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Analyzing bicycle level of service using virtual reality and deep learning technologies

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ABSTRACT

Bicycle Level of Service (BLOS) provides an essential tool for evaluating the operations of low-carbon bicycle facilities and prioritizing investment in new bicycle facilities under various constraints. This study aimed at developing a LOS method for assessing bicycle facilities in the metropolitan areas of China. Using this method, we addressed major challenges in obtaining user ratings of bicycle facilities and captured *senses of satisfaction* of bike users riding on bicycle facilities. Virtual Reality (VR) technique was introduced to obtain data by creating 120 immersive settings or scenarios for participants. A hundred of bicyclists or participants with a wide range of characters were recruited. These participants were asked to express their senses of satisfaction under predefined physical conditions of bike facilities and traffic conditions. Their Satisfaction Rating Scores (SRS) were documented. The statistical relationships between rider's feelings and bike facilities/traffic conditions were modeled and verified through a symbolic regression (or an effective deep learning) approach. The model is demonstrated to be reliable in predicting SRS of bicyclists with a high correlation coefficient. This study also developed a set of LOS criteria based on the cumulative distribution of satisfaction scores. These LOS criteria are simple to use and effective in assessing operational performance of existing bicycle facilities and providing decision makers with insightful guidance for planning, designing, and operating new active transportation facilities.

1. Introduction

Many countries, when coping with social, economic, environmental, and public health issues caused by motorized transportation, are looking for active transportation modes to change people's travel behaviors. One of the most recommended active and low-carbon transportation modes is bicycle (Gatersleben and Appleton, 2007; Teixeira and Lopes, 2020). To promote this mode, transportation agencies are encouraged to construct new bicycle facilities and improve/upgrade existing bicycle facilities. In Beijing, China, a 3200 km bike network within the 5th Ring Road is under construction, according to the five-year strategic plan (2016–2020) of the Beijing Municipal Commission of Transport (BMCT, 2016).

There are four bike facility types in China, that is, bike paths separated by greenbelt, bike paths separated by guardrail, bike lanes,

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and bike routes as shown in Fig. 1. Bike paths provide a dedicated right of way for bicyclists and channel non-motorized traffic away from motorized vehicles. Normally, these bike paths, which are aligned with vehicle lanes (see Fig. 1(a) and (b)), are wide enough to allow bicyclists to ride side to side at a high speed (approximately 25 km/h or 15 mile/h) or seek sufficient spaces to pass other preceding bicyclists if necessary. These bike paths are on-road one-way facilities, different from off-road bike paths in United States and other countries that allow bicyclists to ride in two directions. In addition, these bike paths are different from shared-use bike paths where bicyclists and other users often share their right of way, causing their travel speed to be low.

Bike lanes allow bike users to travel side by side (see Fig. 1(c)). Bike users on these bike lanes are often influenced by traffic on adjacent vehicle lanes. Different from bike lanes, bike routes enable vehicles to share right of way with bike users (as shown in Fig. 1 (d)).

There were researchers who quantified bicycle level of service (BLOS) using a concept of events (that is, "passing" or "meeting" maneuvers) and hindrances (or delays) experienced by riders during events (Botma, 1995; Li et al., 2013; Hallett et al., 2006; Hummer et al., 2006; and Liang et al., 2017). The BLOS criteria were defined by the frequency of events and their statistical relationships with other measures such as directional volumes, speed, lane width, etc. The Highway Capacity Manual (HCM) has adopted this concept and developed a framework of BLOS measurements through the cumulative distribution probability of "meeting" and "passing" per minute (HCM, 2016). For dedicated off-road bike paths, the BLOS is classified into six categories: A-F. The pro of this method is that the BLOS is clearly linked to physical settings and its classification can be derived by a concise mathematical model. The con of this method is that it is not fitted to all bike facility types.

Another set of studies on BLOS attempted to establish statistical relationships between operational performances of bicycle facilities and their influencing factors (Dixon, 1996; Landis et al., 1997; Harkey et al., 1998; Noël et al., 2003; Jensen, 2007; Petritsch et al., 2007; Dowling et al., 2008; Li et al., 2012; Foster et al., 2015; Asadi-Shekari et al., 2015; Fang et al., 2016; Bai et al., 2017; Chen et al., 2017; and Griswold et al., 2018). These studies evaluated BLOS from the perspectives of bike riders. The researchers asked riders to rate the quality of bicycle facilities through questionnaires/roadside surveys (Dixon, 1996; Landis et al., 1997; Noël et al., 2003; Li et al., 2012; Bai et al., 2017) or watching videos clips (Petritsch et al., 2007; Harkey et al., 1998; Jensen, 2007; Dowling et al., 2008; Foster et al., 2015; Chen et al., 2017; and Griswold et al., 2018). Statistical or regression models were developed to link bike operation to geometric factors (such as width of bike facilities and number of vehicle lanes) and traffic conditions (such as traffic volume and speed, percentage of heavy vehicles, bus stop, presence of parking, and pavement quality). As indicated in the literature review research undertaken by Kazemzadeh and his team, the methods for analyzing the characteristics of on-road and off-road bike facilities should be improved (Kazemzadeh et al., 2020). We believe that one of the improvements for developing statistical models among the performance of bike facilities, bike flow, and other exogenous factors is to collect satisfaction ratings of bicyclists by immersing bicyclists into their riding settings either through actual-riding-on-bike-facility or Virtual-Reality-(VR)-riding surveys. The traditional questionnaire-based video techniques do not put surveyors (as bicyclists) into actual bike flows and rate the performance of bike facilities. Therefore, their ratings and the models developed from these ratings most likely do not truly reflect the perspectives of actual bike riders.

Another improvement on BLOS is to develop customized methods or models that can be used as guidance for decision-makers and planners. Currently, there have not been an effective method available in China for analyzing characteristics of bike flows, assessing operational performance (such as Level of Service (LOS)) of bike facilities, and providing guidance for planning, design, construction,

(a) bike path separated by greenbelt
(b) bike path separated by guardrail
(c) bike lane separated by strip
(d) bike route without any separator

Fig. 1. Bike facilities in China.

and operation of bike facilities. The current methods and the Code used in China determine BLOS through three factors only: riding speed, occupied road area, and Volume/Capacity (V/C) (%) (MOHURD, 2016). They do not consider other important factors such as bicycle facility type, width of bike facilities, bus stops, presence of buses at bus stops, on-street parking, and influence of motorized vehicles on adjacent lane. In addition, the Code defines the four levels of service based on engineering judgment and experience.

The approaches used in Highway Capacity Manual (HCM, 2016) could be adopted to improve BLOS determination in China. However, these approaches do not address unidirectional bike paths in China where passing maneuvers are often encountered. As bicycle travel environment and dynamics (characterized by large bicycle volume, high speed of bike flow, and unique traffic regulations) in China are different from those described in HCM, the HCM approaches might not be suitable for China. The Chinese highway design manuals have not yet provided specific approaches or guidelines to determine LOS of bike facilities. As a result, developing a LOS method adaptive to the bicycle travel environment in China is very important.

