



Urban road segment level of service based on bicycle users' perception under mixed traffic conditions

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Abstract During the past two decades, several methodologies are endorsed to assess the compatibility of roadways for bicycle use under homogeneous traffic conditions. However, these methodologies cannot be adopted under heterogeneous traffic where on-street bicyclists encounter a complex interaction with various types of vehicles and show divergent operational characteristics. Thus, the present study proposes an initial model suitable for urban road segments in mid-sized cities under such complex situations. For analysis purpose, various operational and physical factors along with user perception data sets (13,624 effective ratings in total) were collected from 74 road segments. Eight important road attributes affecting the bicycle service quality were identified using the most recent and most promising machine learning technique namely, random forest. The identified variables are namely, effective width of outside through lane, pavement condition index, traffic volume, traffic speed, roadside commercial activities, interruptions by unauthorized stoppages of intermittent public transits, vehicular ingress–egress to on-street parking area, and frequency of driveways carrying a high volume of traffic. Service prediction models were developed using ordered probit and ordered logit modeling structures which meet a confidence level of 95%. Prediction performances of developed models were

assessed in terms of several statistical parameters and the ordered probit model outperformed the ordered logit model. Incorporating outputs of the probit model, a predictive equation is presented that can identify under what level a segment is offering services for bicycle use. The service levels offered by roadways were classified into six categories varying from 'excellent' to 'worst' (A–F).

Keywords Heterogeneous traffic · Bicycle level of service · Perceived satisfaction · Random forest · Ordered probit · Ordered logit

1 Introduction

In response to the renewed appreciations of bicycle mode for its environmental and health-related benefits, public officials around the world are working to establish bicycle friendly road infrastructures. Now, 30%–50% of households in a developing country like India own a bicycle according to census 2011. However, the road facilities in the country are not developed with perceived satisfactions and safety of bicyclists as the prime objectives. With the rapid urbanization, motor vehicle use has tremendously increased, and thus planners and engineers have been primarily focusing on safe management of motorized traffic. On the contrary, non-motorized modes are highly neglected, and transportation infrastructures are facing challenges to accommodate on-street bicyclists within the mainstream traffic. A thorough understanding of operational characteristics of bicycle users and prediction of the satisfaction levels perceived by them are two important issues when making any plan of actions for establishing bicycle friendly networks.

Several researchers have attempted to develop service prediction models suitable for homogeneous traffic flow

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conditions only. This flow is composed of identical vehicles where drivers follow the lane discipline. But the traffic flow in developing countries like India is often characterized by a diverse mix of heterogeneous vehicles, where motorized two-wheelers, three-wheelers, cars, buses, and several non-motorized vehicles ply with no-lane discipline. Bicyclists are often forced to find their required space on the on-street facilities which are predominated by motor vehicle users. In this situation, bicyclists encounter a complex interaction of several kinds of vehicles and generally feel unsafe, unpleasant, and frustrated. The operational conditions of bicyclists under this situation are significantly different from those under homogeneous traffic conditions. Thus, none of the models discussed earlier can be suitably applied here to quantify bicyclists' perceived satisfactions. In this regard, the present study primarily focuses on (1) the analysis of how various operational and physical factors (roadway geometrics, built environment, traffic flow parameters, etc.) is influencing perceived satisfactions of bicyclists under mixed traffic flow conditions, (2) identification of the important (significant) variables using a promising technique, (3) development of service prediction models using ordered probit and ordered logit techniques, and (4) assessment of developed models for service predictions under prevailing conditions and subsequently, report the better one for the present context.

In this study, required data sets were collected from 74 road segments of four Indian cities and were thoroughly analyzed. Influencing variables were identified with the help of a most recent and most promising machine learning technique, namely random forest. It was also observed that traffic volume followed by width of the outermost lane, roadside commercial activities, on-street parking turnover and pavement condition index, etc., has the highest influence on perceived satisfaction levels of on-street bicyclists. Ordered probit and ordered logit modeling structures were used to develop predictive models which would help transportation engineering professionals while rating urban road segments from a bicyclist's perspective. Using outputs of these models, necessary actions could be taken for the betterment of bicyclists. Prediction performance of both models was tested using several statistical parameters such as Akaike's information criterion (AIC) and pseudo- R^2 , and it was observed that the probit model has better performance in the present context. In addition to the development of a reliable service prediction model, this study introduces influences of two new parameters such as interruptions by unauthorized stoppages of intermittent public transits (pick-up vans, 3-wheeler autos, etc.) and frequency of driveways carrying a high volume of traffic which perhaps are not considered in any previous such studies.

2 Review of literature

Several researchers in the field of transportation engineering have contributed significantly to explore the operational characteristics of bicyclists under homogeneous traffic flow environment. Influencing variables are identified, and several service prediction models are proposed to efficiently predict the users' perceived satisfaction levels in developed countries. Roadway segment index (RSI) model [1], modified roadway condition index (modified RCI) model [2], interaction hazard score (IHS) model [3], bicycle stress level (BSL) model [4], bicycle suitability rating (BSR) model [5], bicycle compatibility index (BCI) model [6], and bicycle level of service (bicycle LOS or BLOS) models [7–12] are some of the successful attempts in this regard. RSI model [1] is a function of traffic volume, number of lanes, speed limit, outside lane width, pavement conditions, and location factors. It neglects the influences of several other factors like percentage of heavy vehicles and on-street parking turnover. Modified RCI [2] model is the revised version of RSI model in which the authors have modified location and pavement factors. In addition to this, the authors have multiplied the lane width term with speed limit to place greater weightage on narrow roads with high traffic speeds. IHS model [3] has revealed the important roles of roadside land use pattern and on-street parking activity in perceived satisfactions of bicyclists. BSL model [4] primarily reflects the importance of curb-lane in riding quality of bicyclists, and considers curb-lane width, curb-lane traffic volume and curb-lane traffic speed parameters to predict the service quality. BSR model [5] is also a modified version of RSI model which signifies important roles of traffic volume and traffic speed in the bicycle service quality.

BCI model [6] has revealed the important roles of bicycle lane and right-turning vehicles in user satisfactions. Several other researchers have also identified the key variables that influence perceived satisfactions of bicyclists. Well-conditioned pavement surface and the provision of separate bicycle lane have significant positive influence on the riding quality of bicyclists [7–9]. Bicycle service assessment methodologies proposed in 2000 version of Highway Capacity Manual (HCM) [10] are based on the average travel speed, average delay, and hindrance. However, HCM [11] considers a wide range of parameters such as the number of through lanes, effective width of the outside through lane, pavement conditions, mid-segment demand flow rate, traffic speed, and the percentage of heavy vehicles. A BLOS model developed from user's perspective concludes that bicyclists' satisfaction is largely determined by the width of the roadway on which bicycle is ridden. Other factors included in this model are number

of lanes, pedestrian volume, and number of encounters [12]. Interaction with on-street pedestrians and non-motorized vehicles has substantial negative influences on riding quality of bicyclists [13]. With the provision of bicycle lane facilities, bicyclists gain more confidence to ride further from the edge of roadways because they feel that motorists will observe and respect the bicycle lane line as the boundary of bicycle zone [14, 15].

An investigation on factors influencing bicycling in an Indian city, namely Bangalore, concludes that segregated bicycle lanes and signals at intersections are two essential requirements of a safe bicycling environment [16]. Recent investigations on bicycle operations under heterogeneous traffic flow conditions have concluded that the quality of bicycling is largely influenced by vehicular traffic volume [17, 18]. On-road bicyclists under such conditions encounter a very complex interaction with several small to big vehicles and subsequently have their quality of riding to be largely influenced by the same. However, a detailed investigation of factors influencing bicyclists' perceived satisfaction levels have not been carried out as yet. Existing bicycle models are solely based on homogeneous traffic flow conditions and do not consider the influence of several potential variables, such as interruptions by unauthorized stoppages of intermittent public transits and frequency of driveways carrying a high volume of traffic. These variables, however, have considerable adverse effect on quality of bicycling from an ordinary citizen's point of view and thus need thorough investigation. The present study thus did a detailed investigation to identify all potential variables and developed a new reliable model for its applications under heterogeneous traffic flow environment.

