclist safety.

The following studies investigated the role of the bicyclist in the occurrence of crashes. A novel approach consisting of a unique bicycle simulator equipped with sensors capable of capturing the behavior of bicyclists was suggested by (Englund et al, 2016) to model the visual distraction of bicyclists. (Ghodrat Abadi et al, 2019) suggested a high-fidelity full-scale bicycling simulator that examined the interaction of bicyclists and trucks near Commercial Vehicle Loading Zones (CVLZ) in urban areas. They investigated the influence of engineering treatments on bicyclist performance.

Additionally, a factorial design with three levels of pavement markings (white lane marking, solid green, and dashed green), two levels of signage (no signs and warning signs), and three levels of truck maneuvers (no truck, parked trucked, and exiting truck) was developed by (Kaß et al, 2020) evaluated and investigated cyclists' behavior during dynamically evolving interactions. Furthermore, they measured the dynamic behavior patterns. The research focused on external human-machine interface (eHMI) as a communication interface of automated vehicles.

Researchers such as (Lindström et al, 2019) have evaluated how radar sensors and technologies common in automotive vehicles can be transferred for use on bicycles. A bicycle simulator was used for testing and evaluation. Moreover, high-risk scenarios and requirements were identified, followed by identified design challenges and design activities. To facilitate road safety for children, (Matviienko et al, 2018) explored the use of multimodal warning signals to increase their awareness and prime action in critical situations. A BS linked to these signals and the results showed that the participants spent significantly more time perceiving visual than auditory cues. A better understanding of bicyclists' perceived safety and their preferences for currently unavailable and/or unknown facilities was studied by (Nazemi, 2020) who used different survey methods ranging from verbal descriptions of facilities to surveys including images and videos. There is evidence that some aspects of cyclist performance when interacting with the road environment can be investigated by using a BS. (O'Hern et al, 2017) concentrated on the cyclist spatial position measures to investigate the bicyclists' interaction. They assessed the validity of the participants' performance using a BS compared to riding on road. In line with former research, (O'Hern et al, 2018) examined how bicycle lane width and perceptual countermeasures can influence cyclist speed and position. Researchers such as (Powell, 2017) concentrated on the injuries caused by bicyclists and motor vehicle crashes. They used a particular BS to provide a virtual environment and reduce crashes by safely investigating the interaction between bicycle riders and traffic, particularly when bicyclists were crossing streets. (Sawitzky et al, 2020) studied the effects of new infrastructural concepts and technologies, such as a head-up display (HUD) for cyclists' potential crash possibilities brought by automated vehicles, and smart, connected traffic, on actual cyclist road safety. Some researchers studied the hazard of biking on sidewalks. (Suzuki, 2013) is a good example, concentrating on a particular BS that is available for analysis of the safety and influence on other transport modes.

Using BSs and VR technology for assessing bicyclists' safety was studied by (Tsuboi et al, 2018). They proposed methods to improve the awareness of bicycle riding safety by experiencing virtual accidents in a virtual space. The study helped the participants learn desirable and safe bicycle riding behavior. The role of bicyclists in injury or fatal crashes was assessed by (Warner et al, 2017). They concentrated on the right-hook crash, which is a crash between a right-turning motor vehicle and an adjacent by-moving bicycle. They evaluated driver behavior in collisions that occur during the latter green phase (the second portion of the green signal phase, after the initial vehicle queue has cleared) at signalized intersections with a bicycle lane and a shared right-turn lane.

Researchers like (Brown et al, 2017) and (Yamaguchi et al, 2018) investigated the role of the road and its characteristics on bicyclists' crashes. Alternative pavement markings were investigated by Brown et al. for bicycle wayfinding and proper bicycle placement at signalized intersections. Yamaguchi et al. proposed an innovative method to detect road hazards using sensors attached to a bicycle. The built-in sensors send the speed and front-wheel angle information to the control unit. The proposed system allows for dangerous situations to be easily and repeatedly created with no danger to the bicyclists.

Overall, in many studies a BS was used to simulate the behavior of bike riders under different environmental conditions and on different road types. As explained in this section, the application of BS in safety-related studies improved the adaptability of bicyclists in interaction time intervals. Furthermore, BS as an efficient instrument can be utilized in safety-related studies to investigate the bicyclist's lateral and longitudinal movements which is not easy to measure in the real world.

2.7. Installing Various Sensors on the BS to Record Different Characteristics

The studies in this section installed specific sensors on the BS to record characteristics of the participant's body. (Alemeida et al, 2020), (Caro et al, 2015), (Dialynas et al, 2019), (Herpers et al, 2011), and (Rittenbruch et al, 2020) present the most important research conducted in this area. (Alemeida et al, 2020) presented a virtual BS (SimBike) that used non-conventional motor, sensors, sensorimotor devices to provide greater user involvement and comfort. They used special sensors to investigate how the devices in SimBike contributed to the user experience in the virtual simulator, including the level of immersion, realism, and cyber-sickness symptoms. The results suggested improvements to make the simulator more suitable for all types of users, regardless of characteristics such as weight and height. The role of the different sensory information available was determined by (Caro et al, 2015). They concentrated on the mechanisms of perception of the natural speed which affect the adopted speed. Natural speed defines the speed limits of vehicles specified on traffic signs while the adopted speed is defined as the adaptive speed of the driver during interaction with other road users. An experiment was carried out on a BS where three sensory datapoints were separately manipulated: the speed of the image, the resistance to pedaling, and the airflow. Based on this research, "airflow" had no effect. This indicator should be better evaluated by conducting more accurate models. A step-by-step guide (Dialynas et al, 2019) to building a BS was presented at TU Delft University, highlighting the mechanical and mechatronic aspects. They used special sensors in their proposed prototype to effectively simulate a mountain bike placed on top of rollers and later fitted with a haptic steering device. The FIVIS simulator system was constructed by (Herpers et al, 2011). It addressed the visual and acoustic cues as well as vestibular and physiological cues. Sensory feedback from skin, muscles, and joints was integrated within this VR visualization environment, allowing the BS to simulate otherwise dangerous traffic situations in a controlled laboratory environment. They developed a BS that was embedded into an immersive visualization environment, which provided visual cues to peripheral areas of the visual field of the trainee. A physical computing toolkit (Rittenbruch et al, 2020) was presented to support the rapid exploration and co-design of on-bicycle interfaces. Physical plug-and-play interaction modules controlled by an orchestration interface allowed participants to explore different tangible and ambient interaction approaches on a BS. Results revealed how this toolkit can combine with a lightweight bicycle simulator and simulate hazards to evaluate different designs and elicit rich feedback.

2.8. Usage of Car Following Models for Bicyclists

Bicycle traffic operations have become increasingly important, yet have been largely ignored in the traffic flow community until recently. Some researchers hypothesized that there is no qualitative difference between vehicular and bicycle traffic flow dynamics, so the latter can be described by re-parameterized car following models, such as those tested by (Kurtc and Treiber, 2020). They reproduced bicycle experiments on a ring with an Intelligent-Driver model and compared its fit quality (calibration) and predictive power (validation) with that of a Necessary-Deceleration-Model specifically designed for bike traffic. The results showed that there are similar quality metrics for both models, so the above hypothesis of a qualitative equivalence cannot be rejected. Follow-the-leader is one of the fundamental behaviors in bicycle traffic that describes the longitudinal interactions between two consecutive bicycles. It plays a predominant role in the development of micro-simulation models, safety evaluation, and the capacity estimation of bicycle infrastructure. To understand bicycle-following movements, previous studies have either adopted car-following models or developed specialized bicycle-following models. However, these models were not calibrated and validated in a unified configuration using empirical data derived from realistic cycling behaviors.

(Xue et al, 2020) investigated the single-file dynamics of bicycle traffic from the perspective of car-following models. Using empirical datasets from a series of bicycle experiments, the proposed models were calibrated and validated. The results demonstrated that the assumptions, such as keeping a velocity-based distance from the leader, was a robust behavioral mechanism across all of the empirical datasets. The results could enhance the understanding of the behavioral dynamics of bicycle traffic, meanwhile providing deeper insights into the mechanisms of developing bicycle simulation models.

In order to develop traffic modeling, it is necessary to consider adapting these models to bicycle traffic and thus benefit from all of the research efforts in the field of traffic theory. Since, the objective function of a driver or cyclist is to control the vehicle's speed and direction while maintaining his/her desired speed and avoiding accidents, it is likely that despite the difference in vehicle type, the driving logic and driver behavior will be similar. (Abdelaziz and Gang, 2014) presented three aspects of traffic vehicle science adapted to bicycle traffic: car-following models, the fundamental relationships of traffic flow, and the action point model. The results obtained using car-following models were compared to empirical data collected with global positioning system devices installed on a pair of cyclists in a following situation with no opportunity to overtake. The fundamental relationships were examined using data collected by video at a fixed location at a bike facility. The results indicated that car-following models, fundamental relationships, and the action point model all have the potential to reproduce real-world data for bicycle traffic.

2.9. Summary of Literature Review

After reviewing the previous studies regarding the bicyclist traffic safety and interactions with vehicle traffic, it is clear that the proposed research effort will be the first of its kind to develop a dynamics-based model for the longitudinal motion of bicycles in both constrained and unconstrained conditions. Bicyclist behavior variability and bicyclists' motions are modeled during our manuscript. Furthermore, previous studies that investigated bicycle-following behavior were based solely on ring-road experimental data, which is not typically reflective of bicycle riding. For that reason, our study involves testing a developed model using collected bike simulator data. This review showed that previous studies carry certain shortcomings, and further investigation is required for a reliable evaluation of bicyclist safety research. Future research is also required to better understand and evaluate bicyclists' motion while addressing the gaps in the existing methods and the challenges in the bicyclist behavior evaluation.

3. METHODOLOGY

Thirty-three participants were recruited via flyers distributed manually, online, and through social media. Flier content included contact information, a summary of the requirements for the study, and an explanation of the monetary compensation for driving the bike and car simulators. Subsequently, prospective participants were screened for eligibility and scheduled to drive in the simulator environment. Participants were required to possess a valid driver's license and were compensated $15 per hour for their participation. In addition, participants were asked about their biking experience. We provided them with water and candy when they felt tired or had headaches while driving with simulators.

Under the supervision of an advisor, a team of undergraduate and graduate student research assistants observed the IRB-approved driving tasks, and questionnaire. Participants were asked to fill out a pre-survey questionnaire, drive for about two hours in different simulated scenarios, and fill out the post-survey questionnaire to find the effect of their experience on driver behavior.