This paper is aimed at developing a BLOS method for metropolitan areas of China. The contribution of this paper has three aspects. First, this paper provides a new method of using VR technologies to collect *satisfaction rating scores* (SRS) of bicyclists riding on bike facilities in Beijing, China. Different from collecting SRS through direct interviews or roadside surveys, the VR approach enabled bicyclists or participants to wear VR goggles to immerse themselves into bike flows and experience bike dynamics without exposing themselves to the dangers of traffic, while they assessed the performance of bike facilities and provided their SRS values. This VR approach is proven in this study to be effective and accurate in representing actual bicyclists on bike facilities experiencing their interactions with other bicyclists and surrounding settings.

Second, a deep-learning method (or a symbolic regression method in particular) was used in the study to establish statistical relationships among satisfaction rating scores, bike flows, physical settings of bike facilities, and traffic conditions. The symbolic regression method does not need a priori assumptions on a specific form of functions to be modeled. In this research, the symbolic regression method was first introduced to study BLOS in Beijing, China and a suitable mathematical model was established to link SRS to its influencing factors through deep learning. The model is demonstrated to be reliable in predicting SRS of bicyclists with a high correlation coefficient.

Third, a set of LOS criteria was developed for all types of bike facilities based on the cumulative distribution of satisfaction scores and the symbolic regression model. These LOS criteria are simple to use and effective in assessing operational performance of existing bicycle facilities and providing decision makers with insightful guidance for planning, designing, and operating new active transportation facilities.

This paper is structured as follows. Section two describes the use of VR technologies in collecting satisfaction rating scores of bicyclists riding bikes in VR scenes. This section also highlights that the VR-based SRS are equivalent to those collected from bicyclists

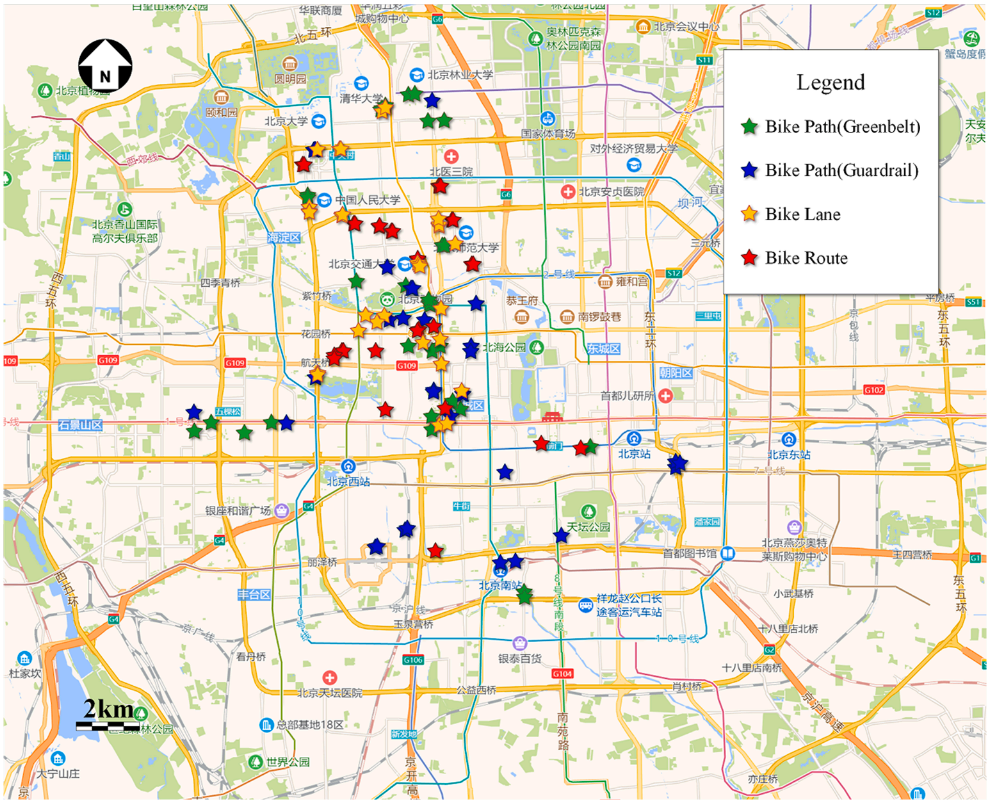

Fig. 2. Field investigation sites or segments.

riding on actual bike facilities. Section three provides the development process of a symbolic regression model for all types of bike facilities. The symbolic regression model is furthered used in Section four to establish the relationships between bicycle level of service and satisfaction rating scores. In the next section, the BLOS criteria are also described according to the cumulative distribution of satisfaction scores. A discussion is followed by describing the potential use of the BLOS criteria in policy development for bicycle facilities. The last section concludes the paper by summarizing the research findings of this study and outlining the direction of future research.

2. Data collection using VR technologies

Senses of satisfaction of bike users riding on bicycle facilities were collected using Virtual Reality techniques. As shown in Fig. 2, the data collection started from identifying testing sites or segments of bike facilities. A total of 120 video clips or VR scenes (on 95 road segments) were established to reflect actual riding environments of bicyclists. Using these clips, we collected riders' feelings from immersive environments. A hundred of bicyclists or participants with a wide range of characters were recruited. These participants, while riding bicycles, were asked to express their senses of satisfaction when riding under VR scenes. Their Satisfaction Rating Scores were documented. The details of the data collection process are as follows:

2.1. Site characteristics

The sites selected for the study are located in the Center District of Beijing, China. They are 95 road segments (with approximately equal length) where bicyclists were observed (see Fig. 2). These testing segments were surrounded by a diverse range of roadside land developments (for residential, commercial, and educational use) and environmental conditions. Among these segments, 24 segments came from greenbelt separated bike paths, 27 segments from guardrail separated bike paths, 22 segments from bike lanes, and 22 segments from bike routes.

Table 1 provides a list of attributes and traffic conditions of the testing segments. The actual widths of the segments are ranged from 1.2 m to 7.0 m. In detail, the average actual and effective widths of the segments in the greenbelt separated bike paths are 4.04 m and 3.86 m, respectively. Similarly, the widths of the segments in the guardrail separated bike paths are 2.93 m and 2.93 m. The widths of the segments in the bike lanes are 3.21 m and 2.91 m, while the actual and effective widths of the segments in bike routes are 3.97 m and 3.61 m.

There were two segments of greenbelt separated bike paths where pedestrian fences were provided. Additionally, pedestrian fences existed within nine segments of guardrail separated bike paths, 11 segments of bike lanes, and five segments of bike routes, respectively. Bus stops were observed during the investigation. There were ten segments of bike lanes and five segments of bike routes where bus stops were found. During the field investigation, buses were observed to stop at 11 stops within the segments of bike lanes and five

Table 1
Data collected from the sites or the segments.