3 Methodological approach

In this study, a perception survey of 154 participants was carried out to assess their perceived satisfactions on studied road segments under peak hour conditions. Participants rated each of 74 segments with one of the descriptors in an ordinal scoring system: 'A' = 1 = excellent, 'B' = 2 = very good, 'C' = 3 = good, 'D' = 4 = fair, 'E' = 5 = poor, or 'F' = 6 = very poor. The number of service levels was kept as six for general correspondence with the HCM [10, 11] and several other relevant studies. A wide range of road geometric, traffic and built environmental variables along with user-perceived ratings was analyzed using random forest technique. Road attributes significantly affecting the perceived service quality were identified and were ranked in descending order of their relative importance in service quality predictions.

Ordered probit and logit modeling structures were applied to establish the kind of relationship that does exist

among important road attributes and user-perceived service levels. These analytical tools are probably the best choices particularly when the response variable is a categorical variable ordered in a meaningful way. For instance, the user-perceived scores (output variable) collected in this study varies from 1 (excellent service quality, 'A') to 6 (very poor service quality, 'F') in a very meaningful way at a discrete interval of 1. Unlike interval scales, ordinal scales have two unique features: a clear ordering of the categories such as 'A' is superior to 'B,' and 'B' is superior to 'C' and unobservable absolute distances among the categories. Hence, when standard multinomial discrete-outcome modeling techniques such as multinomial probit and logit approaches are used to model the categorical data set by considering them as nominal, it often results in inaccurate and biased outputs. On the contrary, treating ordered categorical variables as ordinal is advantageous in terms of parsimoniousness, simpler interpretations, superior detection power, better flexibility, and more similarity to the ordinary regression modeling.

As observed in this study, regression techniques were not appropriate for modeling the ordered response variables. The reason is that such methods assume that for a measured change in the explanatory variables (or some transformation thereof), there is a measured linear change in the dependent variable. Moreover, these methods produce a continuous estimate of the dependent variable, which is different from what is reported by the participants during the survey conducted in this study. Lastly, regression models cannot guarantee that the estimated LOS responses will be bounded between 1 and 6 without artificially setting some upper and lower bounds exogenously. These limitations led the researchers to investigate the feasibility of using probit and logit regressions. These are the classes of models which have the ability to predict the probability of responses in each LOS category based on a combination of explanatory variables. This property also well allowed to model nearly 10,434 observations stored in the database.

Modeling and interpretations of the ordered probit and ordered logit models are noticeably similar. Nevertheless, these methods differ in their error distribution. In the former method, the error term is assumed to be normally distributed with a mean of 0 and a variance of 1.0; and in the other one, the same is assumed to follow a Gumble distribution. A logit model is often preferred to the probit model as it needs lesser computational effort than the other. But at present with improved computing power, computational efforts are negligible in most cases. Consequently, the choice between these two methods has typically become an analyst's preference. Thus, this research has tested the performance of both methods in solving the present problem and reported the better one. The Statistical

Analysis System (SAS) modeling programs were used to carry out probit and logistic transformations, and estimate model parameters (coefficients, etc.). For continuous functions, ordinary least squares (OLS) method is used which estimates model parameters by minimizing the square of the difference between actual and predicted outputs (error). But this approach cannot be used to model categorical responses as probability distributions do not produce an error term which can be minimized. Thus, the maximum likelihood estimation (MLE) method is used as an alternate method. MLE estimates model parameters by maximizing the likelihood that the predicted probability of the event matches the actual one. The following subsection gives a brief discussion on the random forest procedure followed by discussions on the underlying principles of ordered probit and ordered logit modeling structures.

3.1 Random forest technique

Random forest technique, proposed by Breiman [19], is one of the most recent and most promising machine learning techniques, well known for its capability to identify significant variables from a set of them. In this method, numerous trees are attempted by randomly selecting some observations from the original data set with replacement, and then searching over a randomly selected subset of covariates at each split [20, 21]. To examine whether attempted numbers of trees are adequate to reach reasonably stable outputs, the out-of-bag (OOB) error rate parameter is used. The best number of trees has the minimum error rate and a constant error rate nearby. In order to identify the relative importance of each variable from a set of them, a mean decrease Gini IncNodePurity diagram can be produced using the R-package [22]. By using this diagram, a node purity value for every variable (node of a tree) can be determined by means of the Gini index [21]. The higher the value of node purity, the higher the importance of a variable is. Breiman [19] can be followed for further details on this technique.

3.2 Ordered probit modeling

An ordered probit-based service prediction model incorporates a continuous latent measure underlying each service level (A–F) and explains which level of satisfaction bicyclists perceive (on average) in a certain roadway environment. The model is derived by defining an unobserved variable, Z_n , which is used as the basis for modeling the ordinal ranking of service levels (A–F). The relationship between a vector of independent variables, X_n , and the perceived satisfaction of a bicyclist on any segment can be

written as follows to determine the perceptions of BLOS as a linear function for each observation n (defined as each participant's evaluation of the 74 segments):

$$Z_n = \alpha X_n + \varepsilon_n, \quad (1)$$

where α represents the vector of coefficients estimated using the standard MLE procedure, and ε_n represents a random disturbance term assumed to be independent and normally distributed across all individuals.

Bicyclists' preference of rating a certain roadway segment (i.e., observed BLOS or y_n) from a sets of alternatives j ($j = 1, 2, \dots, 6$) is computed by a stepwise function of latent measures, Z_n , as follows (with BLOS 'A,' 'B,' 'C,' 'D,' 'E,' and 'F' corresponding to $y_n = 1, 2, 3, 4, 5,$ and $6,$ respectively):

$$y_n = \begin{cases} 1 & \text{if } Z_n \leq \mu_1 \\ 2 & \text{if } \mu_1 \leq Z_n \leq \mu_2 \\ 3 & \text{if } \mu_2 \leq Z_n \leq \mu_3 \\ 4 & \text{if } \mu_3 \leq Z_n \leq \mu_4 \\ 5 & \text{if } \mu_4 \leq Z_n \leq \mu_5 \\ 6 & \text{if } Z_n \geq \mu_5 \end{cases}, \quad (2)$$

where μ_j ($j = 1, 2, \dots, 6$) terms represent the thresholds estimated jointly with α parameters.

Threshold parameters (μ_j) relate the dormant measures Z_n to bicyclists' preference y_n , in an ordered response manner as shown in above equation. Here, $\mu_0 = -\infty$, $\mu_6 = +\infty$, and $-\infty < \mu_1 < \mu_2 < \mu_3 < \mu_4 < \mu_5 < +\infty$. The estimation problem then becomes one of determining the probability that a particular bicyclist will perceive an ordered response j on a certain roadway segment. A positive increase in the α term implies that an increase in X will increase the probability of getting an excellent BLOS 'A.' Similarly, this increase also implies that the probability of excellent BLOS 'F' is decreased. The probability that an individual will select an alternative j ($j = 1, 2, \dots, 6$) for a particular segment can be calculated as follows:

$$\begin{aligned} P(y=1) &= P(Z_n \leq \mu_1) = \Phi(\mu_1 - \alpha X_n), \\ P(y=2) &= P(\mu_1 \leq Z_n \leq \mu_2) = \Phi(\mu_2 - \alpha X_n) - \Phi(\mu_1 - \alpha X_n), \\ P(y=3) &= P(\mu_2 \leq Z_n \leq \mu_3) = \Phi(\mu_3 - \alpha X_n) - \Phi(\mu_2 - \alpha X_n), \\ P(y=4) &= P(\mu_3 \leq Z_n \leq \mu_4) = \Phi(\mu_4 - \alpha X_n) - \Phi(\mu_3 - \alpha X_n), \\ P(y=5) &= P(\mu_4 \leq Z_n \leq \mu_5) = \Phi(\mu_5 - \alpha X_n) - \Phi(\mu_4 - \alpha X_n), \\ P(y=6) &= P(Z_n \geq \mu_5) = 1 - \Phi(\mu_5 - \alpha X_n), \end{aligned} \quad (3)$$

where $\Phi(t)$, expressed below, is the cumulative normal distribution of any variable t :

$$\Phi(t) = \frac{1}{2\pi} \int_{-\infty}^{|t|} e^{-\frac{1}{2}t^2} dt. \quad (4)$$

