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Forecasting the Quality of Service of Bogota's Sidewalks from Pedestrian Perceptions: An Ordered Probit MIMIC Approach

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Abstract
A variety of different pedestrian performance or service indicators (PPSI), such as the pedestrian level of service (PLOS), or quality of service (QoS), have been developed to evaluate pedestrian infrastructure. Although modeling approaches vary (e.g., ordinal least squares, scoring system), the great majority use on-site measurable attributes, such as sidewalk width or adjacent traffic, to estimate the PPSI. However, most of these models have been developed without jointly considering objective and subjective variables and their interactions. This study had two objectives: (i) to develop a model that simultaneously uses objective and subjective variables to estimate the pedestrian perception of sidewalks' QoS in Bogota, Colombia, and (ii) to identify the interactions between objective variables and pedestrian perceptions of sidewalk attributes. To do so, data was gathered from 1056 users of 30 sidewalks in the city and an Ordered Probit Multiple Indicator and Multiple Cause model was estimated and validated using match score, error distribution, and chi squared test. Using the model, it was possible to correctly forecast the perceived QoS in 26 of the 30 sidewalks, considering the interaction between users' characteristics and on-site sidewalk measured attributes with four latent variables (*sidewalk characteristics, surrounding, discomfort*, and *externalities*) based on pedestrian perceptions. We also proposed guidelines that provide decision makers with the tools to identify which sidewalk attributes actually influence pedestrian perception of QoS.

Pedestrian performance or service indicators (PPSI) have been estimated in transportation studies since 1971 (*1*). These indicators have been defined as pedestrian level of service (PLOS), quality of service (QoS), or satisfaction, and have been calculated using different modeling methodologies, including ordinal least squares (OLS), scoring systems, Delphi studies, multiple-criteria decision-making (MCDM), ordered models, and discrete choice models, where a variety of attributes from the built environment have been used as the main independent variables.

However, most of these models do not consider the simultaneous use of both objective (on-site measurable) attributes and subjective (user perceptions) variables on the estimation of the different PPSI. Furthermore, these models do not usually consider the interactions between on-site measurable attributes and user perceptions about infrastructure characteristics to calculate the dependent variable. User perceptions can enhance such models and their performance (*2*). This can improve the predictive power of the tool to estimate the pedestrian infrastructure QoS.

Given that including user perceptions and their interactions with on-site measurable attributes in a model is a strategy to obtain more information on the PPSI estimation, the objectives of this study were: (i) to develop a model that simultaneously uses objective and subjective variables to estimate the pedestrian perception of the QoS of sidewalks in Bogota, Colombia; and (ii) to identify the interactions between objective variables (related to the infrastructure) and pedestrian perceptions about

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certain characteristics associated with the sidewalk, by means of an ordered probit multiple indicator and multiple cause (MIMIC) model, estimated using on-site measurable attributes and latent variables (LV) specifically determined for Bogota.

This rest of the paper contains: first, a literature review that presents the most relevant studies on PPSI; second, a methodology section, where the data collection techniques, modeling framework, and model performance indicators are explained; third, a results section that shows the LV identification, model estimation, and model validation; fourth, a discussion and analysis section, where the LV and their interactions are explained in relation to their relationship with the QoS; and, finally, a conclusions section.

Literature Review

Throughout the years, many PPSI have been proposed to evaluate pedestrian performance or service on sidewalks. PLOS was initially proposed in the 1970s by Fruin (*1*). It was based on the level of service (LOS) methodology developed for motor vehicles by the Bureau of Public Roads (*3*). Then, in the 1980s, PPSI options were incremented by the addition of quality of service (QoS) as a definition for LOS and pedestrian comfort (*4*, *5*). In the 1990s, the PPSI spectrum also increased through the addition of other terms such as stress and experience (*6*, *7*). Finally, in the new century, the PPSI spectrum was completed by the addition of the term satisfaction (*8*). These PPSI are usually measured by asking the users for their perspective on the overall PPSI provided by the infrastructure. In addition, the PPSI terms are usually used interchangeably in the literature to refer the same output related to pedestrians.

Different methodological approaches have been used in the past to develop the existing PPSI. Some use a Delphi method or multi criteria decision approaches (*9, 10–12*) to understand or forecast the different PPSI. Others use a scoring system to calculate the different PPSI on a sidewalk (*6, 7, 13–20*). Others still, propose a linear relation between the PPSI and the explanatory variables generating an equation to calculate the PPSI through OLS models (*1, 4, 5, 21–26*). In some cases, a stepwise regression is used to select the independent variables (*27–34*). Finally, some studies do not consider a linear relation between the PPSI and the independent variables considering a probability for the PPSI outcome, which is recommended for these models (*8, 35–39*). Measurable physical attributes are usually used in these approaches to explain the PPSI (*40*, *41*). However, it is not common to use both objective and subjective (perceptions) attributes simultaneously to forecast PPSI. Nonetheless, including perceptions in the models may improve the models' performance (*2*).