Variable	Description	Bike Path Greenbelt		Bike Path Guardrail		Bike Lane		Bike Route	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Geometric condition of bike facilities									
Actual Width	Bike facility width (meter)	4.04	1.23	2.93	0.67	3.21	1.26	3.97	0.95
Effective Width	Effective bike facility width (meter)	3.86	1.30	2.93	0.67	2.91	1.49	3.61	1.17
Vehicle Lanes	number of through lanes in the same direction of travel as the bicycle facility	–	–	–	–	2.20	1.17	1.07	0.25
Pedestrian fencing	0 (absence)	22		18		11		17	
	1 (presence)	2		9		11		5	
Bus Stops	0 (absence)	24		27		12		17	
	1 (presence)	0		0		10		5	
	Buses at bus stop	0		0		11		5	
On-Street Parking	0 (absence)	19		27		17		9	
	1 (one side)	5		0		5		10	
	2 (two sides)	0		0		0		3	
	On-street parking rate*	24.24%	0.37	0%	0	10.94%	0.25	63.91%	0.43
Traffic condition									
Flow Rate	Bicycle flow (bike/hour)	1067	457	1018	499	944	593	802	439
	E-bicycle flow (bike/hour)	413	510	421	470	346	492	272	360
	Other non-motorized flow (bike/hour)	54	153	96	140	0	0	33	89
	Pedestrian flow (pedestrian/hour)	222	335	114	284	60	180	110	226
	Vehicle flow on adjacent lane(vehicle/h)	/	/	/	/	792	480	652	479
Average Speed	Average bicycle speed (km/h)	15.52	1.28	15.54	1.72	13.52	2.02	13.96	1.45
	Average E-bicycle speed (km/h)	20.97	3.13	19.99	3.69	19.75	3.23	17.73	2.92
	Average other non-motorized speed (km/h)	15.42	5.19	14.90	3.85	–	–	14.03	1.47
	Average vehicle speed on adjacent lane (km/h)	/	/	/	/	30.05	10.91	24.25	5.03

* Calculated by the ratio of actual parking spaces over the total available parking spaces.

stops within the segments of bike routes, respectively. On-street parking affected the performance of bike lanes and bike routes. There were five one-side on-street parking spaces observed on the segments of greenbelt separated bike paths and on the segments of bike lanes, respectively. Additionally, ten one-side on-street parking spaces and three two-side on-street parking spaces were found within the segments of bike routes. The actual use of on-street-parking (or the ratio of actual parking spaces over the total available parking spaces) during the investigation period was 26.76%, 0%, 14.02%, and 60.56%, respectively for the segments of greenbelt-separated bike paths, guardrail-separated bike paths, bike lanes, and bike routes.

2.2. Third-person perspective, first-person perspective, and VR scenes

After the testing segments were identified for this study, we installed a camera (or a fixed camera) at a pre-set angel along a roadside of a testing segment or on a nearby bridge overpassing a testing segment. Six volunteers were then recruited to ride on the testing segments between May 4 to June 25, 2018. A binocular camera was mounted on the forehead of each volunteer, slightly higher than the eyes of the volunteer. The camera was set to shoot ahead to capture concurrently bike segments and traffic details by its left and right eyes. The images from the left and right eyes are further composited into mosaic images to reconstruct 3D environmental settings. At the same time, the fixed camera was synchronized to record the bike flow on the same testing segment. The original video clips obtained from the fixed camera are later referenced to as *third-person perspective* (TPP) clips or scenes.

Each volunteer rode his or her bike on a testing segment alone, conducted a run during peak hours (AM or PM peak) or off-peak hours, and recorded the actual surroundings of the bike segment. There were 120 runs produced on the four types of bike facilities (see Table 2a). These runs crossed over all the 95 subject segments. Some segments were visited by individual volunteer at different times with different traffic conditions. For example, 19 of the greenbelt separated segments were visited once, 4 twice, and 1 three times. We produced 30 video clips ($19 \times 1 + 4 \times 2 + 1 \times 3$) for the greenbelt separated bike facilities. Table 2b lists the segments visited and the video clips produced by each volunteer. Each time when a volunteer traveled through a segment, he or she was required to keep his or her bicycle stable and maintain the speed same as that of the surrounding bicyclists.

In this study, each video clip lasts 9–22 s long and is referenced later to as the *first-person perspective* (FPP) clip, same as the term used in video games. These clips documented the actual interactions of all the factors as outlined in Table 1. They covered different scenarios of bike and vehicle flows, compositions, and speeds. Additionally, they recorded cases where buses were stopped at their stops and cars were parked at on-street parking spaces.

The FPP clips were randomly sorted and regrouped, and a complete video movie that covered 120 series of scenes was created. Within the movie, every video clip was numbered at its beginning and added extra 5 s blank at its end. The recorded movie was uploaded into the VR devices to form a video of VR scenes for this study. These VR scenes represented simulated environments in which riders wearing VR headsets were immersed in realistic images, sounds, and physical presences of various bike riding settings.

In this study, we asked the volunteers to provide their satisfaction ratings (Jensen, 2007; Asadi-Shekari et al., 2013) as they rode on testing segments. There are five categories of ratings ranging from “excellent”, “good”, “fair”, “bad”, to “terrible” (Li et al., 2012; Fang et al., 2016; Bai et al., 2017; Chen et al., 2017). The “excellent” rating indicates that a volunteer feels extremely comfortable in navigating and riding in the bike flow on a testing segment. Wherever a volunteer feels that the riding environment is extremely uncomfortable, compressed, or even intolerable, the volunteer rates the riding experience as “terrible”. The “good”, “fair”, and “bad” ratings are the ones describing the intermediate perceptions of volunteers in experiencing their riding journeys on testing segments. The “excellent” rating is scored to be 5, the “good” rating 4, the “fair” rating 3, the “bad” rating 2, and the “terrible” rating 1, respectively. It is noted that the volunteers were asked to perceive senses of satisfaction alone and make their ratings based on their own understanding of riding settings.

2.3. A bicycle experimental system and comparison of TPP, FPP, and VR methods

A Bicycle Experimental System (BES), which consists of a standard bicycle, a magnetic steel stand, a VR headset with a Bluetooth remote controller, and a cell phone with the pre-recorded VR video, was developed (see Fig. 3(a)). The steel stand was an inverted V-shaped bracket on which the bicycle could be easily and firmly mounted for each experiment. The control roller on the stand was used to apply a resistant force to the bike and enable participants to mimic some cycling experience on bike facilities.

Before an experiment starts, the BES should be calibrated and adjusted so that the bicycle’s saddles can be set up to consider the height of a tester. In addition, a resistant force is pre-set on the control roller of the BES for each testing segment, which simulates the riding difficulties on the segment. During the experiment, testers wearing the VR headset are asked to call out their satisfactory level as

Table 2a
Number of runsby facility type and number of visits.

	Greenbelt Separated Bike Paths	Guardrail Separated Bike Paths	Segments on Bike Lanes	Segments on Bike Routes	Runs
Segment Visited Once	19	24	15	15	73
Segment Visited Twice	4	3	6	6	38
Segment Visited Three Times	1	0	1	1	9
Total Segments	24	27	22	22	95
Total Visits	30	30	30	30	120

Table 2b
Segments visited and video clips produced by each volunteer.

Volunteer No.	#1	#2	#3	#4	#5	#6	Total
Different Segments Visited	16	17	13	20	17	12	95
Video Clips	22	18	21	21	21	17	120

(a) VR method

(b) FPP method

(c) TPP method

Fig. 3. Three settings for VR, FPP, and TPP methods.