3.3 Ordered logit modeling

The ordered logit modeling procedures are quite similar to ordered logit modeling procedures. In this case, a bicyclist’s preference of rating a certain roadway segment, y_n , from a set of alternatives j ($j = 1, 2, \dots, 6$) can also be determined in a very similar way by using Eq. (1). However, the error term, ε_n , is assumed to follow a Gumble distribution. Subsequently, a bicyclists’ preference of rating a certain roadway segment, y_n , from a set of alternatives j ($j = 1, 2, \dots, 6$) is also computed by the stepwise function of latent measures Z_n as shown in Eq. (2). The estimation problem then becomes one of determining the probability that a particular bicyclist will perceive an ordered response j on a certain roadway segment. In order to accomplish this, the logit transformation is applied to the cumulative probabilities as follows:

$$\text{logit}[P(Y \leq j)] = \log \frac{P(Y \leq j)}{1 - P(Y \leq j)}. \tag{5}$$

A distinctive model for the cumulative logits can be written as follows:

$$\begin{aligned} Z_j &= \text{logit}[P(Y \leq j)] = a_j + \alpha_{11}x_1 + \alpha_{21}x_2 + \dots + \alpha_{n1}x_n \\ &= a_j + \alpha X_n, \end{aligned} \tag{6}$$

where a_j is the intercet; $\alpha_{11}, \alpha_{21}, \dots, \alpha_{n1}$ are the elements of α ; and x_1, x_2, \dots, x_n are the elements of X_n .

The probability of obtaining an alternative j in a certain observation can be calculated by using the following equation which is obtained by solving Eqs. (5) and (6).

$$P(Y \leq j) = \frac{e^{\alpha_j}}{1 + e^{\alpha_j}} = \frac{1}{1 + e^{-\alpha_j}}. \tag{7}$$

The above system of equations can be expanded as follows to obtain the probability that an individual will perceive any particular alternative j from the ordered response categories $j = 1, 2, \dots, 6$ on a roadway segment:

$$\begin{aligned} P(y = 1) &= P(y \leq 1), \\ P(y = 2) &= P(y \leq 2) - P(y \leq 1), \\ P(y = 3) &= P(y \leq 3) - P(y \leq 2), \\ P(y = 4) &= P(y \leq 4) - P(y \leq 3), \\ P(y = 5) &= P(y \leq 5) - P(y \leq 4), \\ P(y = 6) &= 1 - P(y \leq 5), \end{aligned} \tag{8}$$

where $P(y \leq 1), P(y \leq 2), \dots, P(y \leq 5)$ are the values obtained using Eq. (7).

3.4 Model evaluation criteria

Before assessing the significance of individual components of an ordered probit or logit model, it is first necessary to test the precision of the model as a whole. In view of this, following criteria are used in this study for the same purpose.

1. Log likelihood measures of fit: This test evaluates whether the presence of exogenous variables significantly improves the quality of the model estimation. If log likelihood of the final model, $L(\beta)$, is substantially larger than that of the intercept intercept-only model, $L(0)$, it indicates that the model is providing a more accurate and meaningful estimation of the output than the model with constant terms only.
2. AIC: AIC, defined below, rewards the goodness-of-fit or quality of model fitting using the likelihood function [23]:

$$AIC = 2k - 2L(\beta), \tag{9}$$

where k is the number of parameters estimated in the model; $L(\beta)$ is the log likelihood of the final model (i.e., the model with input parameters).

Given a set of candidate models for the data set, the preferred model is the one with the least AIC value.

3. Pseudo- R^2 : It is known that models derived using OLS procedure use coefficient of determination (R^2) as a measure of ‘goodness-of-fit.’ But the MLE-based models are evaluated with the help of log-likelihood-ratio test. A pseudo- R^2 compares the likelihood for the intercept-only model to the likelihood for the model with predictors, and returns an indication on the strength of the model. Values of pseudo- R^2 s can be as low as zero but can never equal one, and a higher value of these parameters indicates a better-fitted model. In the present study, two pseudo- R^2 s such as Cox and Snell R^2 (R^2_{CS}) and McFadden R^2 (R^2_{McF}) are used as likelihood-ratio indexes. The mathematical expressions of these two parameters are given below:

$$R^2_{CS} = 1 - \exp \left[-\frac{2}{t} \{L(\beta) - L(0)\} \right], \tag{10}$$

where t is the total number of observations in the data sets used.

$$R^2_{McF} = 1 - \frac{L(\beta)}{L(0)}. \tag{11}$$

4 Data source

A field survey was conducted in this study for the collection of built environment and roadway characteristics data. In addition, a stated preference survey was used to assess the perceived satisfaction of bicycle users on the investigated segments. Following subsections discuss on data collection locations and the surveys conducted.

4.1 Collection locations

Roadway geometrics and traffic flow data were collected from 74 road segments for analyzing operational conditions

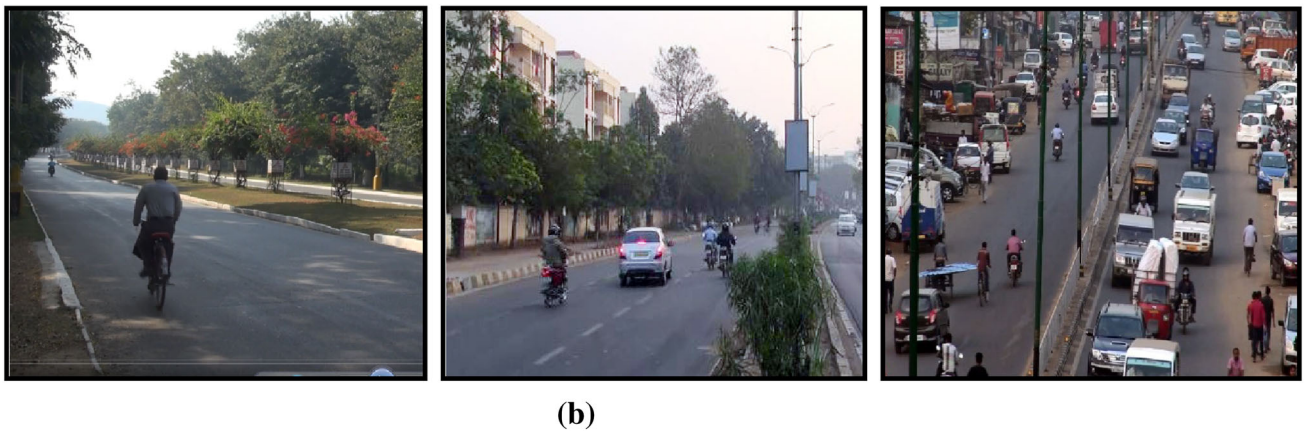
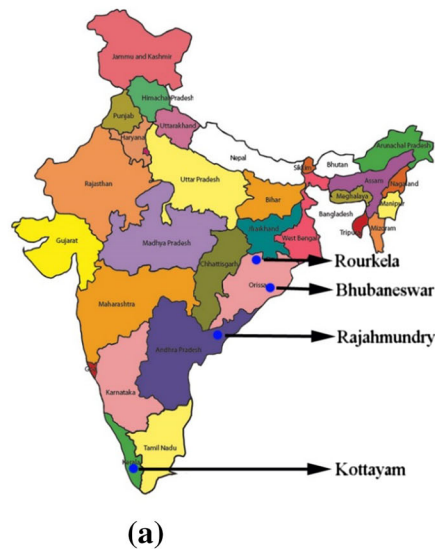


Fig. 1 Study locations and typical bicycle activities under differing conditions: **a** locations of studied cities in India; **b** schematic photographs of few bicycle facilities in the study locations

of on-street bicyclists. These segments belong to four mid-sized cities (population size 0.5–1.0 million) of India, namely Bhubaneswar (29 segments), Rourkela (19 segments), Rajahmundry (14 segments), and Kottayam (12 segments). Figure 1a shows locations of these cities, and Fig. 1b shows some typical bicycle activities under varying road conditions. Bhubaneswar is the administrative capital of Odisha State, and primarily attracts tourists across the world. It has emerged as one fast-growing, important trading, and commercial hub in the eastern India. Rourkela, commonly known as the steel city of Odisha, is one of the largest cities located at northern west of the State. Rajahmundry is one of the major cities in the Andhra Pradesh State. Kottayam city is the administrative capital of Kottayam district and is located in south-central Kerala State.