The observer made sure that the participants completely understood the objectives of this project. They instructed the participants to briefly familiarize themselves with the simulator environment and explained the procedure before each scenario. Two Participants were instructed to drive bike and car simulators at the same time. When each scenario was run, one participant had to follow the other vehicle in the study. All the scenarios were designed to investigate changes in bicyclist behavior = toward vehicle traffic. The participants started driving in a base scenario with no vehicle traffic to compare their driving behavior with other high traffic condition scenarios. Participants then drove seven different in-vehicle scenarios – including:

- Scenario 1-1: Bicycle only (traffic scenario independent) - without traffic
- Scenario 1-2: Bicycle only (traffic scenario independent) - with traffic
- Scenario 2: Car moving straight (Bicycle ahead of Car, Bicycle in path, same direction velocity vector)
- Scenario 3: Car moving straight (Bicycle ahead of Car, Bicycle in path stationary)
- Scenario 4: Car moving straight (Bicycle behind Car, Bicycle in path, same direction velocity vector)
- Scenario 5: Car moving straight (Bicycle behind Car, Bicycle in path stationary)
- Scenario 6: Car moving turning right (Bicycle ahead of Car, Bicycle in path, same direction velocity vector)

A simple real-world network consisting of a straight two-way, two-lane route and two signalized intersections with four phases and a 110 second cycle length was designed for both participants driving the scenarios with different initial start points. The location of bike and car was defined in the software and the following attributes were considered for the simulation:

- Minimum Weight of bicyclists[1]: 50 kg

[1] Weight of the car. Minimum and maximum values are used to simulate the different loads of each vehicle

- Maximum Weight of bicycle: 7.5 kg
- The tolerance of bicyclist plus bicycle weight: 55 kg ~ 87 kg
- Max brake force[2]: 1000 N
- Front layout[3]: 0%
- Rear layout: 100%
- Estimated acceleration[4]: 3.5 $\frac{m}{s^2}$
- Air friction[5]: 0.4
- Pitch Inertia[6]: 17 $\frac{kg}{m^2}$
- Roll Inertia: 13 $\frac{kg}{m^2}$
- Yaw Inertia: 10 $\frac{kg}{m^2}$

As shown in **Figure 1**, the simulated network for bicyclists and car drivers was considered as below:

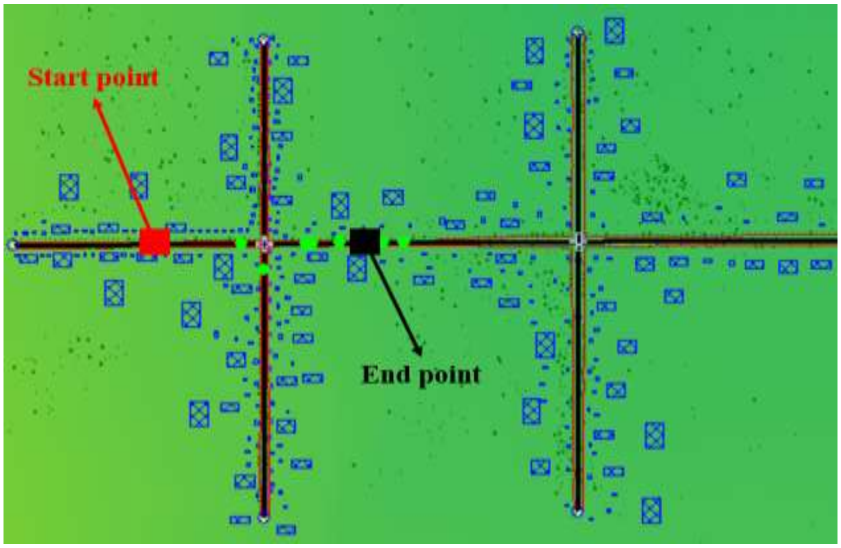

Figure 1 The simulated network

It is worth mentioning that, 25 $\frac{mile}{hour}$ (or 40 $\frac{km}{hour}$) was defined for the cars, and the speed limit of bicyclists was defined as 12 $\frac{mile}{hour}$ (or 20 $\frac{km}{hour}$) .

In the scenario 1-1, only one bicycle was assigned on the network. We tried to investigate the longitudinal motion of bicyclists without vehicle traffic conditions.

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[2] the maximum force that the brakes can apply on the wheels
[3] Layout of the car drive wheels: front-wheel drive, rear-wheel drive, or four-wheel drive.
[4] The amount of acceleration drivers are using
[5] Friction the coefficient for the car, used to compute the air drag
[6] consists of inertia of the vehicle, Roll Inertia, Pitch Inertia, and Yaw Inertia

In the scenario 1-2, the first scenario with heavy traffic, (500 $\frac{veh}{hour}$) was modeled.
In the second scenario (scenario 2), the bike is ahead of the car, and the bicycle goes straight before the signalized intersection. The bicycle stops before the intersection. The software stops analyzing when the bike arrives at the stop line of the first intersection.
In the third scenario, the location of the bicycle was defined in front of the car. Bicycles and cars were run from 492 ft (150m) before the signalized intersection to 492 ft (150m) after the signalized intersection. The "same direction velocity vector" means "the same direction". Additionally, the bicycle must pass the intersection and both the bike and car must stop after the signalized intersection.
Scenario 4 is the same as the second scenario. In scenario 4, the bicycle is behind the car.
Scenario 5 is the same as the third scenario. In scenario 5, the bicycle is behind the car.
In scenario 6, the car should turn right, the bicycle is ahead of the car, and the bike goes straight until it passes the signalized intersection. We ignored the left turn in scenario 6. The conflict between the bike when passing the intersection and the car when turning right is investigated in this scenario.

During each driving scenario, participants were instructed to drive as they typically would on a real road for approximately 5 min and comply with the speed limit. The daytime scenery closely matched driving situations in the Baltimore metropolitan area and was designed to create a sense of real-world driving for each participant. Traffic flow and density were designed similarly in all seven scenarios. The driving experience in each scenario progresses in urban downtown routes. The bike and car simulators were integrated together for this project. When both simulators are integrated, the car simulator participant can watch the scenario on the car simulator's screen. Therefore, both participants can follow each other and they can be informed about the location of one another during the simulation. As shown in **Figure 2**, two participants can follow each other in the same scenario.

Figure 2 Integration of bike and car simulators

The questionnaires asked about demographic information and real driving behavior before the driving simulator experience (pre-survey), and driving behavior after driving the simulator (post-survey). Observers gave participants the option of completing the questionnaire on their own or with the assistance of the observer. The simulation was displayed on three, 40-inch LCD screens. Participants sat within the simulator's driver compartment, which provided a view of the roadway and dashboard instruments, including a speedometer (**Figure 2**). Naturalistic engine sounds, road noises, and sounds of passing traffic were provided to simulate the real world. Simulated vehicles with varying speed and volume were randomly programmed with assigned low traffic volume to represent off-peak conditions in the area. The special collision sound and a message consisting of "Collision" word were designed for scenarios where the participant collides with other vehicles or bicyclists. Different information about the driver's behavior including speed, throttle, brake, steering velocity, offset from road center, and lane change was also calculated. For example, offset from the road center, which was reported as the deviated distance from the road center toward the right or left side, was calculated and saved as an indicator of impaired driving performance. Greater within-lane deviation indicated poorer driving precision.

Average driving speed when participants exited from the bike lane was calculated based on the speed of the vehicle and computed as the degree to which drivers changed their speed for each scenario. Lane change frequency was used as an indicator and defined as the number of times the driver changed lanes. The brake force and throttle, which are indicators of distraction, were compared for each scenario. The severity with which participants hit the brakes demonstrated inattention to the road and taking the mind off the road.

Descriptive statistics were also obtained on pre-survey questionnaire data regarding participant characteristics. Some 43.8% of participants were male and 56.2% were female. The age group of participants was: 42.4% between 18 to 25 years old; 18.2% between 26 to 35 years old; 18.2% between 36 to 45 years old; 18.2% between 46 to 65 years old; and 3% in more than 65 years old.

Additionally, the ethnicity (**Figure 3**), educational status (**Figure 4**), condition of employment (**Figure 5**), annual household income (**Figure 6**), were collected.