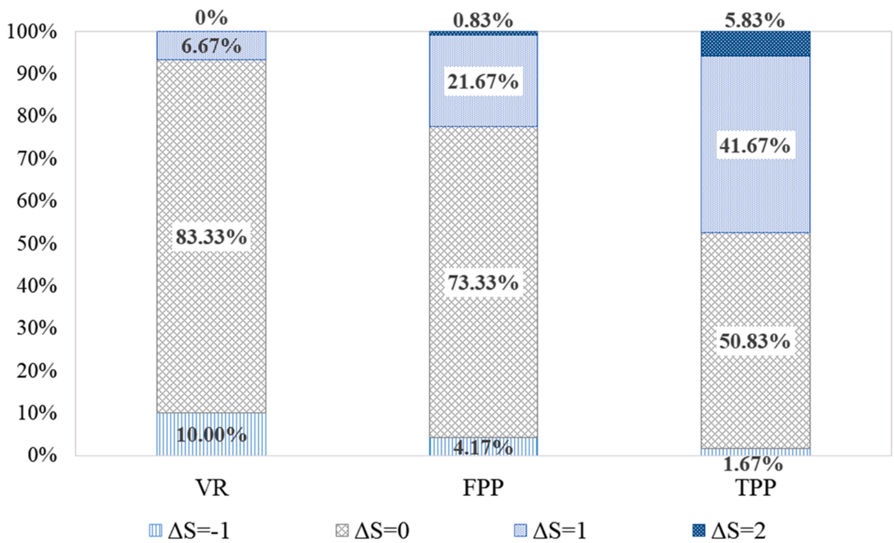

Fig. 4. Satisfaction ratings from VR, FPP, and TPP videos against field ratings. Note: ΔS was defined as the rating score difference of video as comapred with the field rating score.

they ride on testing segments (as presented by the VR video). An assistant standing beside the bike then records the satisfaction score for each subject segment. Testers are asked to ride their bike at the same speed as they perceive in the bike flow. Each tester normally takes about 45 min to complete the rating process of 120 VR scenes (with each clip representing one riding scenario of bike flows and physical conditions of a testing segment).

We asked six volunteers to rate their satisfaction through the immersive VR scenes. We assumed that all the volunteers did not have any collections of their riding experiences several months after they rode on the actual testing segments for the 120 recorded runs. The rating method on VR scenes is referenced later to as the VR method. When the volunteers were asked to rate their satisfaction by watching the FPP and TPP scenes on a computer screen, we named such rating methods as FPP and TPP methods, respectively. Fig. 3 shows the three rating methods.

The six volunteers' satisfaction scores with 120 experimental scenarios were collated to form a matrix (4×120), in which the field ratings and the ratings from the VR, FTT, and TPP methods were compared. The Kappa statistics were employed to quantify and compare frequencies of VR, FPP, and TPP ratings against those of the field ratings. The Kappa coefficients for the VR, FPP and TPP ratings were 0.781, 0.646, and 0.356 ($P < 0.001$), respectively. The results demonstrate that the VR method is the best in keeping the consistency with the field ratings, as we compare it against the TPP and FPP methods.

The research team also conducted an analysis of the VR, FPP, and TPP ratings against the field ratings. The results indicate that the VR ratings match well to the field ratings, while the FPP and TPP ratings have a significant deviation from the field ratings. From Fig. 4, it is noted that 83.33% of the 120 VR scenarios receive the same ratings as those from the field method, 6.67% of the VR scenarios receive the better ratings, and the 10.0% of the VR scenarios receive the worse ratings. When we compare the FPP method with the field method, the FPP method gives 22.50% of the FPP scenarios the better ratings, 4.17% the worse ratings, and 73.33% the same ratings as those with the field method. Similarly, when we compare the TPP method with the field method, we find that the two methods share 50.83% of the runs with the same ratings. The TPP method gives 47.50% of the TPP scenarios the better ratings and 1.67% of the TPP scenarios the worse ratings.

Using the ratings, we can briefly conclude that the TPP method is not a good one. The TPP method provides the volunteers with images which span a large portion of the testing segments from the bystander's point of view. As a result, the volunteers do not feel the interactions between them and other bicyclists in the flow and the TPP ratings, thus, cannot truly represent the operations of the bike facilities. Similarly, the FPP method, which projects the bike flows and other physical conditions of bike facilities onto a computer screen, also cannot make the volunteers immersed in the bike flows. The FPP ratings thus cannot reflect the feelings of the bicyclists. The VR method however is a cost effective and practical method which is equivalent to the field method. It can produce majority of ratings on bike facilities same as those rated from the field observations. As the VR method enables the volunteers to be immersed in bike flows and psychologically experience various forces (including driving forces, collision avoidance forces, boundary forces, contact forces, and sliding friction forces as described in Liang's microscopic model (Liang et al, 2018)) from other bicyclists, it is highly suggested that the labor-intensive field method be replaced by the VR method.

2.4. Satisfaction rating scores from VR scenes

A hundred of bicyclists with their age ranging from 18 to 35 were further recruited as the participants in this study. These bicyclists wore VR headsets, experienced the simulated settings provided by VR videos described in Section 2.3, and gave their satisfaction scores about the traffic flows and the physical conditions of the testing segments.

It is noted that the participants were young bicyclists representing most bike users in China (iiMedia Research, 2018). The sex ratio, 57 males to 43 females, was consistent with the gender profile of bike users in Beijing, China. The selected participants, proficient in riding bicycles for at least one year, self-reported that they did not have any musculoskeletal, neurological, or psychological problems. Before any riding experiments, they practiced themselves with the VR headset and got used to the VR video (without any concerns of dizziness and fatigue). In addition, they did not take any medicines which could cause them to lose their orientation and perception skills.

The experiments were carried out indoor on the BES from September 15 to October 30, 2018 and from October 10 to October 27, 2019. Each participant first completed a registration form with his or her personal profile such as gender, age, and character. Participants claimed themselves to be introversive/extroversive, perceptual/rational, optimistic/pessimistic, impulsive/calm, and a leader/a follower. These 100 participants provided satisfaction scores by watching 120 clips of VR scenes and a total of 12,000 (or 100×120) sets of SRS data were collected for this study.

3. Symbolic regression modeling of SRS

The symbolic regression method was used in this study to establish the relationships among SRS, bike flows, physical settings of bike facilities, and traffic conditions. This method, first introduced by Koza (Koza, 1992), has recently been enhanced to be a strong deep learning method for social studies (Pan et al., 2019), financial analyses (Yang et al., 2015), medical applications (Bhardwaj and Tiwari, 2015; Hughes et al. 2020), biological and ecological assessment (Klotz et al., 2017), applications in physics and chemistry (Sanjuán et al., 2019), analyses along with other artificial intelligence techniques to build symbolic expressions (Staelens et al., 2013; Brunton et al., 2016), traffic studies (Li et al., 2017; Das et al., 2020), and engineering applications (Domínguez-Sáez et al., 2018; Diveev and Shmalko, 2020). Different from conventional regression techniques which optimize parameters based on the statistical relationships of dependent variable and independent variables, the symbolic regression method does not need a priori assumptions on a specific form of the function to be modeled and finds the hidden mathematical formula to predict the target variables with characteristic variables. As a supervised learning method, this symbolic regression method just needs a mathematical expression space which contains candidate function building blocks, e.g., mathematical operators, state variables, constants, and analytic functions. It then searches through the space spanned by the primitive building blocks to find the most appropriate solution. Because this method does not rely on prior knowledge or models, it is especially suitable for finding the implicit relationship between independent variables and dependent variables.