Studied sites differ from one another in terms of geometric designs and other operational characteristics. These dissimilarities well represent the observed variability and complexity of road conditions in mid-sized cities.

Considered roads are basically one to four-lane roads. Traffic movements are restricted to one-way on some roads, and some are allowed for two-way movements. Another important feature of these sites is the wide variability in roadside developments: residential, commercial, office, and institutional, etc. Roads are mostly arranged in a grid, meeting at signalized intersections that are often installed with crosswalks. Several roads are characterized by on-street parking lane, sidewalk, and median facilities. Observed variations in some major variables (in specific directions of roadways) are such as roadway width: 3–14 m, effective width of the outside lane (sum total of the outermost through lane width, paved shoulder width and width of extra paving between the outermost lane strip and edge of pavement, minus the average width reduction due to encroachments in the outermost lane [7]): 2–7 m, peak hour traffic volume: 148–2,586 PCUs/h/lane (PCUs stand for passenger car units), average traffic speed: 23–46 km/h, pavement condition index: 2.5–4.5 on a 5-point scale

(5 = excellent and 1 = worst pavement quality), and on-street parking turnover: very high to minimal, etc.

4.2 Built environment and road characteristics data

Road geometrics data such as width of the roadway in the subject direction, outside lane width, median width, sidewalk width, shoulder width, parking lane width, curb width, gutter pan width, and width of extra paving beyond outermost lane stripe were collected using a measuring tape. Information on the presence of curb, gutter pan, median, bicycle lane, and sidewalk facilities were collected using a 2-point scale: 1 = yes and 0 = no. Commercial activities on roadside area were rated on a 3-point scale: 1 = high, 0.5 = moderate and 0 = negligible. The quality of roadway surface was rated using a 5-point scale that varies from 5 (excellent) to 1 (worst). Interruptions by unauthorized stoppages of intermittent public transits were rated on a 3-point scale: 1 = high, 0.5 = moderate and 0 = negligible. The frequency of all driveways and frequency of driveways carrying a high volume of traffic (driveways/km) were also collected during this survey.

Video footage of traffic movements on each road segment was collected during the rush hours of traffic flow. The rush hours were chosen to reflect the worst conditions encountered by bicyclists. In Indian mid-sized cities, the traffic flow generally attains its peak commuting hours twice a day: once in the morning (8.30–11.30 a.m.) and once in the afternoon–evening time (3.30–6.30 p.m.). Video footages were not collected on weekends and other holidays as the traffic volume reasonably decreases on these days. The average operating speed on Indian roads is generally not as high as in developed countries, and a large variation in vehicle speeds observed in the mixed traffic flow conditions. Thus, the spot speed or space mean speed, as normally considered for the homogeneous traffic, should not be considered for the heterogeneous traffic. In this regard, the video footages mentioned earlier were collected over a long longitudinal trap of 30 m for the effective measurement of average travel speed.

Each video clip was played on a large screen, and desired traffic data sets were extracted. Running average method was used to decide peak 1 h of traffic flow among expected 3 h of rush conditions. Traffic volume (PCUs/h) in that hour called, peak hour volume (PHV) was calculated by using equivalent PCU values proposed in Indian Road Congress (IRC)-106 [24]. In addition, pedestrian volume (ped/h), percentage of heavy vehicles (%), and approximate volume of vehicular ingress–egress to on-street parking area (veh/h/km) during the peak 1 h were also extracted from the videos. Average operating speed (km/h) on each segment was calculated by dividing the

length of the trap (30 m) by the average time taken by motor vehicles to cross the trap.

4.3 Opinion survey and assessment of individual's satisfaction score

A perception survey was conducted to test how bicyclists perceive their satisfaction levels under varying roadway environments. Videography survey (showing roadway environments to the participants through suitable video clips and asking them to rate the road under shown conditions) and traveler intercept survey (on-site face-to-face interaction with the users of interest) are commonly followed methods to assess user's satisfaction levels. It is well accepted that, videography survey is an established method and has several advantages like (1) the number of street segments that participants can rate during a reasonable period of time is generally high, (2) more diverse group of participants can be included, (3) it is more cost-effective than having respondents on site, and many more. Thus, an extensive videography survey was carried out in this study to gather a huge amount of data sets. These data sets were utilized for the development of BLOS models. However, videography survey has several limitations as well, and those bicyclists who travel regularly on a road segment are the best examiners of the perceived bicycling quality of that particular roadway section. Thus, a traveler intercept survey was also carried out at some identified locations (22 segments), and the proposed BLOS model was validated with so obtained data sets.

4.3.1 Videography survey

One important criterion in such surveys is that the demographics of the selected sample should approximately represent the population as a whole. In this regard, enough care was taken, and people of varying categories were tried to be included in this survey. Residents of an institute of national importance, NIT Rourkela, and people from nearby localities were informed about the consequence of the survey through a common e-mail and were invited to participate in a large number. However, children of age less than 14 years were requested to avoid their participation. This eligibility criterion was used to ensure that the participants are matured and experienced enough to give proper judgment on road conditions. In this self-administered questionnaire survey, a total of 154 self-interested residents participated. The survey was conducted inside institute auditorium in five different sessions. Roughly 25–35 participants participated in each session. The participation rate was approximately 37%, 26%, 17%, and 20% for the institute students, faculties, staffs, and local people, respectively. The gender distributions of

participants were roughly even with 71 (46%) women and 83 (54%) men in total. The age distributions of participants were around 5%, 38%, 17%, 10%, and 4% for age groups of ≤ 20 , 21–30, 31–40, 40–50, and ≥ 60 years. Roughly 44% of the participants are students (NIT Rourkela students and others), 33% are full-time workers, 3% are part-time workers, and remaining 20% are homemakers, the unemployed, or retirees.

Survey participants were shown a representative video clip from each segment illustrating a variety of conditions including lane configuration, shoulder configuration, average traffic volume and speed, heavy vehicle percentage, presence of curb, gutter pan, and median facilities. These footages were shown with a high-definition video projector and wall-mounted screen, placed as close as possible to the eye level and located at 10–20 ft. away. The volume of audio speakers was adjusted to replicate the approximate sound in the real traffic. Each clip was about 1.5 min long, which was chosen on the basis of events in the video that the researchers wanted to include or exclude, as well as with participants' attention span in mind. There is a possibility that some participants may lose their interest to watch the entire video and start filling the survey forms up. However, they were instructed to watch individual clip entirely before rating it.