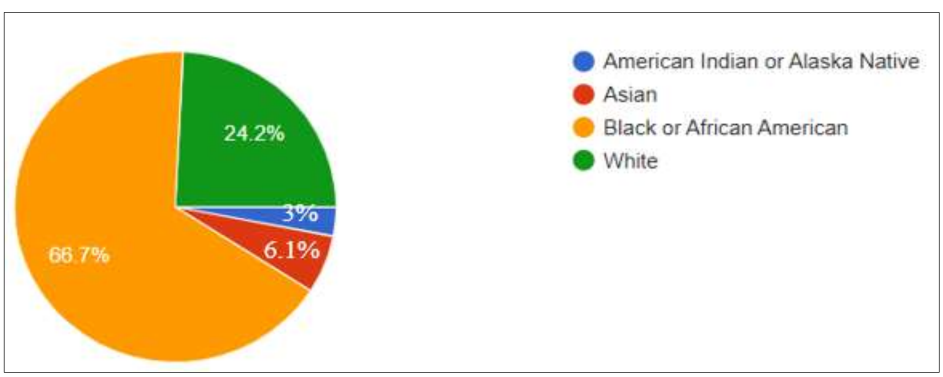

Figure 3 Ethnicity of the participants

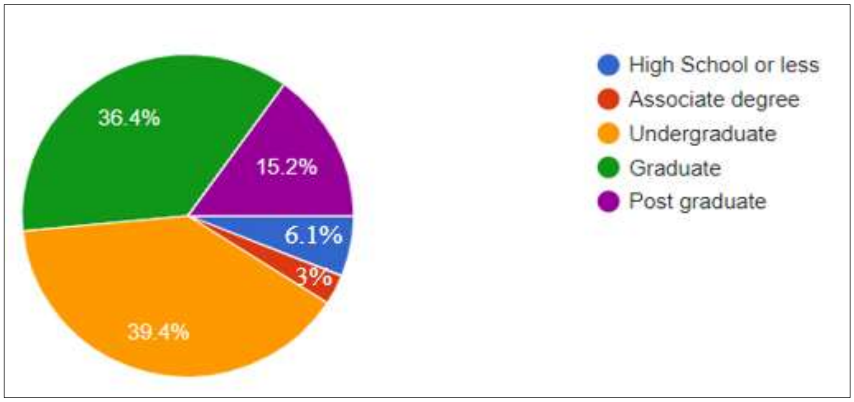

Figure 4 Educational status of participants

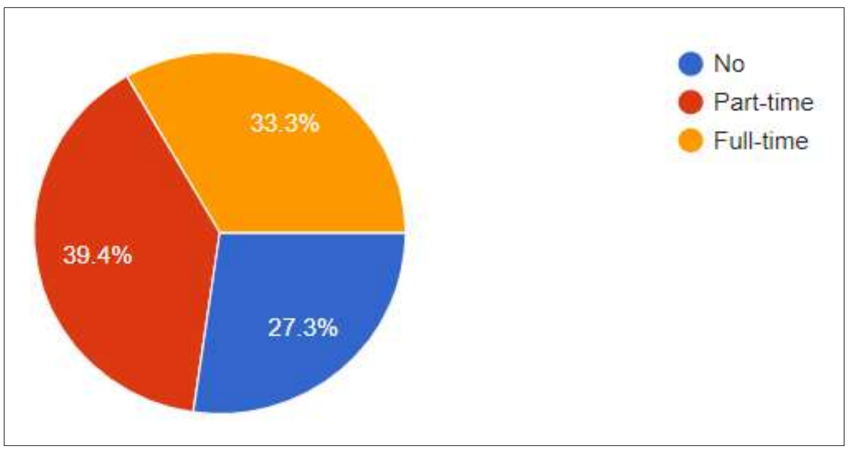

Figure 5 The participant's employment condition

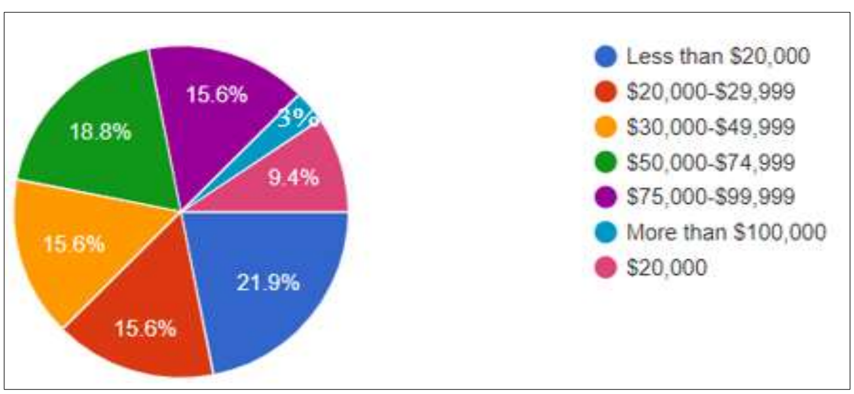

Figure 6 The participant's annual household income

Participants were classified to different sessions, each consisting of two participants with one riding the bike simulator and the other driving the car simulator. They then switched, and the participant who rode the bike simulator drove the car simulator and vice versa. Afterwards, we asked each participant to express his/her opinions regarding their perceived safety by selecting a number between 1 and 5. The descriptions of each value are shown in **Table 1**.

Table 1 Description of the safety of bike lane from participants' point of view

Number	1	2	3	4	5
Description	Pretty unsafe	unsafe	Not safe not unsafe	safe	Pretty safe

We asked the participants to consider the weather conditions and the number of other vehicles around the bike when judging the safety of the bike lane. A simple average was calculated for 33 obtained results. **Table 2** shows the results of bike riders, and **Table 3** shows the result of car drivers.

Table 2 Bike rider's opinion about the safety of the road (Average percentage - %)

Scenario	Pretty unsafe (1)	Unsafe (2)	Not safe and not unsafe (3)	Safe (4)	Pretty safe (5)
Scenario 1-1	0	21.2	21.2	24.2	33.3
Scenario 1-2	6.1	36.4	33.3	18.2	6.1
Scenario 2	0	27.3	24.2	39.4	9.1
Scenario 3	9.1	21.2	36.4	24.2	9.1
Scenario 4	0	39.4	24.2	30.3	6.1
Scenario 5	9.1	30.3	27.3	30.3	3
Scenario 6	9.1	27.3	33.3	24.2	6.1

Table 3 Car driver's opinion about the safety of the road (Average percentage - %)

Scenario	Pretty unsafe (1)	Unsafe (2)	Not safe and not unsafe (3)	Safe (4)	Pretty safe (5)
Scenario 1-1	0	9.1	24.2	36.4	30.3
Scenario 1-2	0	21.2	45.5	21.2	12.1
Scenario 2	0	15.2	27.3	48.5	9.1
Scenario 3	0	9.1	48.5	33.3	9.1
Scenario 4	0	15.2	33.3	36.4	15.2
Scenario 5	0	15.2	39.4	39.4	6.1
Scenario 6	3	15.2	33.3	42.4	6.1

In a post-survey questionnaire, six solutions proposed to improve the safety of bike lane were designed. Participants could choose up to three solutions. The bike lane was designed without any barriers or separate markings with a carriageway. The bike lane marking was designed in the software as shown in **Figure 7**. Bike route signs were located every 100m along the road.

Figure 7 The simulated cross section of the shared bike lane

Figure 8 shows the results of post-survey questionnaire:

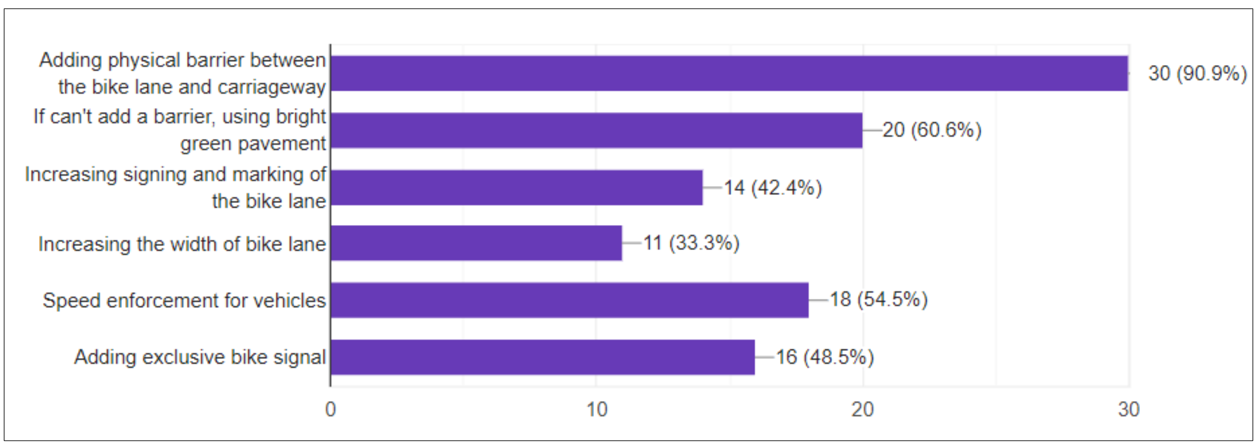

Figure 8 The participants' opinion regarding the improvement of the designed bike lane

As shown in **Table 1** and **Table 2**, the safety of the designed bike lane was diminished when high traffic volume (500 veh/hour) was assigned on the network. As shown in **Figure 8**, adding physical barrier between the bike lane and carriageway (declared by 30 participants), using bright green pavement (declared by 20 participants), and providing speed enforcement (speeds less than 40 km/hour – declared by 18 participants) were three frequently-selected safety promotion solutions among participants.

4. DATA ANALYSIS

4.1. Methodology for FR car-following validation model

In order to analyze the Fodholun-Rakha (FR) car following model, the values of the following equations were obtained., the following variables are introduced:

n= the index of the lead vehicle

n+1= the index of the subject (following) vehicle

$X_{n+1} = position\ of\ the\ subject\ (following)\ vehicle$

$U_{n+1} = speed\ of\ the\ subject\ (following)\ vehicle,$

$U_n = speed\ of\ the\ lead\ vehicle$

$a_{n+1} = acceleration\ of\ the\ subject\ vehicle$

$u_f = the\ vehicle's\ desired\ speed\ (also\ known\ as\ the\ roadway\ free -$
$flow\ speed)$=11.17m/se

$d_{desired} =\ a\ desired\ comfortable\ vehicle\ deceleration\ level\ (typically\ taken\ to\ be - 3\ m/s2)$

$S_{n+1} =\ the\ vehicle\ spacing\ from\ the\ back\ bumper\ of\ the\ subject\ vehicle\ to\ the\ back\ bumper\ of\ the\ lead$
$vehicle$

$S_j = the\ vehicle\ spacing\ at\ a\ speed\ of\ zero\ (i.e., the\ jam\ density\ spacing)$

τ= $the\ driver's\ perception - reaction\ time$. The driver's perception-reaction time varies as a function of the roadway parameters ($u_f = 11.17\frac{m}{se}, u_c = 8.3775, q_c = 0.61, k_j = 0.1886$) and the vehicle's speed.

β = the gearshift impacts at low traveling speeds when trucks are accelerating. This factor is set to 1.0 for light duty vehicles.

η = the driveline efficiency (unitless)=0.9

P = the vehicle power (kW) = 381hp ~ (1hp=0.746 kw) = 284.2 kw

ɣ = a constant reduction factor of the vehicle power aiming to represent the throttle level (when the objective is to determine the maximum acceleration that a vehicle is able to achieve, the value of this factor is set equal to 1).

M_{ta} = the mass of the vehicle on the tractive axle (kg) =0.55*2700=1485kg

g = the gravitational acceleration (9.8067 m/s2)

μ = the coefficient of road adhesion or the coefficient of friction (unitless) = (air friction coefficient: 0.4)

ρ = the air density at sea level and a temperature of 15◦C (1.2256 kg/m3)

C_d = the vehicle drag coefficient (unitless), typically 0.30

C_h = the altitude correction factor equal to 1–0.000085 h where h is the altitude in meters (unitless)=1

A_f = the vehicle frontal area (m2), typically 0.85 multiplied by the height and width of the vehicle (height= 1.96m , width= 1.72m) □ 0.85*1.96*1.72 = 2.865m^2

C_{r0} = a rolling resistance constant that varies as a function of the pavement type and condition (unitless) =1.25

C_{r1} = the second rolling resistance constant (h/km) = 0.0328

C_{r2} = the third rolling resistance constant (unitless)= 4.575

M = the total vehicle mass (kg) (weight: 2700kg = 6000lb)

G = the roadway grade (unitless), Longitudinal slope

$f_p = the\ driver\ throttle\ input, the\ range\ is\ between$ 0.0 and 1.0.