Before a symbolic regression model was developed, the satisfaction rating scores were integrated with 29 exogenous factors collected from the field investigation and VR clips. A data set of 120,00 experimental records was created to link the original observations of SRS to their potential factors. This data set was further divided into two subsets: one subset with 75% of the experimental records for model development through training and deep learning, while the other with 25% of the records for validation.

Initially, the research team thought that participants' gender and character might have strong impacts on their ratings of bike flows and bike facilities. In this study, we used the Levene's test and the paired *t*-test to assess if male participants were different from female participants in rating satisfaction on VR clips (see Table 3). The Levene's test is an inferential statistic used to assess the equality of variances for male/ female, introversion/ extroversion, rational/ perceptual, pessimism/ optimism, impulsive/ calm, and followership/ leadership groups, while the paired *t*-test is the one to assess the equality of means for gender and character of the participants. As the resulting p-values of the Levene's test and the paired *t*-test for gender and character were greater than the significance level ($\alpha = 0.05$) (see Table 3), it is concluded that gender and character do not give significant difference in SRS. In other words, male and female participants are same in "feeling" bike flows and physical conditions of bike facilities. In this study, the participant's gender and character were excluded from the SRS model development.

3.1. SRS models

In this study, 29 variables collected from the field observations and captured from the VR video clips or scenarios were considered as independent variables, while the SRS was the dependent variable (see Table 4). It is noted from the table that there are five sets of satisfaction rating scores: one for segments of all the bike facility types, one for segments of greenbelt separated bike paths, one for segments of guardrail separated bike paths, one for segments of bike lanes, and one for segments of bike routes. The 29 variables provide information about bike facility type, number of vehicle lanes, width of bike facility, presence of bus stop, on-street parking, traffic volume, traffic composition, and traffic speed. The range and the average value of these variables are also listed in Table 4.

Three dummy variables were introduced to represent bike facility types,

Where,

$$x_1 = \begin{cases} 1 & \text{bike route} \\ 0 & \text{other} \end{cases} \tag{1}$$

$$x_2 = \begin{cases} 1 & \text{bike lane} \\ 0 & \text{other} \end{cases} \tag{2}$$

$$x_3 = \begin{cases} 1 & \text{guardrail separated bike path} \\ 0 & \text{other} \end{cases} \tag{3}$$

The variable for bike facility type is expressed as:

$$T = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 \tag{4}$$

where $(x_1, x_2, x_3) = (0, 0, 0)$, it represents a greenbelt separated bike path, (0, 0, 1), it represents a guardrail separated bike path, (0, 1, 0), it represents a strip separated bike lane, (1, 0, 0), it represents a bike route.

Table 3
Gender and character of participants in relation to SRS.

	Class	N	Mean	Std. Deviation	Equal variances assumed			
					Levene's test for Equality of Variances		T-test for Equality of Means	
					F	Sig.	T	Sig. (2-tailed)
Gender	Male	57	3.179	0.338	0.097	0.756	1.392	0.167
	Female	43	3.081	0.365				
Character	Introversion	42	3.182	0.374	0.731	0.395	1.097	0.275
	Extroversion	58	3.104	0.334				
	Rational	64	3.143	0.322	1.454	0.231	0.222	0.825
	Perceptual	36	3.127	0.403				
	Pessimism	14	3.157	0.301	0.131	0.719	0.222	0.824
	Optimism	86	3.134	0.360				
	Impulsive	36	3.183	0.346	0.148	0.701	0.987	0.326
	Calm	64	3.111	0.355				
	Followership	56	3.161	0.379	0.896	0.346	0.757	0.451
	Leadership	44	3.107	0.314				

Table 4
Definitions of variables.

Description	Variable		Range of Variables	Average Value	Parameter
Satisfaction Rating Scores	SRS value for all the types of bike facilities		[1.37,4.54]	3.14	y_{SRS}
	SRS value for greenbelt separated bike path		[2.63,4.54]	3.78	y^{gb}_{SRS}
	SRS value for guardrail separated bike path		[2.40,4.30]	3.53	y^{gd}_{SRS}
	SRS value for bike lane		[1.56,4.13]	2.84	y^{st}_{SRS}
	SRS value for bike route		[1.37,3.22]	2.40	y^{ns}_{SRS}
Type of Bike Facility	Type of Bike Facility[1]	dummy variable 1	{0,1}	–	x_1
		dummy variable 2	{0,1}	–	x_2
		dummy variable 3	{0,1}	–	x_3
	Pedestrian fencing		{0,1}	–	M
Number of vehicle lanes	Number of through lanes in the direction of bike travel		{0,1,2,3,4}	–	N_v
Width of Bike Facility	Actual width (m)		[1.2,7.0]	3.51	w_a
	Effective width (m)		[0.3,7.0]	3.26	w_e
Presence of bus stop	Presence of bus stop		{0,1}	–	P_{bs}
	Buses at bus stop		{0,1,2}	–	N_{bs}
On-street parking	Presence of on-street parking		{0,1,2}	–	P_{pk}
	Parking rate[2]		[0,155%]	24.77%	k_{pk}
Traffic volume	Bicycle flow (b/h)		[212,2700]	957.87	Q_b
	E-bicycle flow (b/h)		[0,1800]	360.85	Q_e
	Other non-motorized flow (b/h)		[0,720]	48.50	Q_o
	Pedestrian flow in traveling direction (p/h)		[0,1385]	126.33	Q_p^+
	Total non-motorized flow[3] (b/h)		[212,5143]	1596.15	Q_n
	Total pedestrian flow (p/h)		[0,4255]	205.49	Q_p
	Total non-motorized and pedestrian flow[4] (b/h)		[212,5143]	1698.89	Q
	Passenger car equivalent volume on adjacent lane[5] (vehicle/h)		[0,1800]	657.54	Q_v
Traffic composition	Proportion of bus[6]		[0,100%]	20.52%	k
	Proportion of bicycle[7]		[7.14%,100%]	66.48%	k_b
	Proportion of E-bicycle[8]		[0%,85.71%]	23.04%	k_e
	Proportion of pedestrian[9]		[0%,50%]	5.90%	k_p
Speed	Average speed of bicycle (km/h)		[7.5,20.2]	14.64	v_b
	Average speed of E-bicycle (km/h)		[11.2,26.9]	19.56	v_e
	Average speed of other non-motorized flows (km/h)		[10.2,23.4]	14.66	v_o
	Average speed of non-motorized flow (km/h)		[7.2,22.8]	15.41	v_n
	Average speed of vehicles on adjacent lane (km/h)		[10.8,63.4]	27.63	v_v
	Maximum speed difference (km/h)		[0,12.1]	2.45	v_Δ

1 Three dummy variables were used to represent lane types.
2 Ratio of actual one-side or two-sides on-street parking spaces to parking spaces avialble one side. For example, a testing segment allows on-street parking on two sides with each side having 5 parking spaces, the maximum value for this variable is 200%, that is, 10 parking spaces from the two sides/5 parking spaces available on one side.
3 Bicycle equivalent units (BEUs) (Jin et al., 2015) converted from non-motorized flow. BEUs were calculated by $Q_b + 1.5\ Q_e + 2\ Q_o$.
4 BEUs converted from all the non-motorized flows and pedestrians. They were calculated by $0.5Q_p + Q_n$.
5 Passenger car equivalent (PCE) (MOT, 2014) calculated by passenger cars plus 1.5 × buses.
6 Calculated by 1.5 × buses/Q_v.
7 Calculated by Q_b/Q.
8 Calculated by $1.5Q_e/Q$.
9 Calculated by $0.5Q_p/Q$.