The rating was obtained based on a short question: 'How much satisfied are you as a bicyclist on the shown road segment under the shown conditions?' Participants rated their satisfaction levels on a Likert scale varying from 1 (excellent) to 6 (very poor). This kind of scaling system with ordinal features is commonly used in traffic engineering studies. Participants had roughly 10–15 s between successive video clips to make their perceived ratings. During the survey sessions, 'repeater' video clips were used to assess individual respondent's ability to detect minor changes in the traffic flow. These clips were videotaped at the same part of the segment as its original, but with differing traffic volumes. Repeater clips were played one by one at a fixed interval during the survey sessions. It was observed during post-data analyses that, each participant was soundly able to detect minor changes and had given their ratings quite consciously. Ratings obtained for these repeater clips were not used in the model building process.

The authors thoroughly investigated the ratings obtained for repeater clips during the post-data analyses. It was expected that, each participant would have given a higher rating where traffic flow is higher and a lower rating where the traffic volume is lower. However, around 13 participants violated this assumption. They were either unable to detect minor changes in the traffic flow, or had given the ratings unconsciously. Thus, any information obtained from these participants were not included in the model building process. From remaining 141 participants, a total of 10,434

(141 \times 74) effective ratings or BLOS scores were obtained. To check the sufficiency of these numbers of perceived ratings for the model building, Cochran's sample size formula [25] was used and the allowed error in estimation of the mean perceived ratings (3.48) was calculated. The error in using this amount of data set was found to be limited to 1% only (estimated at 95% confidence level). Thus, the data set was reasonably sufficient for the model estimation.

4.3.2 Traveler intercept survey

A traveler intercept survey was carried out on 22 road segments located in different parts of the study area. These segments were basically selected from varying road conditions (excellent-worst). Similar to the videography survey, this traveler intercept survey was also carried out during the peak hours of traffic flow to reflect the worst perceived conditions. Team members were employed to conduct on-site face-to-face interactions with at least 145 on-street bicycle users from each segment and collect their responses. The socio-demographic diversities among these participants were kept approximately similar to those in videography survey participants.

Survey participants were asked to rate the roadway segments based on a simple question: 'What is your perceived level of satisfaction while riding on the road segment?' The rating scale was kept same as the 6-point Likert scale used in the videography survey. Approximately 3,190 (145 \times 22) effective responses were collected in this survey and were reserved for model validation purpose. To check the sufficiency of these numbers of perceived ratings for the model validation, Cochran's sample size formula [25] was used and the allowed error in estimation of the mean perceived ratings (3.49) was calculated. The error in using this amount of data set was found to be limited to 1% only (estimated at 95% confidence level). Thus, the data set was reasonably sufficient for the model validation.

4.4 Perception survey results

The perception survey carried out in this study resulted in a total of 13,624 effective perceived ratings, i.e., 10,434 ratings from the videography survey plus 3,190 rating from the traveler intercept survey. The percentage composition of user-perceived ratings in each level (1–6) is shown in Table 1. It can be observed that very few (below 1%) of the perceived scores are 1.0; thus, very few facilities in Indian mid-sized cities are offering excellent quality of services for bicycle use. The table also shows that very few facilities are offering the worst quality of services (BLOS score = 6). However, most of the perceived BLOS scores are 3 or 4, which indicates that bicyclists are moderately satisfied with the existing facilities.

Table 1 Perception survey results

Perceived BLOS score	Frequency	Marginal percentage (%)
1.00	119	0.87
2.00	1,194	8.76
3.00	5,526	40.56
4.00	5,705	41.87
5.00	994	7.29
6.00	86	0.65
Total	13,624	100.0

5 Model development, results, and discussion

In this study, important road attributes were identified using the random forest technique and analyzed using ordered probit and ordered logit regression analyses. This section gives a detailed discussion on each aspect and also represents the results obtained from ordered probit and logit analyses. The performance of these models was assessed in terms of several statistical parameters, and the better model has been reported.

5.1 Selection and ranking of important road attributes

Random forest technique was applied on all collected road attributes to screen out the unimportant ones. Remaining significant variables were only inputted in the model building process. R-package was used to screen the variables via the library ‘randomForest’ [22]. This technique was executed with 160 trees grown in the input data sets. To check whether this number of trees could lead to the best outcomes, a plot of OOB error rate versus different number of trees was plotted and shown in Fig. 2. As

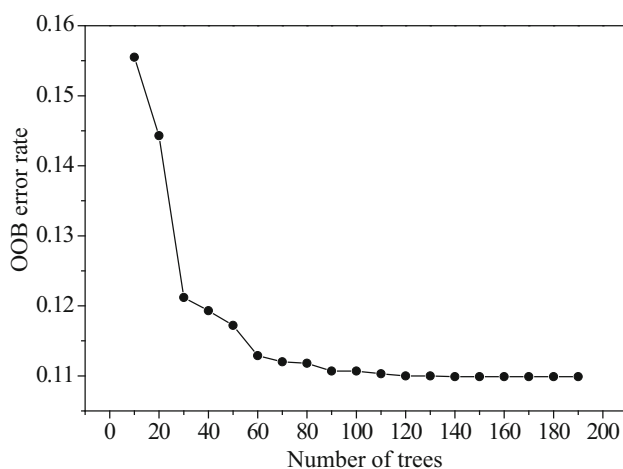


Fig. 2 Plot of OOB error rate against different number of trees in random forest

depicted in this figure, after a growth of approximately 120 trees, the OOB error rate has started to be stabilized. Hence, the attempted number of trees (160) was reasonably sufficient to attain stable outcomes for the present problem.

As indicated in the earlier discussion, a node purity value for each road attribute was produced using the random forest technique to identify its importance in contributing to the perceived satisfactions of bicyclists. By using a cut-off purity value of 1.5, important variables were screened as shown in Fig. 3. This figure depicts that the peak hour traffic volume is the most important variable with the highest node purity value of 13.64, and interruptions by unauthorized stoppages of public transits are the least important variable with the lowest node purity value of 1.74. Other significant variables and their respective order of importance are also shown in this figure. However, road attributes such as the presence of median, sidewalk facilities, on-street pedestrians, curb and gutter were observed to have an insignificant effect on the perceived satisfactions of bicyclists (node purity value below 1.5). Hence, these parameters were excluded from the model building process.

Table 2 shows the detailed statistics of data sets used in this study to develop service prediction models, where each attribute is subjected to the specific direction of the roadway. The correlations between each independent variable with the output variable (perceived BLOS score) were assessed using Spearman’s correlation analysis, and the results are shown in Table 3. Each independent variable was observed to have a significant correlation with the output variable. It might be noted here that, the correlation among independent variables with Spearman’s rho (ρ) value above 0.4 indicates the presence of multicollinearity among inputs. Thus, the correlations among selected variables were tested through Spearman’s correlation analysis. As observed in Table 3, ρ values among independent variables are not very high and indicate the poor correlations. Thus, the variables selected in this study are well able to contribute independently in the BLOS model building process.

5.2 Ordered probit model development

The ordered probit analysis was carried out by taking multiple important road attributes into considerations, and the results are presented in Table 4. The parallel-lines assumption for each variable was tested using a series of Wald-statistics (ratio of coefficient estimate and its standard error). As shown in this table, all coefficient estimates are associated with negligible standard errors (SEs) and also satisfy the required criteria of Wald-statistics. Thus, the coefficients are not biased and able to provide accurate and stable results. It can also be observed that all important