The time headway ensures that the subject vehicle, n +1 follows its lead vehicle at a safe spacing in order to avoid a collision under state-state conditions (i.e., when both vehicles are traveling at the same constant velocity and assuming that the subject vehicle's deceleration maneuver starts τ seconds after the lead vehicle decelerates). $[S_{n+1}^{\sim} = s_j + \tau u_{n+1}]$

$$\tau = \frac{1}{k_j * u_c^2}\left[\frac{k_j * u_c^2}{q_c} - u_f + \frac{(u_f - u_c)^2}{u_f(u_f - u_{n+1})}\right] \tag{1}$$

If the lead vehicle is traveling at a higher velocity (non-steady-state conditions) then the desired safe following spacing can be computed by the following equation. This equation allows the driver to drive at a spacing less than the steady-state spacing when the vehicle ahead of it is driving at a higher speed. In equation (2), the following variables are considered:

$c_1 = 0.796, c_2 = 0.169, c_3 = 0.121$

$$S_{n+1}^{\sim} = \left(c_1 + \frac{c_2}{(u_f - u_n)} + c_3 u_n - \frac{u_{n+1}^2 - u_n^2 - \sqrt{(u_{n+1}^2 - u_n^2)^2}}{4d_{des}}, s_j\right) \tag{2}$$

The FR model includes two terms. The first term is the vehicle acceleration term, while the second term is the vehicle deceleration term. Both terms ensure that the vehicle does not collide with its lead vehicle.

$$a_{n+1} = f_p a_{max} + \frac{[u_{n+1}^2 - u_n^2 + \sqrt{(u_{n+1}^2 - u_n^2)^2}]^2}{16(d_{desired} + gG) * (s_{n+1} - s_j)^2} \tag{3}$$

$$f_p = e^{-aX_{n+1}}(1 - X_{n+1}^b e^{b(1 - X_{n+1})})^d \tag{4}$$

$$X_{n+1} = \frac{s_{\widetilde{n+1}}}{s_{n+1}} * \frac{u_{n+1}}{u_{\widetilde{n+1}}} \tag{5}$$

$S_{\widetilde{n+1}}$= the desired spacing for the current speed. This variable is acquired from equation (6):

$$S_{\widetilde{n+1}} = s_j + \tau u_{n+1} \tag{6}$$

$u_{\widetilde{n+1}}$ = the desired speed for the current spacing. This variable is calculated from equation (7).

$$U_{n+1}^{VA} = \frac{0.555 + S_{n+1} - \sqrt{(-0.556 - S_{n+1})^2 - 0.484 * (11.17 * S_{n+1} - 9.06)}}{0.242}$$

$$U_{n+1}^{VA} = \frac{0.555 + S_{n+1} - \sqrt{(-0.556 - S_{n+1})^2 - (5.406 * S_{n+1} - 4.385)}}{0.242} \tag{7}$$

The acceleration, position, and speed of the user-vehicle in each time stamp is obtained by equations (10-12). In each time stamp, the Euler's method is followed to update the new speed and new position for the next time stamp. Based on Euler's method, the new position and speed are obtained by equations (8-9):

$$\mathrm{v}(t_2)=\mathrm{v}(t_1)+\mathrm{a}(t_1)*(t_2-t_1) \tag{8}$$
$$\mathrm{x}(t_2)=\mathrm{x}(t_1)+\mathrm{v}(t_1)*(t_2-t_1) \tag{9}$$

Variables like "a, b, and d" are model parameters that are calibrated to a specific driver and model the driver input to the gas pedal. The required parameters for FR model are the acceleration parameters: a, b, d, $d_{desired}$.

$$a_{max} = \frac{F_{n+1} - R_{n+1}}{M} \tag{10}$$

$$F_{n+1} = min(3600 * \frac{\eta \gamma \beta P}{u_{n+1}}, M_{ta} g \mu) \tag{11}$$

$$R_{n+1} = \frac{\rho C_d C_h A_f g u_{n+1}^2}{2} + MgC_{r0}(C_{r1} u_{n+1} + C_{r2}) + MgG \tag{12}$$

FR car-following model was calibrated for the scenarios 2, 3, 4, 5, 6. The user vehicle ($or\ following\ vehicle$) and front vehicle (lead vehicle) were investigated in each scenario. The "bike as the front vehicle" was excluded from the calibration analysis, meaning that the participants who follow the bike as the front (lead) vehicle was completely excluded. **Table 4** shows the number of correct participants in each scenario for calibrating the FR car-following model. It is worth mentioning that 33 participants were recruited to drive the car simulator and ride the bike simulator in each scenario.

Table 4 Number of reliable participants after removing bike as the front vehicle

Scenario	Number of the correct participants
2	20
3	15
4	18
5	18
6	12

Equations (1-12) were rewritten as a MATLAB code. A reliable sample consisting of 100 values of (a,b,d) was determined to analyze the FR car-following model. The speed plots were drawn for each participant in each scenario. The obtained speed values from MATLAB code were compared to the collected speed values by the car simulator. Eventually, Root-mean-square (RMSE) was obtained for each pair of (a,b,d) for each participant in each scenario. RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells how concentrated the data is around the line of best fit. RMSE is calculated by equation (13):

$$RMSE = \sqrt{\frac{(\sum_{i=1}^{N}(x_{f_i} - x_{o_i})^2}{N}} \tag{13}$$

In equation (13), $(x_{f_i} - x_{o_i})$ is the difference of forecasts (expected values or unknown results; the obtained speed values from MATLAB code) from observed values (known results; the collected speed values by the car simulator), and N is the sample size.

4.2. Discussion

As shown in Table 4, a total 83 reliable participants were obtained to validate the FR car-following model. In each scenario, the speed-time chart obtained by MATLAB code (consisting of equations 1-12) and the speed collected by the car simulator were drawn. It is worth noting that the time intervals for each participant may be different from one another since the values recorded when the bicycle was the front vehicle were excluded from the data analysis. Diverse time intervals were therefore seen for each participant when the front (lead) vehicle was not a bicycle. As mentioned before, a consistent sample including 100 (a,b,d) values was selected to run the FR car-following model for each participant in each scenario. Each (a,b,d) pair was utilized to run the MATLAB code. Position, speed, and acceleration were then obtained. After finding position, speed, and acceleration values, equation 13 was used to calculate the RMSE. In total, 100 RMSEs were obtained for each participant in each scenario. Respectively, 2000, 1500, 1800, 1800, and 1200 RMSEs were obtained in scenarios 2, 3, 4, 5, 6.

The smallest RMSE was selected for each participant in each scenario. Finally, 20, 15, 18, 18, and 12 smallest RMSEs were selected for statistical analysis. Subsections 4.2.1 to 4.2.5 explain the smallest RMSE values in scenarios 2 to 6. Scenario 1 was designed to evaluate the performance of bicycles on the road. In scenario 1, no interaction between the car and the bike was applied. Nevertheless, this scenario is excluded from the RMSE computational analysis.

4.2.1. Scenario 2

The second scenario stated that the bike is ahead of the car, and that the bike stops before the signalized intersection. **Table 5** shows the obtained results of the smallest RMSEs for each participant.

Table 5 Smallest RMSEs in Scenario 2

Participant ID #	Smallest RMSE (x)	Normal distribution
1201	7.9	0.0442
1202	8.9	0.0492
1204	11.0	0.0578
1209	9.9	0.0539
1212	13.8	0.0608
1216	29.3	0.0028
1218	4.0	0.0227
1220	7.2	0.0402
1221	9.2	0.0508
1223	15.1	0.0586
1224	19.1	0.0404
1228	14.9	0.0589
1230	13.6	0.0610
1231	3.0	0.0182
1235	20.9	0.0304
1236	21.8	0.0255
1239	12.0	0.0601
1243	9.9	0.0540
1245	4.9	0.0272
1247	18.2	0.0453

As shown in **Table 5**, the RMSE of participant 1231 (RMSE=3) was selected as the smallest RMSE. Mean (=13.15), variance (=42.61), and standard deviation (=6.52) were acquired for **Table 5**. The bell-shaped standard normal distribution chart for **Table 5** is shown in **Figure 9**.

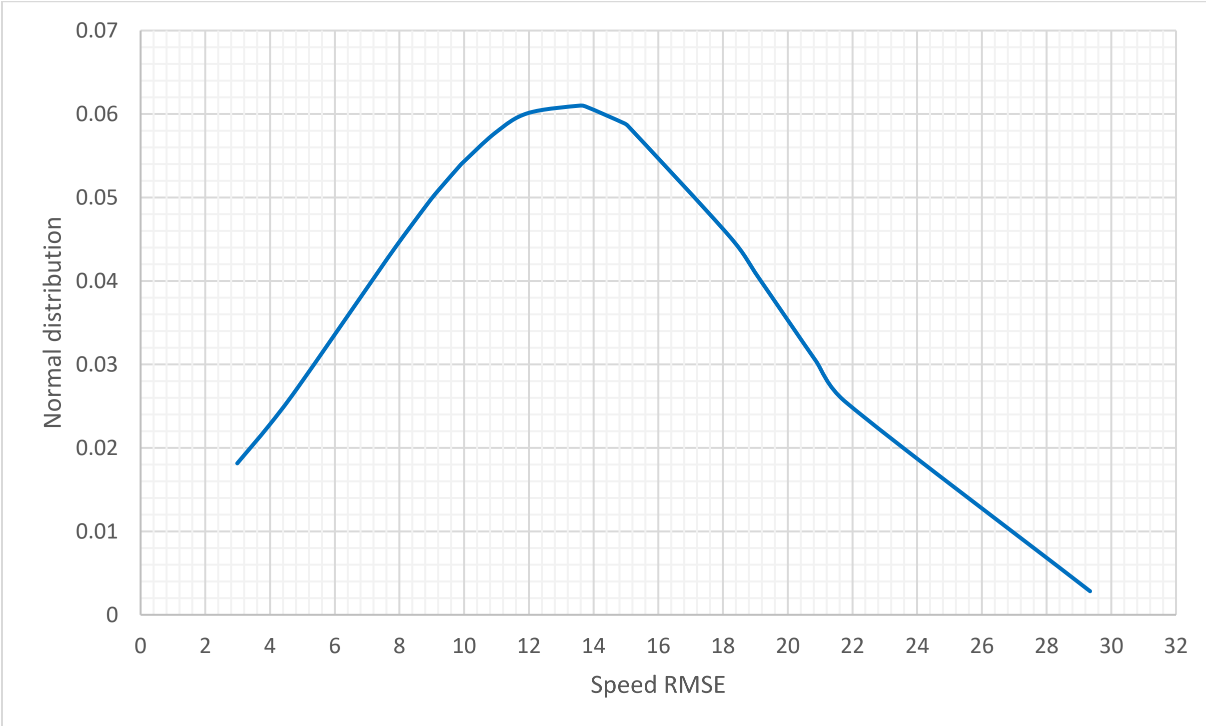

Figure 9 Standard normal distribution chart in scenario 2

The speed trajectory for participant #1231 is shown in **Figure 10**.