In addition to PPSI, other approaches have been developed to understand how the design of walkable areas contributes to the perception of the quality of service using stated preferences from image-based experiments (*42–45*). Considering satisfaction theories, it has been established in the literature that there are direct and positive effects generated on user satisfaction, comfort, and stress reduction based on their perceived QoS. These theories also establish that user perceptions of the different elements with which they interact influence their perception of QoS (*46–49*). In pedestrians, these interactions can result in positive or negative effects on the perceived QoS, indirectly affecting the other PPSI.

Thus, understanding the positive and negative effects on perceived QoS of the interaction between pedestrians and sidewalks provides a basis to later understand the effects on PPSI. For example, there is much evidence supporting the idea that sidewalk characteristics impact PPSI positively (e.g., sidewalk accessibility, sidewalk width, sidewalk condition, furniture, and public transport access) (*40*, *41*). In the same line, surrounding characteristics such as the cleanliness, odor (*9*, *13*, *20*), and landscape (*12*, *13*), also have a positive impact on pedestrian QoS perceptions.

In contrast, there are a number of sidewalk attributes leading to pedestrian interactions negatively impacting the different PPSI. For example, the discomfort pedestrians feel when interacting with other pedestrians has a negative impact on pedestrian perception of QoS (*16*, *20*, *21*, *34*, *36*). Similarly, the effects on pedestrians of motor vehicles (externalities) such as the flow of heavy goods vehicles (HGV), vehicular speed, and vehicular flow also affect the PPSI negatively and the pedestrian perception of their QoS (*6–10, 13, 16–18, 25, 27–34*).

Methodology

Data Collection

The last origin–destination (OD) survey for Bogota showed that 53.01% of the travelers are women, that 33.34% of the travelers are 25 years or under, and 9.71% are over 65 years old. In relation to socio-economic strata (see note in Table 1), approximately 10.1% of the travelers are strata 1, almost 40% are strata 2, 35.4% are strata 3, 10% are strata 4, 2.5% are strata 5, and less than 2% are strata 6. Finally, the OD survey showed that 48.11% of the travelers are employed and that 18.21% are students (*50*).

The fieldwork comprised a simultaneous survey and in-situ objective data collection at 30 different locations around the city of Bogotá, Colombia (see examples in Figure 1). The locations selected for this survey were chosen to attain a variety of local characteristics and a diversity of typologies, traffic, and environments. In the end, 1056 valid responses were obtained (see Table 1). The

Table 1. Pedestrian Survey Sample Description

Indicator	Number (%)
Sex	
Female	508 (49.32)
Male	522 (50.68)
Age	
First quartile	22
Median	30
Mean	34.97
Third quartile	46
Socio-economic strata[a]	
1 (lowest)	83 (8.34)
2	374 (37.59)
3	373 (37.49)
4	90 (9.05)
5	58 (5.83)
6 (highest)	17 (1.71)
Occupation	
Employee	391 (37.52)
Student	259 (24.86)
Unemployed	69 (6.62)
Self-employed	217 (20.83)
Retired	56 (5.37)
Other	50 (4.80)
Marital status	
Single	593 (56.64)
Married	198 (18.91)
Domestic partnership	203 (19.39)
Widow(er)	14 (1.34)
Divorced	12 (1.15)
Separated	27 (2.58)

[a]In Colombia the socio-economic strata serve to differentiate people based on their income level, with 1 being the poorest and 6 the richest.

surveys were applied between June 2 and June 19, 2018, during working days from 8 a.m. to 6 p.m. Each survey lasted 8 minutes approximately and the overall response rate was 33.2%. Surveyors picked respondents at random (one in every three passing pedestrians).

The survey included questions on the overall perceived QoS of a specific sidewalk general perception questions, sidewalk-related perception statements or questions, answered on a 10 point Likert scale (0 poor and 10 excellent), and questions related to the trip undertaken by the pedestrians, as well as their socio-demographic characteristics. For the purpose of this paper, only the dependent variable, general perceptions, and the sidewalk-related perception statements or questions were used. In addition, various physical characteristics of each sidewalk were measured to include objective variables in the analysis (see Table 2 and Figure 2). From now on the independent variables (objective and latent) will be denoted in italics.