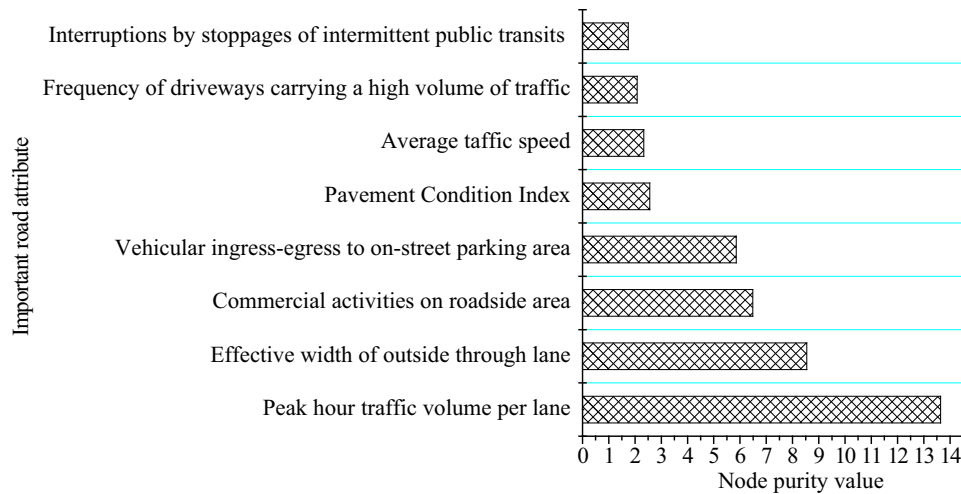


Fig. 3 Node purity values of important road attributes

Table 2 Descriptive statistics of data sets used in this research

Serial no.	Variable	Unit/scale	Min.	Max.	Mean	SD
1	Effective width of the outside through lane (I_1)	m	2	7	3.68	0.90
4	Pavement condition index (I_2)	1–5 (scale)	205	4.5	3.85	0.37
2	Peak hour traffic volume per lane (I_3)	PCUs/h/lane	148	2,586	1,069.6	489.10
3	Average traffic speed (I_4)	km/h	23	46	33.94	4.88
5	Commercial activities on roadside areas (I_5)	1 (high), 0.5 (medium), 0 (minimal)	0	1	0.49	0.44
6	Interruptions by unauthorized stoppages of intermittent public transits (I_6)	1 (high), 0.5 (medium), 0 (minimal)	0	1	0.45	0.39
7	Volume of vehicular ingress and egress to the on-street parking area (I_7)	veh/h/km	0	6,000	745.78	1,442.45
8	Frequency of driveways carrying a high volume of traffic (I_8)	Number(s)/km	0	3	0.83	0.95
9	Perceived BLOS score (O)	1–6 scale	1.55	5.40	3.49	0.71

Min minimum, Max maximum, SD standard deviation

Table 3 Correlations among used variables

Variable	O	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
O	1.000	–	–	–	–	–	–	–	–
I_1	–0.532	1.000	–	–	–	–	–	–	–
I_2	–0.465	0.022	1.000	–	–	–	–	–	–
I_3	0.550	0.148	–0.206	1.000	–	–	–	–	–
I_4	0.410	–0.204	–0.048	0.104	1.000	–	–	–	–
I_5	0.520	0.166	–0.310	0.233	–0.033	1.000	–	–	–
I_6	0.409	0.024	–0.020	0.244	0.225	0.169	1.000	–	–
I_7	0.530	–0.002	–0.203	0.219	0.136	0.187	0.154	1.000	–
I_8	0.439	0.208	–0.183	0.205	0.074	0.214	0.217	0.220	1.000

attributes are significantly ($p < 0.05$) contributing to the model at the 95% confidence level. From the signs (positive or negative) of attribute coefficients, it can be

concluded that the perceived satisfaction of a bicyclist approaches the ‘excellent’ (BLOS ‘A’), with an increase in effective width of the outside through lane and pavement

Table 4 Ordered probit model parameters

Factor	Coefficient	SE	Wald-statistic	Significance (<i>p</i> value)	95% Confidence interval	
					Lower bound	Upper bound
Threshold parameters						
Threshold 1 (μ_1)	-5.648	0.225	629.383	<0.001	-6.089	-5.207
Threshold 2 (μ_2)	-3.952	0.215	336.866	<0.001	-4.374	-3.530
Threshold 3 (μ_3)	-1.885	0.213	78.131	<0.001	-2.303	-1.467
Threshold 4 (μ_4)	0.652	0.214	9.233	0.002	0.231	1.072
Threshold 5 (μ_5)	3.613	0.226	256.083	<0.001	3.171	4.056
Road conditions						
I_1	-0.215	0.018	148.984	<0.001	-0.250	-0.181
I_2	-1.136	0.043	687.357	<0.001	-1.221	-1.052
Traffic conditions						
I_3	0.00103	0.00003	889.203	<0.001	0.001	0.001
I_4	0.042	0.003	169.017	<0.001	0.036	0.049
Disturbances and obstructions						
I_5	0.511	0.041	151.792	<0.001	0.429	0.592
I_6	0.566	0.045	159.594	<0.001	0.478	0.654
I_7	0.000317	0.00001	503.547	<0.001	0.00029	0.00034
I_8	0.174	0.02	75.662	<0.001	0.135	0.213

Overall goodness-of-fit

$L(0) = -5,892.50$; $L(\beta) = -2,257.03$; AIC = 4,542.06

Pseudo- R^2

$R_{CS}^2 = 0.577$; $R_{McF}^2 = 0.617$

condition index (as their coefficients are negative). Conversely, it approaches the ‘worst’ (BLOS ‘F’) with an increase in numerical values of all remaining variables (as their coefficients are positive).

5.3 Ordered logit model development

The results of the ordered logit analysis are presented in Table 5. The table shows that the coefficient estimates are associated with negligible standard errors and also satisfy the required criteria of Wald-statistics. Thus, the coefficients estimates are able to provide unbiased results. The table also shows that, all important attributes are significantly ($p < 0.05$) contributing to the model at the 95% confidence level.

5.4 Performance assessment of developed models

Tables 2 and 3 show the overall goodness-of-fit of probit and logit models, respectively, measured through the likelihood measures. This test statistic evaluates whether the presence of exogenous variables significantly improves the quality of the model estimation. It is observed that the log likelihood of final models ($L(\beta) = -2,257.03$ and $-2,334.65$ for probit and logit models, respectively) are

substantially larger than the log likelihoods of the intercept-only models ($L(0) = -5,892.50$ and $-5,892.75$, respectively). Hence, it is concluded that both models are providing more accurate and meaningful estimations of BLOS scores than the intercept-only models.

However, while comparing through the application of AIC test statistics, the probit model was observed to have better precession (AIC = 4,542.06) over the logit model (AIC = 4,697.30). Tables 2 and 3 also show values of pseudo- R^2 obtained for both models. It can be observed that the probit model with $R_{CS}^2 = 0.577$ and $R_{McF}^2 = 0.617$ has higher prediction precision over the logit model with $R_{CS}^2 = 0.569$ and $R_{McF}^2 = 0.603$. From all these observations, we can conclude that though both probit and logit models have reasonably fair performances with the data sets used in this research, the ordered probit model is more preferred than the ordered logit one because of its higher degree of precision.

5.5 Model validation with traveler intercept survey data

As explained earlier, the proposed model (the ordered probit model) needed to be validated with perceived BLOS scores collected from the traveler intercept survey. For this

Table 5 Ordered logit model parameters

Factor	Coefficient	SE	Wald-statistic	Significance (<i>p</i> value)	95% Confidence interval	
					Lower bound	Upper bound
Threshold parameters						
Threshold 1 (μ_1)	-9.735	0.412	557.623	<0.001	-10.543	-8.927
Threshold 2 (μ_2)	-6.651	0.390	291.288	<0.001	-7.415	-5.888
Threshold 3 (μ_3)	-3.089	0.387	63.795	<0.001	-3.847	-2.331
Threshold 4 (μ_4)	1.436	0.393	13.351	<0.001	0.666	2.206
Threshold 5 (μ_5)	6.698	0.411	265.096	<0.001	5.892	7.505
Road conditions						
I_1	-0.380	0.032	143.750	<0.001	-0.442	-0.318
I_2	-1.968	0.080	610.992	<0.001	-2.124	-1.812
Traffic conditions						
I_3	0.00179	0.00006	824.521	<0.001	0.002	0.002
I_4	0.078	0.006	173.716	<0.001	0.067	0.090
Disturbances and obstructions						
I_5	0.908	0.074	149.252	<0.001	0.763	1.054
I_6	1.020	0.080	162.019	<0.001	0.863	1.178
I_7	0.00059	0.00002	464.392	<0.001	0.00053	0.00063
I_8	0.287	0.036	63.952	<0.001	0.217	0.357