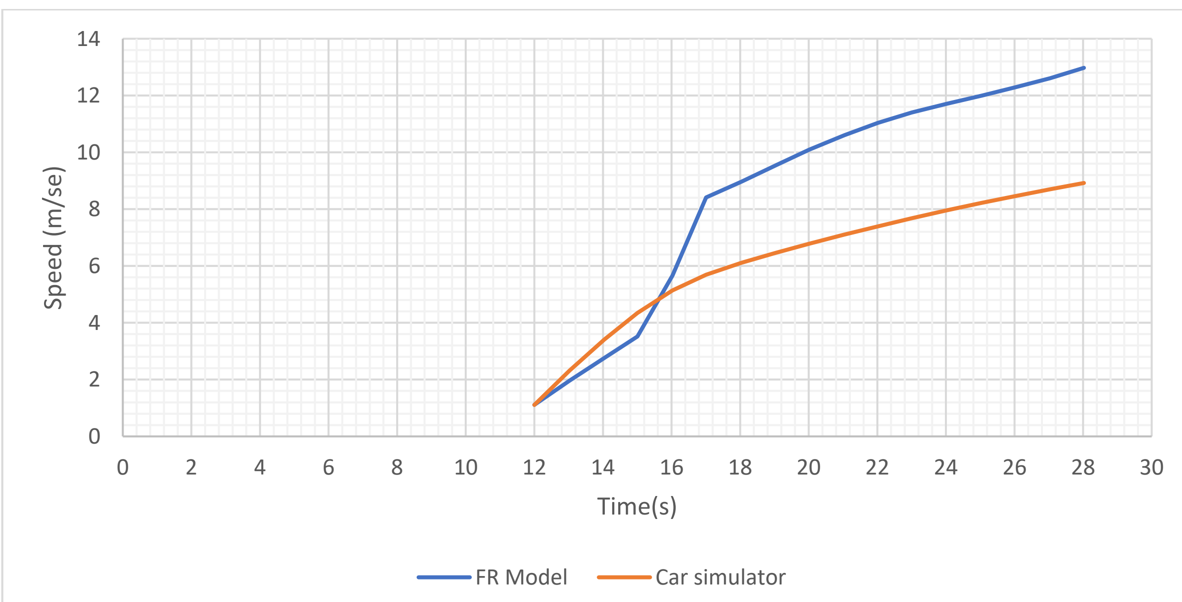

Figure 10 Speed trajectory (RMSE=3) in scenario 2

Figure 10 shows that the obtained speed changes by FR car-following model (MATLAB code) were greater than the values of collected speeds by car simulator. The FR model's speeds experienced a considerable jump after the 16th event. Furthermore, mean (=8.63), variance

(=4.79), and standard deviation (=2.19) were obtained for the smallest RMSE in scenario 2. **Figure 11** shows the acceleration trajectory for the smallest RMSE in scenario 2.

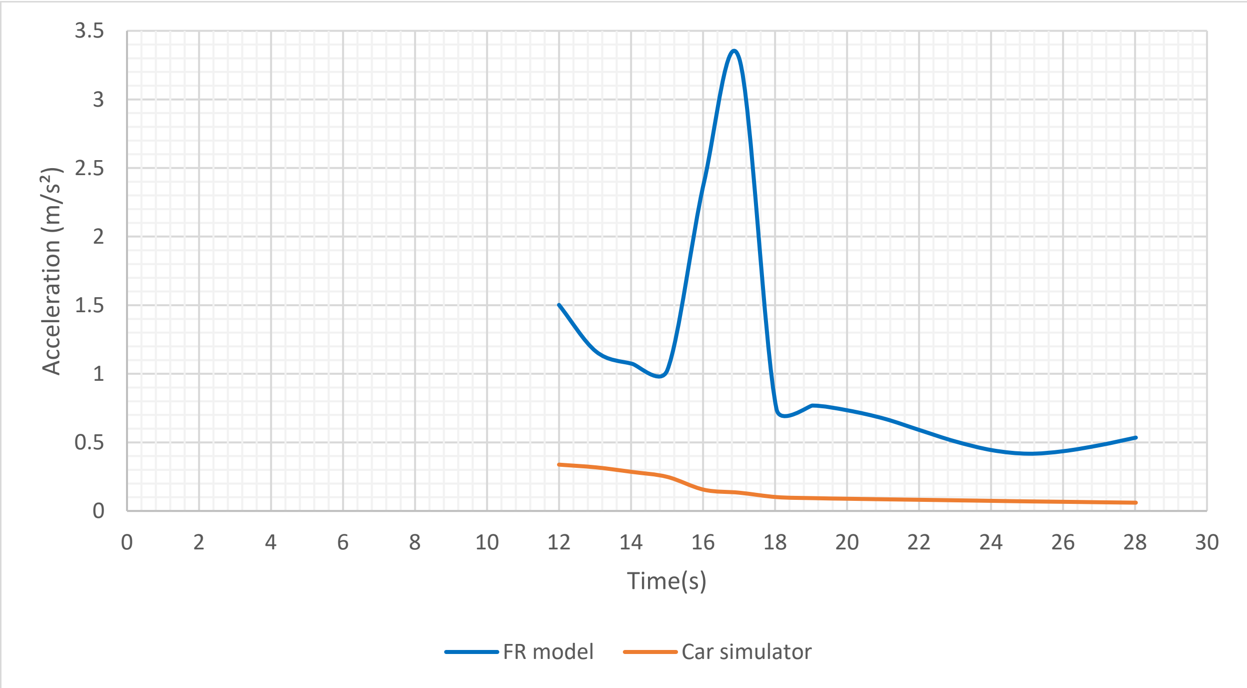

Figure 11 Acceleration trajectory of the smallest RMSE in scenario 2

4.2.2. Scenario 3

In the third scenario, the bike was positioned in front of the car. Bikes and cars were run from 492 ft (150m) before the signalized intersection to 492 ft (150m) after the signalized intersection. The bike had to pass the intersection, and both the bike and the car had to stop after the signalized intersection. **Table 6** shows the obtained results of the smallest RMSEs for each participant in the third scenario. As shown in **Table 6**, the RMSE of participant 1246 (RMSE=3.6) was selected as the smallest RMSE. Mean (=12.32), variance (=51.62), and standard deviation (=7.18) were procured for **Table 6**. The bell-shaped standard normal distribution chart for Table 6 is shown in **Figure 12**.

Table 6 Smallest RMSEs in Scenario 3

Participant ID #	Smallest RMSE (x)	Normal distribution
1203	4.6	0.0313
1204	17.9	0.0411
1206	19.2	0.0351
1209	11.4	0.0551
1220	6.3	0.0389
1224	17.3	0.0437
1228	11.4	0.0551
1230	6.6	0.0406
1236	6.5	0.0398
1239	5.3	0.0344
1242	13.8	0.0544
1243	31.5	0.0016
1244	15.0	0.0517
1246	3.6	0.0267
1247	9.7	0.0521

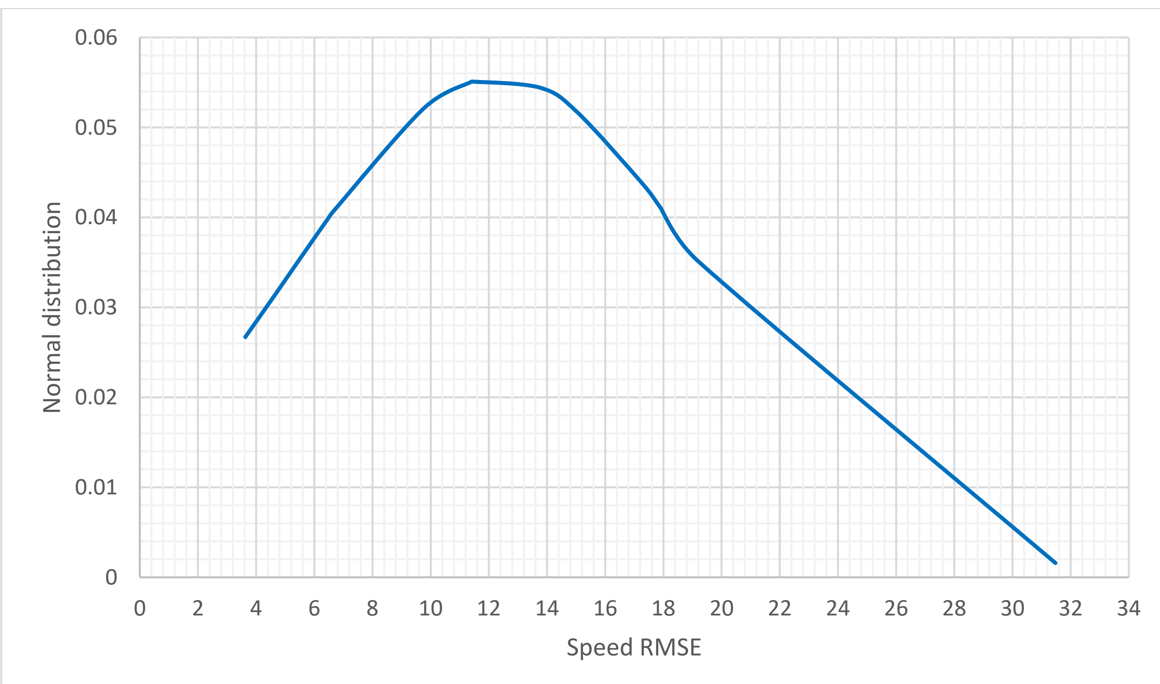

Figure 12 Standard normal distribution chart in scenario 3

The speed trajectory for participant #1246 is shown in **Figure 13**.

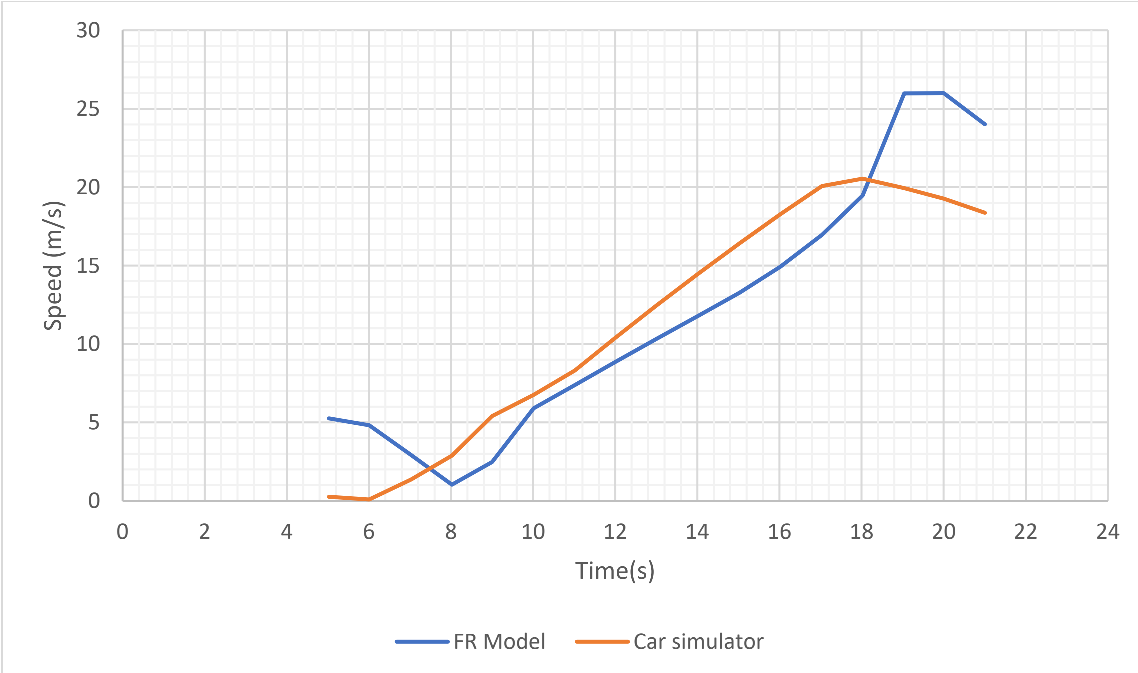

Figure 13 Speed trajectory (RMSE=3.6) in scenario 3

As shown in **Figure 13**, the speed values obtained by the FR model is less than the speed values by collected by the car simulator after the 7th event. The FR speed chart experienced a sharp jump in the 17th event and were greater than speed values collected by the car simulator. Additionally, mean (=11.84), variance (=4.47), and standard deviation (=2.17) were obtained for the smallest RMSE in scenario 3. **Figure 14** shows the acceleration trajectory for the smallest RMSE in scenario 3.