Modeling Approach

Subjective attributes associated with the user perceptions in forecasting models have frequently been used to identify LV (*51*). There are studies that report that models including LV are superior in relation to log-likelihood in comparison with similar models that do not include LV, but this superiority is not necessarily caused by the use of LV (*52*, *53*). However, the inclusion of LV into the models provides the opportunity to identify the effects of the objective attributes on the users' cognitive processes in a way that cannot be considered in the absence of LV (*52*, *53*). For these reasons, an Ordered Probit, MIMIC model was formulated and estimated to forecast the perceived QoS on Bogota's sidewalks.

MIMIC models have been used in the past in transportation studies related to pedestrians to understand pedestrians' street-crossing choices (*54*). MIMIC models are based on the estimation of a structure based on pedestrian perceptions and composed by LV, indicators, attributes, and their relations, to then forecast the desired indicator. As in structural equation modeling (SEM), the MIMIC structure assumes a temporal precedence between the established relations, where the presumed cause occurs before the presumed effect (*55*). The forecasting model was initially estimated using the complete dataset. This was then divided into two parts: 70% to re-estimate the model, and 30% to validate it. Finally, the forecasting performance of the model was evaluated using match score, error distribution, and χ^2 test.

MIMIC Models. MIMIC models are an extension of SEM and can be developed by using the indicators and attributes as numeric or ordinal variables. For MIMIC models, the LV need to be identified or proposed to perform the analysis. To do so, an exploratory factor analysis (EFA) was initially developed, which helps to identify the number of LV and the perception indicators in each of them. EFA is a statistical procedure that through an orthogonal rotation generates a set of uncorrelated LV (*56*). Considering the EFA results and the literature review, a MIMIC model was proposed to forecast the perceived pedestrian QoS.

Figure 3 present a generic MIMIC model considering an ordinal dependent variable. For this study, this model is going to be solved using an ordered probit approach.

Figure 3 shows a generic model with one LV (η), j indicators (y), and i attributes or independent variables (x). Each one of the indicators were measured using the on-site perceptions presented in Table 2 and are a function of two variables (i.e., η and ε_j), with η common to all y_j. The indicators can be calculated using Equation 1, where α represents the intercept term (constant), λ coefficients indicate the change in the value of the observed attributes if there is a change of one unit in the LV respectively, and ε is the error in the measurement equation with an expected value of zero. Additionally, LV η is a function of the independent variables (x_i) and can be calculated using Equation 2, where γ coefficient is the structural parameter that

Figure 1. Audited sidewalk examples.

indicates the change in the value of η if there is a change of one unit in x, and ζ_η is the random error for the LV with a mean expected value of zero.

$$y_j = \alpha_j + \lambda_j \eta + \varepsilon_j \tag{1}$$

$$\eta = \gamma_i x_i + \zeta_\eta \tag{2}$$

The forecasting model was estimated using the R function “sem” of the package called “lavaan” (*57*, *58*). To forecast using the ordered probit MIMIC model, a variable z was defined that is unobserved like the variable used for ordered models. This variable is usually defined as a linear function of each observation and for this study is considered as a linear function of each LV (η) and independent variables (x_i) as in Equation 3.

$$z = \beta\eta + \gamma X + \zeta_z \tag{3}$$

where η is an LV vector, β is the parameters vector associated to the LV vector, X is an attributes vector, γ is the parameters vector associated to the attributes vector, and ζ_z is the random disturbance associated to z. If the random disturbances are assumed independent and normally distributed with mean 0 and variance 1, the probabilities for the ordered probit MIMIC model can be calculated using Equation 4.