Overall goodness-of-fit

$$L(0) = -5,892.75; L(\beta) = -2,334.65; AIC = 4,697.30$$

Pseudo- R^2

$$R^2_{CS} = 0.569; R^2_{McF} = 0.603$$

Table 6 Ordered probit model validation with traveler intercept survey data

Segment no.	$P(y = 1)$		$P(y = 2)$		$P(y = 3)$		$P(y = 4)$		$P(y = 5)$		$P(y = 6)$	
	Observed	Predicted	Observed	Predicted	Observed	Predicted	Observed	Predicted	Observed	Predicted	Observed	Predicted
Observed and predicted probabilities of <i>y</i> at each level (1–6)												
1	0.00	0.00	0.00	0.00	0.15	0.07	0.68	0.79	0.17	0.15	0.00	0.00
2	0.00	0.02	0.30	0.36	0.70	0.58	0.00	0.04	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.02	0.44	0.47	0.56	0.51	0.00	0.01	0.00	0.00
4	0.00	0.00	0.05	0.12	0.60	0.69	0.35	0.19	0.00	0.00	0.00	0.00
5	0.00	0.01	0.10	0.18	0.78	0.69	0.07	0.12	0.05	0.00	0.00	0.00
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.55	0.50	0.45	0.49
21	0.10	0.32	0.71	0.57	0.19	0.11	0.00	0.00	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.10	0.17	0.80	0.77	0.10	0.06	0.00	0.00
Statistics between observed and predicted probabilities at each level (1–6)												
<i>R</i>	0.996		0.912		0.966		0.980		0.988		1.000	
AAE	0.013		0.049		0.071		0.043		0.022		0.008	
RMSE	0.048		0.073		0.081		0.057		0.034		0.039	
MAE	0.224		0.204		0.174		0.162		0.084		0.183	

Overall prediction precision

$$S_B = 0.45$$

purpose, the probability of each response category ($y = 1, 2, \dots,$ or 6) obtained on each segment considered for model validation was calculated from traveler intercept survey

data sets. The same is summarized in Table 6 (Columns: 2, 4, 6, 8, 10 and 12). The predicted probability of each response category (y) on each validation segment was also

calculated with the help of ordered probit model, and the results are summarized in Table 6 (Columns: 3, 5, 7, 9, 11 and 13). In order to assess the prediction precision of the proposed model, several statistical parameters between observed and predicted probabilities are estimated and shown in Table 6 (Rows: 14–17). These parameters include the correlation coefficient (R), the average absolute error (AAE), the root-mean-square error (RMSE), and the maximum absolute error (MAE). As observed, the R value between observed and predicted probabilities is significantly high (i.e., above 0.91). This signifies that the observed and predicted probability values are very much close to each other. The error measuring parameters have also attained reasonably lower values with $AAE \leq 0.071$, $RMSE \leq 0.081$, and $MAE \leq 0.224$ in each case. In order to assess the overall performance of the developed model with validation data sets, the Brier's Score (S_B) [26] expressed below was used in this study:

$$S_B = \frac{1}{t} \sum_{j=1}^r \sum_{i=1}^n (f_{ij} - E_{ij})^2, \quad (12)$$

where t is the total number of occasions (22 segments in this study), r is the number of possible classes or categories in which an event can occur (i.e., six BLOS classes 'A–F' in this study), f_{ij} is the predicted probability that an event will occur in category j , and E_j is the observed probability that an event will occur in category j .

It is obvious that S_B has a minimum value of 'zero' for perfect predictions. This score for the ordered probit model as obtained using Table 6 was found to be 0.45, which is very much close to zero. Thus, it is concluded from all these investigations and observations that, the proposed model is well validated with traveler intercept data sets, and could be well applied for service quality assessments in mid-sized cities.

5.6 Determining overall predicted BLOS scores and bicycle service categories (A–F)

By applying the parameters estimated through ordered probit analysis to the vector of independent variables, we obtain the following model (as derived using Eq. (1)):

$$z_n = \mu_j - 0.38I_1 - 1.968I_2 + 0.00179I_3 + 0.078I_4 + 0.908I_5 + 1.02I_6 + 0.00059I_7 + 0.287I_8, \quad (13)$$

where $j = 1, 2, \dots, 6$, $\mu_1 = -5.648$, $\mu_2 = -3.952$, $\mu_3 = -1.885$, $\mu_4 = 0.652$, and $\mu_5 = 3.613$.

The overall predicted BLOS score ($BLOS_{Pred}$) for a roadway segment is nothing but the sum of probabilities obtained for individual 'y' values ($y = 1, 2, \dots, \text{or } 6$) multiplied by the corresponding numerical equivalent of

that service category 'j' ($j = 1, 2, \dots, 6$). The mathematical expression for the same is as follows:

$$BLOS_{Pred} = \sum_{j=1}^6 P(y=j) \times j, \quad (14)$$

where $P(y=j)$ values can be found out by putting corresponding Z_n values in Eq. (3).

In order to test the performance of above model in the present context, an investigation has been carried out. One roadway segment namely Master canteen to Rajmahal square of Bhubaneswar city was selected randomly from the study corridors, and its overall perceived BLOS score was compared with the model-predicted BLOS score. Field observations for this segment are $I_1 = 3.5$ m, $I_2 = 4$, $I_3 = 1,505.72$ PCUs/h/lane, $I_4 = 40$ km/h, $I_5 = 1$, $I_6 = 1$, $I_7 = 3,000$ veh/km/h, and $I_8 = 2$. The mean perceived BLOS rating for the segment is 4.14. Putting the field observed values in Eq. (13), Z_n values for the segment were calculated. Probabilities of perceived satisfactions of bicyclists in six-ordered response categories (1–6) were then calculated by putting Z_n values in Eq. (3) and shown below.

$$\begin{aligned} P(y=1) &= P(y \leq 1) = 0, \\ P(y=2) &= P(y \leq 2) - P(y \leq 1) = 0.0005, \\ P(y=3) &= P(y \leq 3) - P(y \leq 2) = 0.014, \\ P(y=4) &= P(y \leq 4) - P(y \leq 3) = 0.619, \\ P(y=5) &= P(y \leq 5) - P(y \leq 4) = 0.366, \\ P(y=6) &= 1 - P(y \leq 5) = 0.0005. \end{aligned}$$

The overall predicted BLOS score for the segment under consideration was calculated by using Eq. (14) as: $BLOS_{Pred} = (0 \times 1 + 0.0005 \times 2 + 0.014 \times 3 + 0.619 \times 4 + 0.366 \times 5 + 0.0005 \times 6) = 4.35$. Thus, the absolute deviation in the model prediction from the perceived score is as less as 0.21 (i.e., 4.35–4.14). Thus, the proposed model is convincingly efficient enough for service predictions in the present context.

The BLOS scores obtained for studied segments were used to define the ranges of bicycle service categories 'A–F,' where 'A' designates the 'excellent' service quality and 'F' designates the 'worst.' The ranges are defined in Table 7 by using a simple concept commonly followed in bicycle and pedestrian studies [for example, 7, 27, 28]. The mean perceived rating obtained in the present study was around 3.5, which corresponds to the boundary between LOS class 'C' and 'D.' This means to say that, BLOS scores below a value of 3.5 correspond to the LOS categories 'A–C,' and those above 3.5 correspond to the LOS categories 'D–F.' By considering the symmetry of the boundary point of 3.5, symmetrical cutoffs are made, and the LOS scale shown in Table 7 has been defined to stratify BLOS scores into LOS classes. The predicted BLOS score

Table 7 BLOS score ranges of service categories (A–F)

BLOS category	Overall perceived satisfaction level	Ranges of predicted BLOS score
A	Excellent	≤1.5
B	Very good	1.5–2.5
C	Good	2.5–3.5
D	Fair	3.5–4.5
E	Poor	4.5–5.5
F	Very poor	> 5.5

(4.35) of Master canteen to Rajmahal square of Bhubaneswar, for instance, indicates that the segment is offering a service category 'D' at its present scenario.