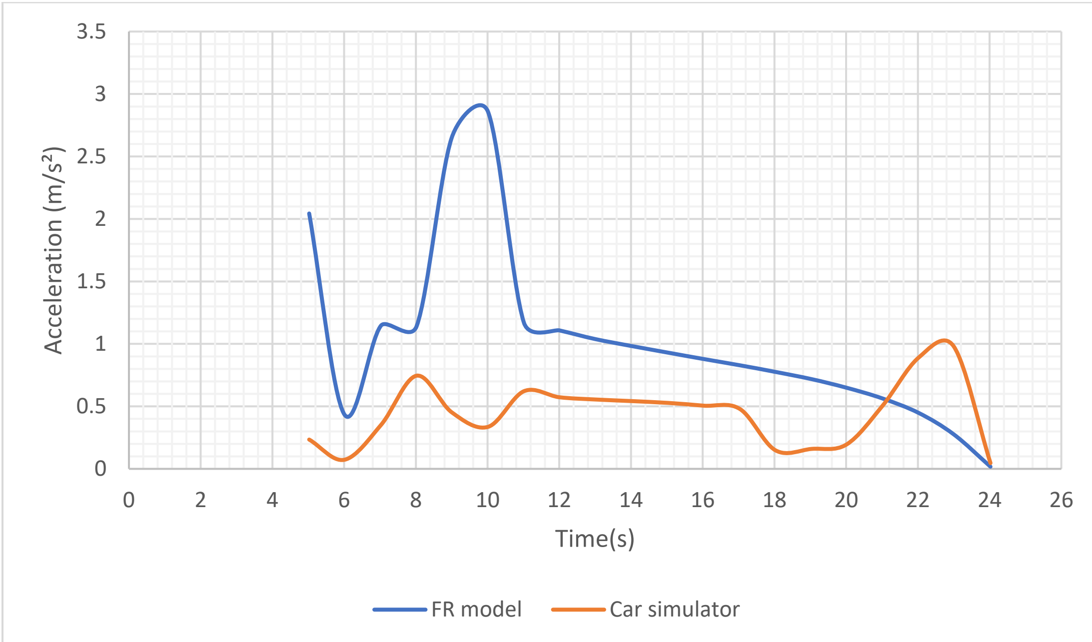

Figure 14 Acceleration trajectory of the smallest RMSE in scenario 3

4.2.3. Scenario 4

Scenario 4 declared that the bike is behind the car and that the bike must stop before the signalized intersection. **Table 7** shows the obtained results of the smallest RMSEs for each participant in the fourth scenario. As shown in **Table 7**, the RMSE of participant 1236 (RMSE=1.3) was selected as the smallest RMSE. Mean (=7.73), variance (=24.22), and standard deviation (=4.92) were obtained for **Table 7**. The bell-shaped standard normal distribution chart for **Table 7** is shown in **Figure 15**.

Table 7 Smallest RMSEs in Scenario 4

Participant ID #	Smallest RMSE (x)	Normal distribution
1201	5.5	0.0734
1206	22.6	0.0008
1210	3.9	0.0598
1212	8.2	0.0807
1218	6.3	0.0778
1220	5.9	0.0753
1221	5.6	0.0735
1222	8.0	0.0809
1223	14.6	0.0304
1224	10.1	0.0721
1233	3.6	0.0567
1236	1.3	0.0346
1242	9.2	0.0773
1244	7.6	0.0810
1245	4.5	0.0655
1246	3.0	0.0513
1247	2.7	0.0480
1250	8.5	0.0802

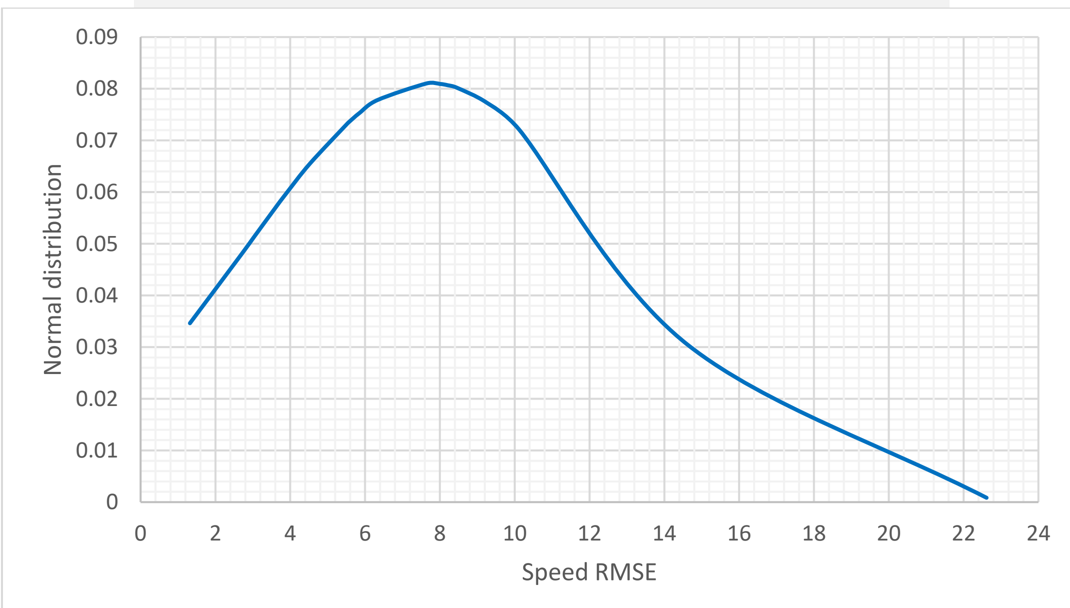

Figure 15 Standard normal distribution chart in scenario 4

The speed trajectory for participant #1236 is shown in **Figure 16**.

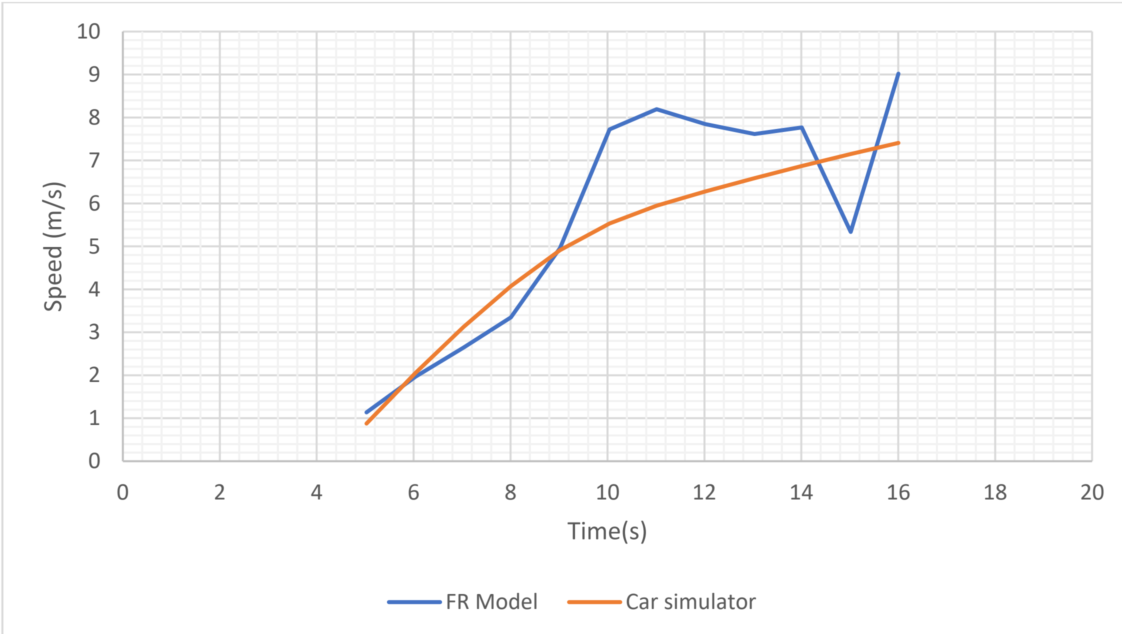

Figure 16 Speed trajectory (RMSE=1.3) in scenario 4

As shown in **Figure 16**, the speed values collected by the FR model were less than those collected by the car simulator from the 6th to 9th events, and in the 15th event. Speed values collected by the FR model also experienced an ascending slope from the 9th to 14th event, and the speed trajectory collected by the car simulator experienced a mild ascending slope from the 5th to 16th event. Moreover, mean (=5.6), variance (=1.55), and standard deviation (=1.24) were obtained for the smallest RMSE in scenario 4. **Figure 17** shows the acceleration trajectory for the smallest RMSE in scenario 4.

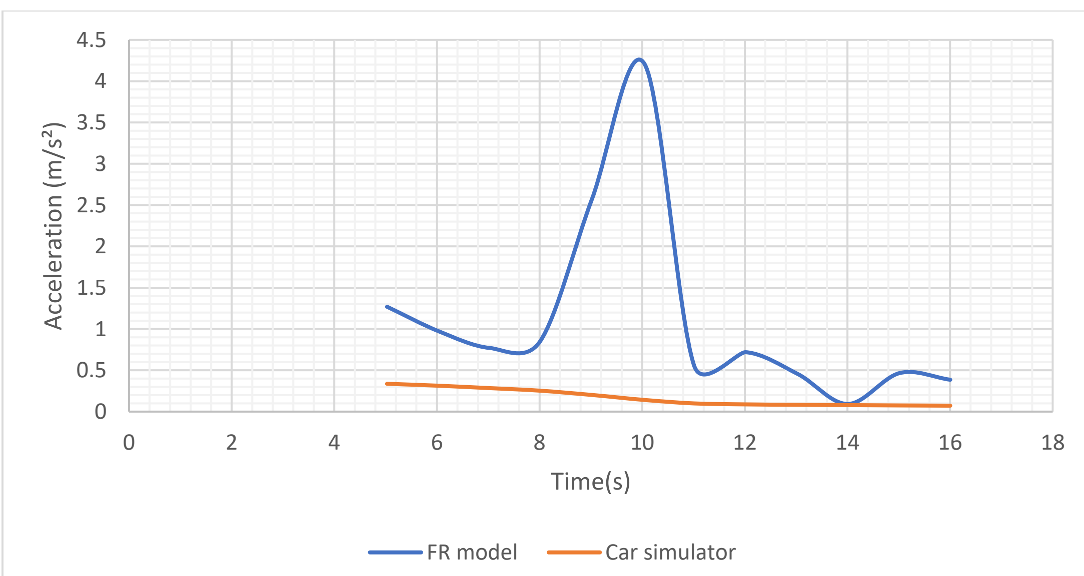

Figure 17 Acceleration trajectory of the smallest RMSE in scenario 4

4.2.4. Scenario 5

Scenario 5 is nearly identical to scenario 3, however the bike is positioned behind the car. Table 8 shows the obtained results of the smallest RMSEs for each participant in scenario 5. As shown in **Table 8**, the RMSE of participant 1231 (RMSE=1.9) was selected as the smallest RMSE. Mean (=6.61), variance (=10.04), and standard deviation (=3.17) were gained for **Table 8**. The bell-shaped standard normal distribution chart for Table 8 is shown in **Figure 18**.