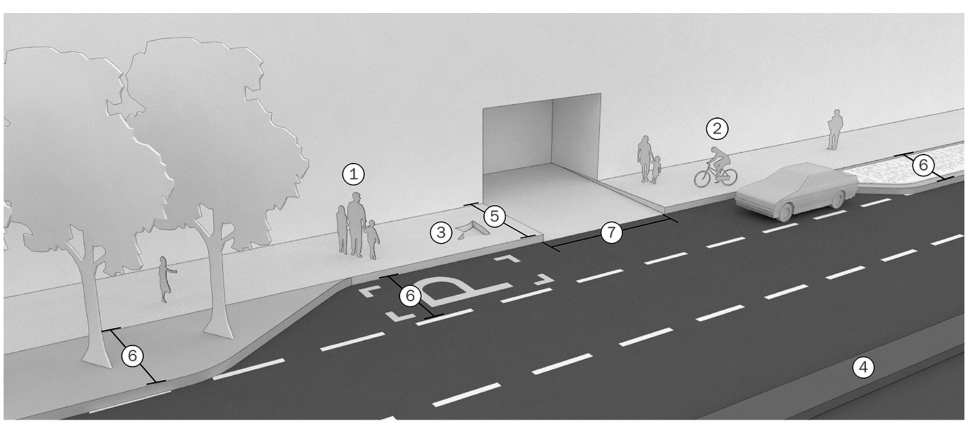
$$\begin{aligned} &P(Y=0) = \Phi(\mu_0 - z) \\ &P(Y=1) = \Phi(\mu_1 - z) - P(Y=0) \\ &P(Y=2) = \Phi(\mu_2 - z) - P(Y=1) - P(Y=0) \\ &P(Y=I-1) = \Phi(\mu_{I-1} - z) - \sum_{k=0}^{I-2} P(Y=k) \\ &P(Y=I) = 1 - \sum_{k=0}^{I-1} P(Y=k) \end{aligned} \tag{4}$$

where $\Phi(^*)$ is the cumulative normal distribution, μ are the estimable thresholds defining Y, and I is the highest ordered response. Equation 4 was adapted from Washington et al. (*59*).

Table 2. On-site Measurable Indicators and Attributes

Type	Variable	Statement/question	Range/units
On-site perceptions	Vehicular flow HGV flow Vehicular speed	Rate from 0 (does not bother me at all) to 10 (bothers me a lot), how much bother you the following characteristics of the sidewalk, here	0–10
	Odor Environment Landscape	Rate from 0 (totally uncomfortable) to 10 (totally comfortable) how comfortable you feel at this moment with the following aspects, here	
	Width Condition Furniture Public transit access	Rate at this point from 0 (lousy) to 10 (excellent) the following	
	Rate from 0 (totally disagree) to 10 (totally agree) the following statements		
	Pedestrians far from me	When walking on this sidewalk, I prefer other pedestrians separated from me	
	Too many pedestrians	On this sidewalk, the number of pedestrians does not let me walk freely	
	I prefer not to walk here	I would rather not walk on this sidewalk	
	Accessibility	On this sidewalk it is easy to go with a stroller or wheelchair	
On-site objective variables[a]	Age		(years)
	Bicyclist presence		(yes/no)
	Potholes presence		(yes/no)
	Median strip presence		(yes/no)
	Sidewalk width		(m)
	Buffer width		(m)
	Driveway length		(m)

[a]See Figure 2 for a description of the on-site objective variables.



Legend
1. *Age*; 2. *Bicyclist presence*; 3. *Pothole presence*; 4. *Median strip presence*; 5. *Sidewalk width*; 6. *Buffer width*; 7. *Driveway length*

Figure 2. Schematic representation of objective variables in the right of way.

To test the generic model, all the assumed relations are considered at the same time, and the fit of the complete model is evaluated to assure that the estimated covariance matrix is significant and similar to the observed covariance (*60*).

Performance Indicators for Model Validation. A match score was defined as one of the performance indicators to test the model. To decide whether there is a match or not, the upper ($\overline{\text{QoS}}$ max) and lower limits ($\overline{\text{QoS}}$ min) were initially calculated of a confidence interval with 95%

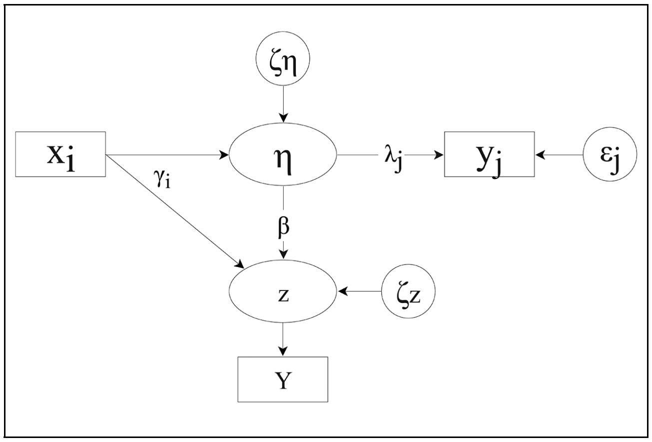


Figure 3. MIMIC generic model with ordinal dependent variable.

confidence level of the actual average QoS ($\overline{\mathrm{QoS}}$) obtained from the survey responses. Then, a score of 1 was assigned to the cases where the forecasted values of the QoS ($\widehat{\mathrm{QoS}}$) were within the interval. In addition, the error distribution was considered using the differences between the forecasted values ($\widehat{\mathrm{QoS}}$) and the actual average of the QoS ($\overline{\mathrm{QoS}}$) for each sidewalk. Using the differences, the minimum and maximum value, and the first, second, and third quartile were then calculated to visualize the error distribution.