The symbolic regression method was used to develop the SRS model to link influential factors (such as physical settings of bike facilities and traffic details) to satisfaction rating scores. The SRS model is expressed in the following general form:

$$y_{\mathrm{SRS}} = f(T, M, \ldots, v_\Delta) \tag{5}$$

It is worth noting that there were 120 VR scenarios and for each VR scenario there were 100 satisfaction rating scores from 100 different participants. In this study, the average of 100 rating scores was calculated for each VR scenario. We believe that the SRS model (and the BLOS criteria to be discussed in later sections) should reflect common or prevailing feelings or perceptions of participants. The average rating score of participants for each scenario represents statistically the common feelings of participants riding on their testing segment. The average rating score is a statistical indicator, while each individual rating of participants (such as excellent, good, fair, bad, and terrible) is a descriptive indicator. Totally, there were 120 average SRS for this study.

Using the average SRS training data subset, we first defined a set of function building blocks such as mathematical operators, constants, and analytic functions. Then we incorporated all the independent variables into the search or training process for an optimal regression model. The regression model which best fits the average SRS training data subset is as follows:

$$\begin{aligned} y_{\mathrm{SRS}} = {} & 3.469 + 4.753 \times 10^{-2} v_n ln w_e - 1.075\sqrt{N_{bs}} - 1.050 x_1 - 3.342 \times 10^{-1} x_2 - 2.294 \times 10^{-1} x_3 \\ & -2.902 \times 10^{-1} k_p - 6.524 \times 10^{-3} v_v - 7.114 \times 10^{-4} Q_p^+ - 2.327 \times 10^{-4} Q \end{aligned} \tag{6}$$

where

y_{SRS}– the average satisfaction rating scores of all the participants for a specific VR scenario where it is casted into the interval of the range [1, 5]. When the calculated $y_{SRS}$is less than 1, it is considered as 1. When the calculated y_{SRS} is greater than 5, it is considered as 5.
v_n– the average speed of non-motorized vehicles (km/h).
w_e– the effective width of bike facility, which is calculated by the actual width of bike facility minus the width of on-street parking space (m).
N_{bs}– the number of buses at bus stops.
k_p– the percentage of on-street parking.
x_1, x_2, x_3 – dummy variables indicating a bike facility type.
v_v– the average speed of vehicles on adjacent lane (km/h). It is noteworthy that this value is considered when the lane types are bike lanes or bike routes.
Q_p^+– the pedestrian volume in the traveling direction (p/h).
Q – the non-motorized flow and pedestrians(b/h).

It is noted that 90 of 120 randomly selected average SRS were used for the training and the model development. The remaining 30 average SRS were used for validation. Fig. 5 shows the fitting of the average SRS derived from the SRS model to the actual average SRS. The goodness of fit R^2 value is 0.894, which indicates that 89.4 percent of the average SRS is explained by the model. The mean squared error and the mean absolute error are 0.057 and 0.173, respectively. The model therefore is reliable in predicting the average SRS of bicyclists.

To illustrate the influence of the variables within the model on the average SRS, an example (later referenced to as the theoretical example) is presented here. Assume a typical urban street segment experiences 1500 bicycles and 500 E-bicycles per hour. The effective width of the bike facility is 5.0 m and the average speed of non-motorized vehicles along this segment is 15 km/h. Additionally, buses are not observed at bus stops and on-street parking is not present. At the same time, pedestrians are not in the bike flow. The average speed of vehicles on adjacent lane for bike lane and bike route are 45 km/h. The average SRS is then calculated to be 4.09, 3.86, 3.47, and 2.75 for bike facility types of greenbelt-separated bike path, guardrail separated bike path, bike lane, and bike route, respectively.

3.2. Discussion

In this model, average speed of non-motorized vehicles and effective width of bike facility provide a positive impact on SRS, while number of buses at bus stops, on-street parking rate, pedestrian volume, total flow, and average speed of vehicles on adjacent lane impact SRS negatively. This further indicates that increasing effective width of bike facility would create more spaces for bike riders and therefore improve SRS. As average speed of non-motorized flow increases, bike riders feel more freedom in navigating in the flow, which results in higher SRS. This finding is consistent with the expectations of bicyclists.

The SRS model indicates that bike facility type significantly affects SRS. As the variable for bike facility type (x_1, x_2, x_3) changes from (0, 0, 0) (greenbelt separated bike path), (0, 0, 1) (guardrail separated bike path), (0, 1, 0) (bike lane), to (1, 0, 0) (bike route), bicyclist's feeling about the bike facility gets worse and SRS turns to be smaller. The greenbelt buffer or the guardrail barrier separates motorized vehicles from bicycles, which provides psychologically a safe and comfort sense to bike riders. The white solid line of bike lane virtually separates vehicles from bicycles and legally locks motorized vehicles and bikes within their own boundary. The reality,

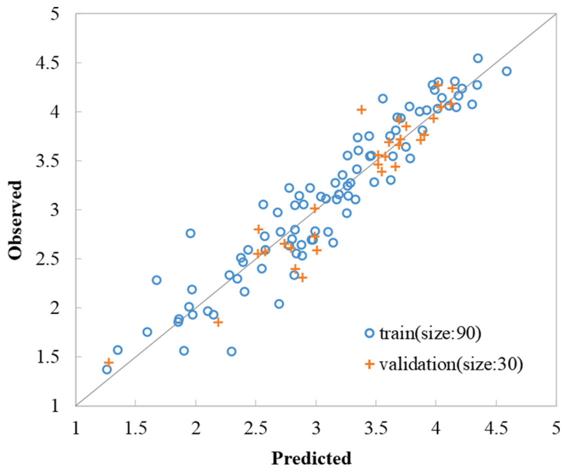

Fig. 5. Cross validation of the SRS model.

however, is that bike riders always worry about adjacent vehicles intentionally or accidentally intruding into their spaces. Bike riders riding on a bike route share right of way with vehicles, and they constantly watch their surroundings to keep a safe distance from any overtaking vehicles. As a result, they increase their psychological pressure and spend more energy to avoid any potential vehicle/ bicycle conflicts.

Buses at bus stops also play a negative role in rating SRS on bike lane and bike route. As the SRS model indicates, buses at bus stops, perceived as disturbance to bike riders, cause SRS to be low. When a bus enters or exits out of a bus stop on a bike lane or a bike route, SRS is reduced by 31.02% or 39.10%, respectively.

Pedestrians in the traveling direction have significant impact on SRS. As more pedestrians are on a bike facility, the interaction time between pedestrians and bike riders in the same direction is longer and the bike riders need to spend more time at a lower speed until they have a chance to overtake the pedestrians. According to the SRS model, an increase of pedestrian volume by 500 per hour results in a decrease of SRS by 0.356. This finding is interesting since it is against the expectations of bike professionals. Normally, bike facilities are reserved for bike users. Actually in real life, pedestrians walk on bike facilities. Within all the VR scenarios, we found that 34 scenarios or 28.33% of the scenarios with pedestrians walking on bike facilities. These pedestrians caused bike riders to have lower SRS.