Table 8 Smallest RMSEs in Scenario 5

Participant ID #	Smallest RMSE (x)	Normal distribution
1201	5.3	0.1108
1202	7.5	0.1119
1203	5.1	0.1091
1205	5.1	0.1087
1209	13.6	0.0124
1218	6.1	0.1171
1220	3.6	0.0823
1222	3.9	0.0317
1223	2.1	0.0525
1231	1.9	0.0488
1233	8.5	0.0975
1235	6.3	0.1176
1239	7.3	0.1140
1242	5.8	0.1160
1243	5.3	0.1113
1244	8.8	0.0928
1245	7.4	0.1134
1247	13.4	0.0139

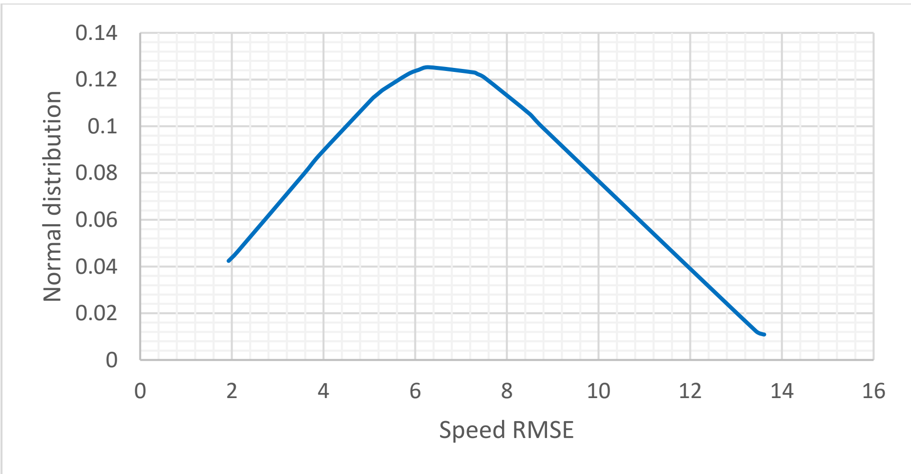

Figure 18 Standard normal distribution chart in scenario 5

The speed trajectory for participant #1231 is shown in **Figure 19**.

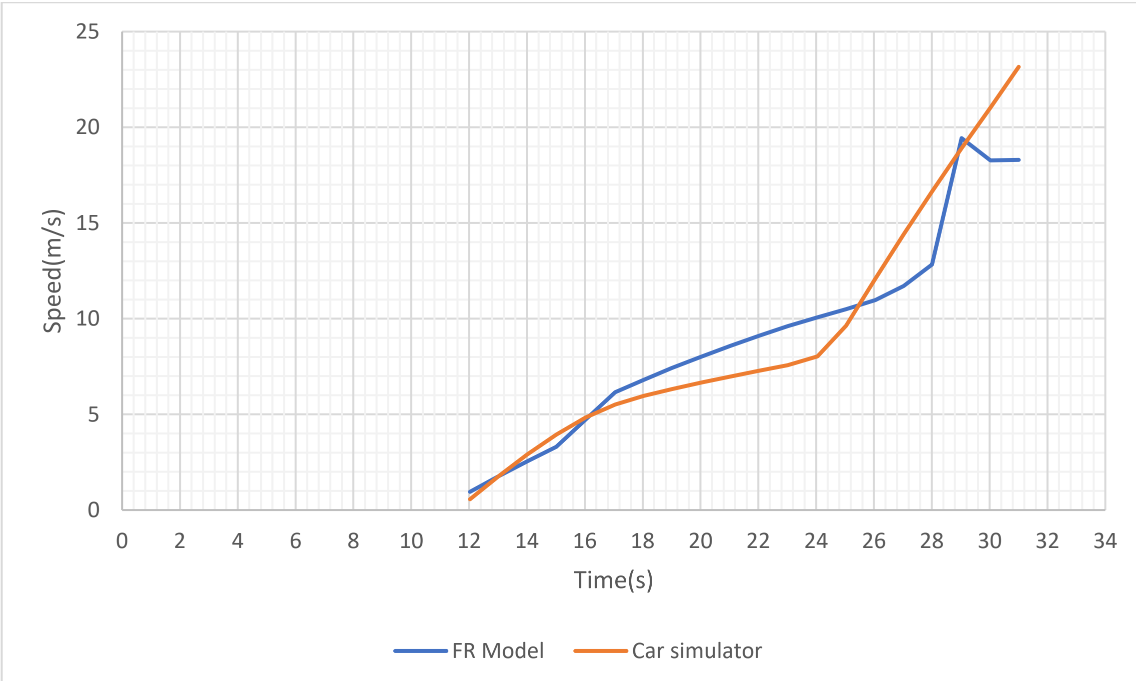

Figure 19 Speed trajectory (RMSE=1.9) in scenario 5

As shown in **Figure 19**, the speeds obtained by the FR model are less than those collected by the car simulator in the 12th to 16th events, and the 25th to 31st events. Both trajectories experienced a mild ascending slope from events 16 to 25. Mean (=9.1), variance (=1.31), and standard deviation (=1.14) were obtained for the smallest RMSE in scenario 5. Goodness of fit for participant 1231 was calculated as 0.997, showing how well sample data resembles a normal distribution. **Figure 20** shows the acceleration trajectory for the smallest RMSE in scenario 5.

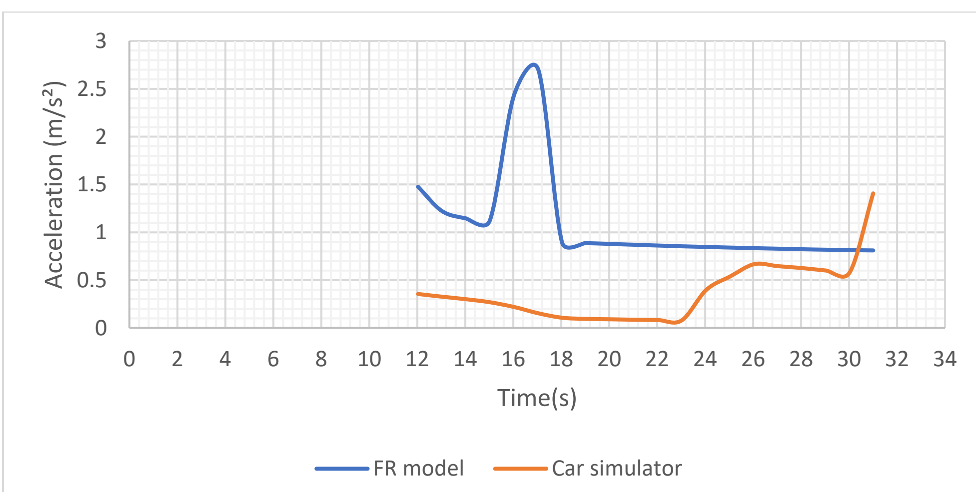

Figure 20 Acceleration trajectory of the smallest RMSE in scenario 5

4.2.5. Scenario 6

Scenario 6 states that the car must turn right in the intersection, the bike is ahead of the car, and the bike must go straight until it passes the signalized intersection. This scenario was designed to investigate the performance of car drivers when interacting with bicyclists at signalized intersections. In the sixth scenario, bicyclists started riding straight and the car driver started to turn right from west bound to south bound. A conflict was seen at the middle of the intersection between car drivers and bicyclists, although most participants respected bicyclists' right-of-way in the conflict area. The confliction area is shown in **Figure 21**.

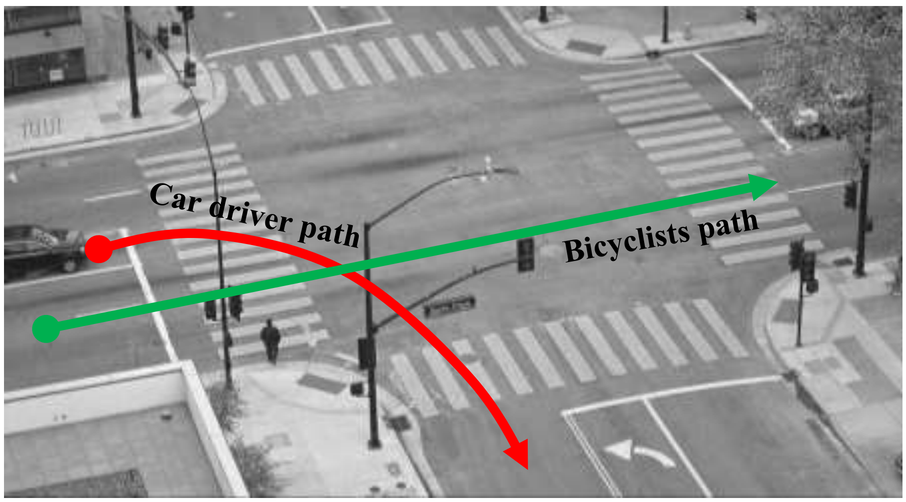

Figure 21 Conflict area

Table 9 shows the obtained results of the smallest RMSEs for each participant in scenario 6. As shown in **Table 9**, the RMSE of participant 1239 (RMSE=2.4) was selected as the smallest RMSE. Mean (=9.3), variance (=35.98), and standard deviation (=5.99) were acquired for **Table 9**. The bell-shaped standard normal distribution chart for Table 9 is shown in **Figure 22**.