A detailed investigation was carried out to evaluate the effectiveness of the model in predicting the service categories of road segments in the real field. Predicted service categories of all studied segment were estimated through the application of the proposed BLOS model (ordered probit based). The survey-observed BLOS categories were compared with corresponding model-predicted BLOS categories, and results are shown in Table 8. The matching between these service categories was observably as high as 86%. On the basis of the model applications and evaluations, it was concluded that the proposed BLOS model is well applicable in the present context for the assessment of urban road segments.

6 Critical observations

It was observed from Table 8 that, around 1%, 4%, 46%, 42%, 6%, 1% of the total segments from study corridors are offering service qualities of 'A,' 'B,' 'C,' 'D,' 'E,' and

'F,' respectively. Thus, bicyclists are perceiving excellent and good levels of satisfactions only on 5% of total segments investigated in this study. This indicates a high requirement for enhancing the service qualities of existing facilities in order to encourage bicycle use in Indian cities. Most of the road facilities that are offering service categories of 'A' and 'B' were observed to carry a less volume of traffic (below 900 PCUs/h/lane) and have the provision of shared-use paths or well-conditioned paved shoulders. Road segments without the provision of these facilities but passing through rural fields and carrying less volume of traffic also came under these categories.

On the contrary, road segments offering service categories of 'C' and 'D' were observed to carry a relatively higher volume of traffic (up to 2600 PCUs/h/lane) and are substantially influenced by commercial and on-street parking activities. Though few segments have the provision of paved shoulders, those were observed to be illegally acquired by street vendors or parked vehicles. The considerable adverse effect from bicycle–vehicle interactions and hindrance from street vendors or on-street parking activities combined together mostly have made these segments to offer average to below average quality of services. These parking and vending activities though seem to be very trivial in Indian cities; actions must be taken by city authorities to rectify them in order to enhance bicycle services.

Road segments on which bicyclists are perceiving poor and very poor quality of services (BLOS 'E' and 'F') are generally passing through market areas and are highly influenced by on-street parking activities. Unavailability of separate bicycle paths, shrinkage of outermost lane width due to high roadside commercial and parking activities, and poor quality of pavement surface altogether have made

Table 8 Matching between observed and predicted BLOS categories (A–F)

Segment no.	Effective width of outside lane (m)	Pavement condition index	Traffic volume (PCUs/h)	Traffic speed (km/h)	Commercial activity	Ingress–egress to parking area (veh/km/h)	Frequency of driveways	Survey-observed BLOS category	Probit model BLOS category
1	3.5	4	1,187.07	37	1	2,010	2	D	D
2	3.5	4	1,403.67	38	1	2,010	2	D	D
3	3.5	4	1,015.75	37	0	0	0	C	C
4	3.5	4	1,165.95	38	0.5	330	1	C	D
5	3.8	2.5	1,112.30	29	0.5	20	0	C	D
6	3.5	3	1,103.00	37	1	6,000	2	E	E
7	7	4.5	190.00	29	0	0	0	B	B
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
74	2.5	2.5	1,700.00	41	1	6,000	3	E	E
Matching between survey-observed and model-predicted BLOS categories									86%

these segment to offer poor and very poor services to bicyclists.

7 Conclusions

Since the traffic flow in Indian cities is highly heterogeneous, perceived satisfactions of on-street bicyclists is affected by a complex bicycle-vehicle interaction and several other variables. The random forest technique, a noble and promising machine learning technique, has reported that eight variables on roadway geometrics, traffic flow conditions, and built environments have a potential effect on the occurrence. A node purity value obtained for each variable in the random forest analysis has reported the relative importance of the variables for the prediction of perceived satisfaction levels of bicyclists. It is observed that, traffic volume, effective width of outside through lane, roadside commercial activities, vehicular ingress–egress to the on-street parking area, pavement surface quality, average traffic speed, frequency of driveways carrying a high volume of traffic and interruptions by unauthorized stoppages of intermittent public transits are significantly affecting the occurrence in a descending order of importance. Traffic volume has the highest impact probably because bicyclists encounter a complex interaction with several kinds of motorized and non-motorized vehicles present in the heterogeneous traffic stream.

Traffic volume and outside lane width being two of the most important variables have concluded that the minimization of bicycle-vehicle interactions and provision of sufficient space for bicycle use are two key factors to enhance the bicycle service qualities. This can be accomplished by providing separate bicycle lane, wide curb-lane, or paved shoulder facilities. It is also concluded that, two traditional activities in Indian cities such as roadside vending activities, illegal on-street parking activities and unauthorized stoppages of intermittent public transits have a potential adverse effect on perceived satisfactions of bicyclists. Thus, these traditional activities must be rectified by the city authorities in order to enhance the bicycle service qualities on urban streets. Some major key innovations of the present study include the identification of two potential parameters not considered in previous studies such as: (1) interruptions by unauthorized stoppages of intermittent public transits, and (2) frequency of driveways carrying a high volume of traffic. In Indian cities, intermittent public transits form a significant percentage of the total traffic and usually stop on roadside areas for boarding and stepping down of passengers. These haphazard activities hinder the path of bicyclists and cause a significant discomfort to them. Likewise, the presence of driveways

also has a considerable adversative effect on perceived satisfactions of bicyclists. In the Spearman's correlation analysis, the frequency of driveways carrying a high volume of traffic had a significant correlation with user-perceived ratings. Conversely, while all driveways (including those carry a less volume of traffic) were considered together, the same parameter had an insignificant correlation with the output. Thus, the former parameter is included in the model development process. Some of these major factors additionally considered in this study feasibly differentiate the BLOS models development in developing countries from those in developed countries.

Though regression analysis has found its wide applications in the development of bicycle LOS models, it is not the best choice particularly in modeling the ordered response variables (e.g., perceived ratings = 1, 2, ..., or 6 in the present case). Regression analysis attempts to develop predictive models using the least-square criterion and predict a continuous variable, which is different than what was asked to the participants during the perception survey. To overcome these limitations, the performance of ordered probit and ordered logit models is investigated in this study. Though both models met a high confidence level of 95% for each input variable, the ordered probit model outperformed the logit model for the service predictions under mixed traffic conditions. The model has produced higher pseudo- R^2 values ($R_{CS}^2 = 0.577$; $R_{McF}^2 = 0.617$) with averaged observations. Thus, the fitting of the model with data sets used in this study is reasonably fair. An empirical equation is presented that can be used to derive a letter grade BLOS category (A–F) for a segment by incorporating the outputs of ordered probit model for the facility (i.e., the probability obtained for each service category, BLOS 'A' through 'F'). The model-predicted BLOS categories of the studied segments have a high matching of 86% with the expected service categories. This concludes that the model has a high application efficiency in the present context.

Another observation of this study concludes that, around 95% of all investigated roadway segments are offering BLOS categories of 'C' or below. Thus, the city authorities in India must take immediate actions by primarily focusing on the findings of the present study as well as other related studies for the betterment of bicyclists and public health as well. The ordered probit analysis-based BLOS model proposed in this research is basically a new decision support system for transportation engineers that will help in long-term transportation planning and designing of bicycle friendly networks primarily under heterogeneous traffic flow conditions. The limitation of this study is that the influence of bicycle lane parameters on bicyclists' perceived satisfactions is not addressed in the model building

process. The reason is the unavailability of such facilities in Indian mid-sized cities. However, researchers in other countries may develop similar BLOS models considering this bicycle lane parameter if such a provision is available. If the ranges of variables shown in Table 2 are satisfied in any big city under heterogeneous traffic conditions, then the proposed model could also be suitably adopted to assess the bicycle service quality.

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