Another interesting note is that on-street parking has a significant negative impact on SRS. When a bike facility has on-street parking (legally or illegally), the effective width of the bike facility is reduced and SRS is perceived lower by bicyclists. For the hypothetical example described in Section 3.1, if the same segment experienced 50% on-street parking, the average SRS would be 3.95, 3.72, 3.32, and 2.60 for the four bike facility types, respectively. While if the on-street parking reached up to 100%, the average SRS would be dramatically dropped to 3.43, 3.21, 2.81, and 2.09, respectively. In China, illegal on-street parking is prevailing. Within 16.67% of the VR scenarios, illegal on-street parking was observed. The impact of this illegal on-street parking is worse on bike lanes where their width is at least 1-meter wide as required by the Chinese Design Code CJJ 37-2012 (MOHURD, 2016). For example, illegal on-street parking was observed on a 2.3 m wide testing segment and the effective width to accommodate bicyclists was only 0.3 m. As such, the average SRS was observed to be 1.56.

When we evaluate bike lanes and bike routes, the average speed of vehicles on adjacent lane also needs to be considered. Since there are not any physical separations between motor vehicle flows and non-motorized flows in these bike facilities, vehicles on adjacent lane often challenge riders to bear more psychological pressures. This impact is especially prevailing when speeds of adjacent vehicles are relatively high. While the average speed of adjacent vehicles reaches 45 km/h and 60 km/h, the SRS decreases by 2.82% and 3.56%, respectively.

4. Bicycle level of service criteria

After the SRS model was developed to link bicyclists' perceived satisfaction to a set of key factors, the next step in this study was to develop a set of BLOS criteria. Considering the previous BLOS studies which defined BLOS into six categories (that is, A to F) (Dixon, 1996; Landis, 1997; Harkey, 1998; Petritsch et al., 2007; Jensen, 2007; Dowling, 2008; HCM, 2016), we converted SRS into six categories too to quantify the bicycle level of service. Different from the previous BLOS research which used the median values of user's numerical ratings as the dividers to define LOS categories (Landis, 1997; Dowling, 2008; Asadi-Shekari et al., 2015; HCM, 2016), we used the quantile concept in statistics to link SRS to BLOS through the accumulative distribution of SRS for a bike facility.

Fig. 6 shows the accumulative distribution of average SRS (obtained from the VR scenarios) and a fitted curve derived from Eq. (7) below:

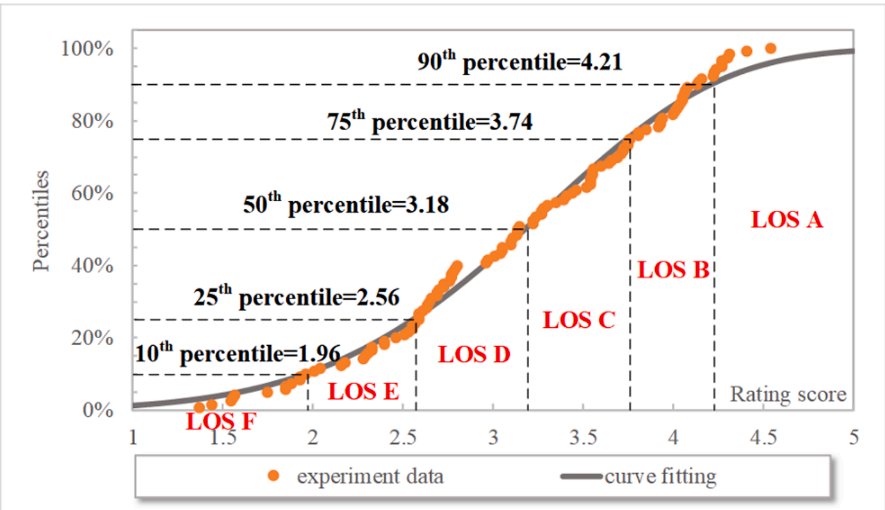

Fig. 6. Distribution of average rating scores used to classify BLOS.

$$f(y_{\mathrm{SRS}}) = 1 - exp\left(-\left(\frac{y_{\mathrm{SRS}} + 0.7324}{4.212}\right)^{5.073}\right) \tag{7}$$

where $f(y_{\mathrm{SRS}})$– the distribution of average rating scores of the participants for all the scenes.

It is noted that the lowest and highest VR-based SRS are 1.37 and 4.54 (as shown in the orange dots), respectively. This wide range of SRS indicates an extensive coverage of diversified bike riding environments in urban areas of China. The R^2 value for the fitted curve is 0.994, which indicates that the curve can match the VR-based SRS very well.

In this study, the pivotal percentiles along the curve were used as the dividers for BLOS categories. The 90th, 75th, 50th, 25th, and 10th percentiles were defined as the lower boundary points of LOS A, LOS B, LOS C, LOS D, and LOS E, respectively. The average satisfaction rating scores corresponding to their percentiles were 4.21, 3.74, 3.18, 2.56, and 1.96, respectively. They were the breakpoints of levels A through F (see Table 5). It is noteworthy that in the total of 12,000 SRS records, 1221 of them were regarded as "terrible" and 1622 were "excellent". These lower and upper extreme levels of SRS accounted for 10.18% and 13.52%, respectively. Considering these patterns, we selected 10% at both ends of the percentiles for the best and worst LOS.

5. Use of bicycle level of service criteria in policy development

Bicycle Level of Service developed in this research is a quantitative measure which relates to the quality of service of bike facilities. It provides a guideline to active transportation professionals to analyze bike facilities by categorizing bike flows and assigning quality of service based on important measures such as type and width of bike facilities, bus stops, presence of buses at bus stops, on-street parking, and influence of motorized vehicles on adjacent lane. The current method adopted in China examines the quality of service through three separate factors: riding speed, occupied road area, and Volume/Capacity (V/C) (%). Using this method, Chinese transportation professionals classify quality of service into four levels (Level 1 to 4, level 1 is the best and level 4 is the worst) (MOHURD, 2016). The method often confuses active transportation professionals with ambiguous results. A given bike facility can end up with three different levels of service, that is, level 1 from riding speed, level 2 from occupied road area, and level 3 from V/C ratio. Such confusion is completely resolved by the SRS model and the BLOS criteria described in this paper. The symbolic regression SRS model produces one and only one SRS for a given segment of bike facility. Thus, it links one and only one level of service for the segment.

The SRS model and the subsequent BLOS criteria provide a theoretical foundation by which practitioners can assess operational performance of existing and planned bicycle facilities. Key applications of the SRS model and the BLOS criteria are as follows:

5.1. Operational analysis and evaluation of existing bike facilities

The BLOS analysis approach is simple to use and effective in determining BLOS of bicycle facilities. Given an existing segment of bike facility, practitioners can 1) determine key factors as described in Eq. (6), 2) estimate the SRS for the bike facility using the SRS model, and 3) classify the BLOS of the given segment through the BLOS criteria. Additionally, a dynamic BLOS map could be generated to describe bicycle traffic flows and physical conditions of bike facilities. Furthermore, practitioners could use the BLOS criteria to identify weak segments in a bike network and determine strategies to improve these segments. Possible improvements may include 1) upgrading bike facilities (such as changing from bike route to bike lane), 2) increasing bike facility width, and 3) removing on-street parking.