Table 9 Smallest RMSEs in Scenario 6

Participant ID #	Smallest RMSE (x)	Normal distribution
1201	5.2	0.0526
1209	15.7	0.0378
1216	12.2	0.0594
1218	4.0	0.0452
1220	16.0	0.0358
1223	17.3	0.0276
1229	4.0	0.0449
1233	5.8	0.0560
1235	6.0	0.0573
1239	2.4	0.0342
1242	3.2	0.0397
1247	18.5	0.0205

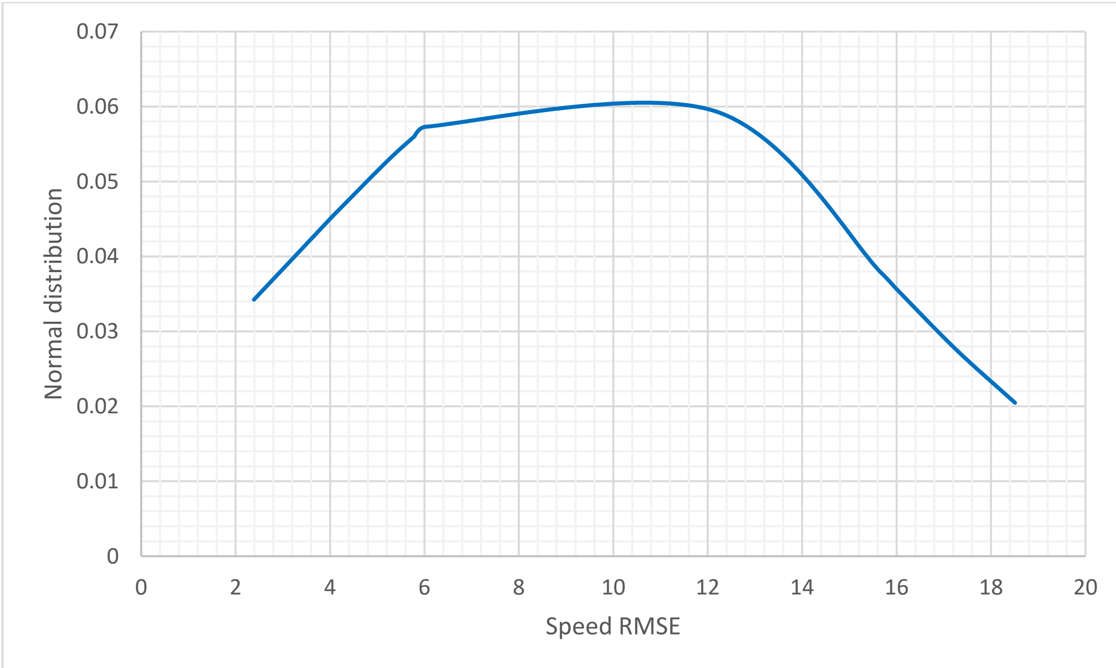

Figure 22 Standard normal distribution chart in scenario 6

The speed trajectory for participant #1239 is shown in **Figure 23**.

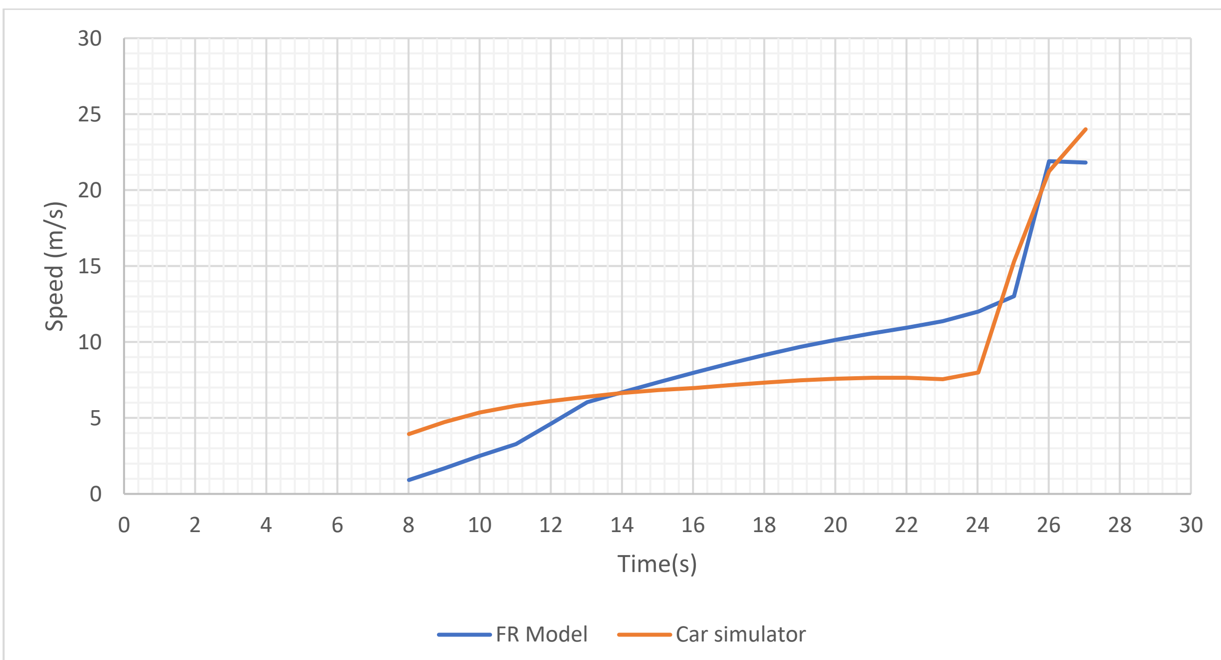

Figure 23 Speed trajectory (RMSE=2.4) in scenario 6

Figure 23 shows that the FR model speed values are less than the car simulator speed values in the8th to 13th and 25th to 27thevents. The FR model speed values experienced an ascending mild slope from the 13th to 25th events, while the car simulator speed values experienced a nearly constant slope in this time interval. The mean (=9.01), variance (=4.12), and standard deviation (=2.03) were obtained for the smallest RMSE in scenario 6. **Figure 24** shows the acceleration trajectory for the smallest RMSE in scenario 6.

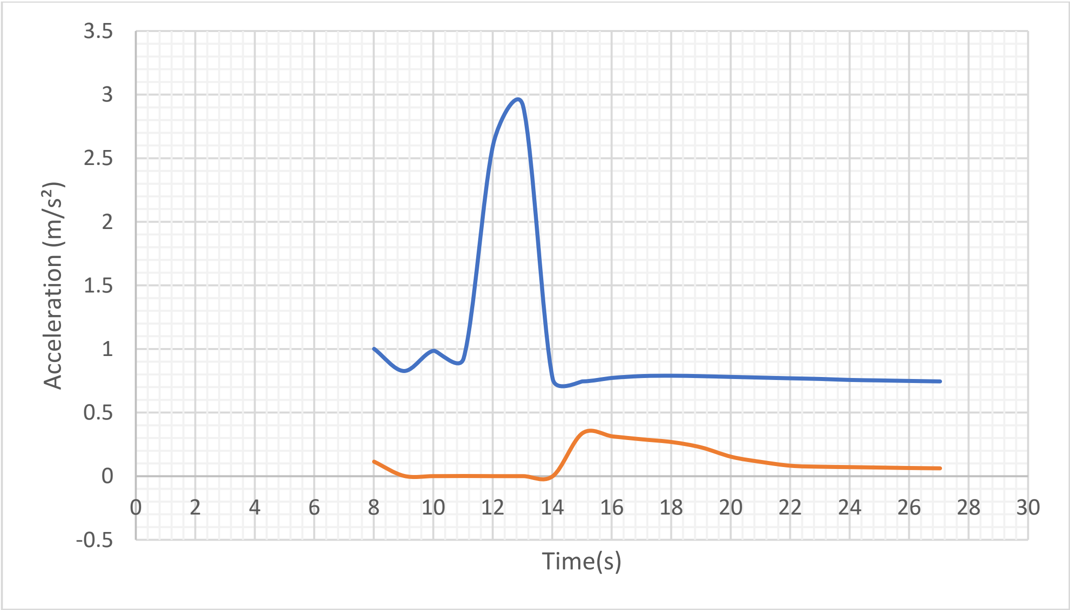

Figure 24 Acceleration trajectory of the smallest RMSE in scenario 6

4.3. Optimal "a, b, and d" model parameters (the driver input to the gas pedal)

The smallest RSMEs in each scenario identified to detect the optimum model parameters. These three values are parameters that are calibrated to a specific driver and model the driver input to the gas pedal. The smallest RMSE in each scenario was scrutinized, and the optimum model parameters for participants #1231 in scenario 2, #1246 in scenario 3, #1236 in scenario 4, #1231 in scenario 5, and #1239 in scenario 6 were specified. **Table 10** shows the optimum model parameters.

Table 10 Optimal model parameters (a,b,d)

Scenario	RMSE	Optimal model parameters		
		a	b	d
2	3.0	1.796533695	0.292836385	0.400371922
3	3.6	1.357236292	0.083090091	0.254186277
4	1.3	0.982307127	0.255301632	0.389939398
5	1.9	1.529238754	0.0391814	0.223062249
6	2.4	1.110173497	0.059169787	0.234473687

5. CONCLUSION

The research presented in this report validates the performance of the Fadhloun-Rakha (FR) car-following model. The FR car following model demonstrates the following unique characteristics:

1) Explicitly modeling the driver throttle and brake pedal input in a single continuous equation
2) Explicitly capturing driver perception and control inaccuracies and errors
3) Modeling vehicle dynamics using a point-mass model
4) Allowing for shorter than steady-state following distances when following faster leading vehicles
5) Ensuring collision-free driving

Thirty-three participants were invited to ride the bike simulator and drive the car simulator simultaneously. Both simulators were integrated together, and each driver could see the location of the other participant in the simulation time interval. Six scenarios were developed. Scenario 1 was designed to investigate the performance of bikes on the road. Scenario 2 to 6 were designed to evaluate the behavior of both participants (bicyclist and car driver) when both simulators are integrated, and especially the interaction time intervals between bicyclists and other road users on the simulated network. The FR model respects vehicle dynamics constraints and uses very similar collision-avoidance strategies to ensure a safe following distance between vehicles. In addition, the FR model explicitly captures human driving variability in its acceleration function. The research investigated the performance of FR model on a laboratory collected dataset. The data includes traffic features collected from both simulators on a real-word simulated network.

The FR car following model was validated based on data collected from33 participants in each scenario. Root Mean Square Error (RMSE) was used as an efficient indicator of the ability of a car-following model to replicate empirical behavior from a statistical perspective. A reliable sample including 100 (a,b,d) pairs was selected to find the RMSE and optimum model parameters. In total, 83 reliable databases were determined and the RMSE values were calculated. The FR model was rewritten in MATLAB software (**Equations 1-12**) to find the speed, position, and acceleration values. First and foremost, the speed values from MATLAB code (FR model) were obtained, then the speed values for each participant were compared with the collected speeds from the car simulator. RMSE values were determined, and the smallest RMSE among 100 RMSEs for each participant in each scenario was specified. Additionally, the speed and acceleration trajectories for the smallest RMSE were drawn. Eventually, the optimal model parameters (a,b,d) values were identified.

This research effort was initiated mainly for the purpose of investigating the performance of the FR model with empirically observed driver behavior and capturing driver perception while controlling inaccuracies. The results highlighted the acceptable performance of the FR model in comparison with the collected speed, acceleration, and deceleration values from the simulators. Furthermore, three parameters a, b, and d (besides the vehicle and roadway parameters, which are typically known) were successfully calibrated as shown in **Table 10**.

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