5.2. Plan and design of new bike facilities

The SRS model and the BLOS criteria are important in the design of new bike facilities. When a new bike facility is planned in a community or a city in China, bike facility designers can specify design elements (such as bike facility type and width, bus stops, presence of buses at bus stops, on-street parking, and influence of motorized vehicles on adjacent lane), develop a set of alternatives, and select the best alternative that can yield the BLOS to be C or better (as described in Code for Design of Urban Road Engineering, CJJ 37-2012). Additionally, bike facility designers can determine one individual design element given the desired (or design) BLOS and other design elements are known. For example, designers can determine bike facility width when the desired BLOS and other elements are specified for a new bike facility. Table 6 shows five hypothetical alternatives for a planned bike facility. Alternative 1 is to design a greenbelt separated bike path along an urban expressway; Alternative 2 is to build a guardrail separated bike path along a major

Table 5
BLOS criteria.

BLOS category	Range of Predicted SRS	Overall Perceived Satisfaction Grade
A	≥4.21	Excellent
B	3.74–4.20	Very good
C	3.18–3.73	Good
D	2.56–3.17	Fair
E	1.96–2.55	Poor
F	<1.96	Very poor

Table 6
Hypothetical alternatives.

	Road Classification	Bike Facility Type	N_{bs}	k_p	Q_b b/h	Q_e b/h	Q_o b/h	Q_p^{+} p/h	v_n km/h	v_v km/h	Effective width, m	Design width, m
Alt. 1	urban expressway	bike path (greenbelt)	0	0	2000	2000	100	100	24	–	4.2	4.7
Alt 2	major arterial	bike path (guardrail)	0	0	1500	1500	50	100	22	–	2.9	3.4
Alt. 3	minor arterial	bike lane	0	80%	1000	1000	100	100	18	45	2.0	4.5
Alt. 4	minor arterial	bike lane	1	0	1000	1000	100	100	18	45	4.6	5.1
Alt. 5	local road	bike route	1	0	800	800	100	100	15	35	3.5	4.0

Note: the terms of N_{bs}, k_p, Q_b, Q_e, Q_o, Q_p^{+}, v_n, v_v are the parameters in Table 4.
Q in Equation (6) can be calculated by $Q = Q_b + 1.5Q_e + 2Q_o + 0.5Q_p$.

arterial; Alternative 3 is to consider a bike lane along a minor arterial where on-street parking is expected; Alternative 4 is to plan a bike lane along with a minor arterial where bus stop is expected; Alternative 5 is to share bike flow with vehicle flow. Additionally, we assume the desired BLOS is C.

In Alternatives 1, the effective width of the bike path is calculated to be 4.2 m. By adding 0.25 m on both sides of the greenbelt separated bike path, the design width of the bike path is 4.7 m. It is noted that the high bike and E-bike flows lead to a wide bike path. Also, the higher the pedestrian flow, the wider the design width of the bike path. Similarly, the effective and design widths for Alternative 2 are 2.9 m and 3.4 m, respectively, given the traffic conditions as described in Table 6.

In Alternative 3, the effective width is calculated to be 2.0 m and the design width is 4.5 m (we assume 2.0 m for on-street parking and 0.5 m for curbs). Different from Alternative 3, Alternative 4 anticipates buses along the planned bike lane, the effective width is thus calculated as 4.6 m and the design width is 5.1 m (we also assume 0.5 m for curbs). From the comparison of the two scenarios, we can conclude that on-street parking and bus stops have greater impacts on the width of bicycle lane.

In Alternative 5, the effective width is calculated to be 3.5 m, and the mix-use bike route design width is 4.0 m. It should be noted that the bike route is shared by motorized and non-motorized vehicles, the effective width should be larger than 2.5 m (Mohurd, 2016).

6. Conclusions and future research

Bicycle is an important low-carbon mode of urban transportation for residents in Chinese cities. It is therefore significant to utilize the bicycle riding scenes in China to study the LOS as well as the design of bicycle facilities. In this study a BLOS method, which can assess the performance of four different types of unidirectional bike facilities (greenbelt separated bike path, guardrail separated bike path, stripe separated bike lane, and bike route) was developed. This method defines a set of BLOS criteria which links satisfaction ratings scores (SRS) of bicyclists to the LOS categories. A total of 12,000 SRS samples were collected from 95 testing segments where different traffic and physical riding conditions in Beijing, China were considered. An SRS model was developed using the symbolic regression model. Additionally, the BLOS categories, which associated with the accumulative distribution (or the percentiles) of observed SRS (or SRS calculated from the SRS model), provide an effective guideline for decision makers in understanding the characteristics of unidirectional bike facilities in China. It enriches the research methods for the BLOS by utilizing VR technology to synthesize riding scenes.

The VR technique has been proved in this study to be more accurate in reflecting the actual perceptions of bicyclists. As the VR-based Bicycle Experimental System (BES) enabled 100 participants to immerge in riding environments, the VR-based SRSs called out from the participants are proven to be the best ones in representing the feelings of the participants experiencing the actual interactions with other bicyclists, pedestrians, on-street parking cars, buses at bus stops, and other entities on the bike facilities. The VR method has significantly improved the conventional time-consuming roadside survey method which requires participants to go to sites for data collection. The VR method instead make participants review and re-use recorded VR scenarios and provide their SRS without exposing themselves to the dangers of traffic. The repeatability of the experiment and the utilization of data are improved.

Additionally, a comparison analysis of three data collection methods (that is, VR, FPP, and TPP methods) was conducted. It is found that the VR ratings (or the VR SRS) were equivalent to the field rating (or the field SRS), while the FPP and TPP satisfaction ratings had a significant deviation from the field ratings.

The symbolic regression method is a simple machining learning tool which can link SRS effectively to exogenous factors affecting the feelings of bike riders. Using the VR-based SRS data, the SRS model was developed and validated. This model shows that bike facility type significantly affects SRS, and average speed of non-motorized vehicles and effective width of bike facility provide a positive impact on SRS, while number of buses at bus stops, on-street parking rate, pedestrian volume, total flow, and the average speed of vehicles on adjacent lane impact SRS negatively.

There are still some limitations in this study. This study did not address the impacts of roadside land development, road/bike physical settings, and grade on SRS. In addition, the VR scenes used in the BES were taken from a binocular camera with two eyes. The VR scenes were not true 3D views. Participants therefore did not have true 3D feel of bike facilities and traffic conditions. Additionally, the participants selected in this study were all young and skilled riders. Middle-aged and elderly bicyclists were not recruited. Furthermore, this study used six volunteers to collect VR, TPP, and FPP ratings to verifying that the VR method is better than the TPP and FPP methods. Our assumption that these volunteers did not have any collections of their riding experiences several months after they rode on the actual testing segments needs to be tested and verified.

In the future, 3D cameras and LIDAR will be considered to capture bike flows and bike facilities in 3D mode. True 3D scenes will be further created and used in the BES. In addition, the BES will be upgraded so that resistance force can be dynamically applied in the system to reflect physical settings of bike facilities. Furthermore, future research should be expanded to include middle-aged and elderly bicyclists in the refinement of the SRS model. Additionally, it is recommended to collect VR, TPP and FPP ratings from testers who do not have any actual experiences of testing segments and compared these ratings with those from field observations. It might be more convincing to show the VR rating scores are closer to the real experience.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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