Similarly, the χ^2 test was used to determine whether the observed data distribution and the forecasted data distribution are not significantly different (null hypothesis). To use this test, it was necessary to compare the expected (E) and observed (O) totals for each defined category (*51*). This comparison can be carried out by calculating the χ^2 statistics using Equation 5.

$$\chi^2{}_{FPR} = \sum_{i=1}^{m} \frac{(O_i - E_i)^2}{E_i} \tag{5}$$

where m is the number of categories, and $\chi^2{}_{FPR}$ must be compared with the critical value $\chi^2{}_{0.95}$ with m-1 degrees of freedom. If $\chi^2{}_{FPR} < \chi^2{}_{0.95;m-1}$ the null hypothesis is consistent and accepted (*51*).

Results

From the EFA and the literature review, four potential LV were identified: *sidewalk characteristics, surrounding, discomfort*, and *externalities*. *Sidewalk characteristics* explains five perception indicators (i.e., accessibility, width, condition, furniture, and public transport access). *Surrounding* explains three perception indicators (i.e., odor, environment, and landscape). *Discomfort* explains three perception indicators (i.e., pedestrians far from me, too many pedestrians, and I prefer not to walk here). Finally, *externalities* explains three perception indicators (i.e., vehicular flow, heavy goods vehicle flow, and vehicular speed).

The perceived QoS is considered as an ordinal variable, explained by the existence of the four previously identified LV. It is possible to forecast the perceived QoS in an ordinal scale, through the inferred LVs and on-site objective variables. The ordered probit model results are presented in Table 3 and Figure 4.

The QoS forecasting ordered probit MIMIC model presents a satisfactory adjustment (see Table 3) and is made up of 11 independent variables (four latent and seven objective) and 14 LV indicators. The perceived QoS is influenced positively by two LV (*sidewalk characteristics* and *surrounding*), and negatively by the presence of *bicyclists*. The LV *sidewalk characteristics* is improved by the effect that *surrounding LV* generates, by the *age* of the pedestrians using the sidewalk, and by increasing the *sidewalk width*. On the other hand, the way that LV *sidewalk characteristics* is perceived decreases with the presence of *potholes* in the sidewalk and by the effect of two LV (*externalities* and *discomfort*). The LV *surrounding* is improved only if the *buffer width* increases. On the other hand, *surrounding* decreases when the driveway's length increases and by the effect of two other LV (*externalities* and *discomfort*). In turn, *discomfort* is one of the LV decreasing the perceived QoS and its effects are aggravated by the influence of the LV *externalities*. Finally, the *externalities* LV decreases the perceived QoS and its effects can be mitigated by increasing the *buffer width* and with a *median strip* presence. However, its effects can be aggravated by the presence of *bicyclists* on the sidewalk.

Model Validation

Equation 6 was developed through a process in which the independent variables (i.e., perceived QoS and LV) presented in Table 3 and Figure 4 were expressed in relation to the objective attributes. Using Equation 6, and assuming independent and normally distributed random errors with mean 0 and variance 1, the unobserved variable z was initially calculated for each sidewalk. Then, using these results and the thresholds presented in Table 3, the probability of obtaining each value (0–10) was calculated using Equation 4. Finally, the expected value was calculated and determined as the estimated QoS ($\widehat{\mathrm{QoS}}$) using the probabilities obtained previously. To decide whether or not there is a match, the upper and lower limits of a confidence interval of the actual average QoS ($\overline{\mathrm{QoS}}$) were calculated. Using the confidence intervals, a score of 1 was assigned to the cases where the forecasted values were within the interval.

Table 3. Forecasting QoS with the Ordered Probit MIMIC Model

Goodness of fit indicators for the MIMIC model	Accepted threshold	Model result
χ^2/DF: Measures the discrepancy between the sample and model covariance matrices corrected for degrees of freedom.	<3.000	1.737
Comparative Fit Index (CFI): Compares the proposed model with a non-correlated model between latent variables.	>0.950	0.989
Root Mean Square Error of Approximation (RMSEA): Determines the model fit to the covariance matrix of the sample with unknown coefficients.	<0.060	0.032
Standardized Root Mean Square Residual (SRMR): Calculates the square root of the difference between the sample and the hypothesized model covariance matrices residuals.	<0.080	0.038

Infrastructure perceived QoS[a]	Estimate	Standard error	*t* statistic	*p*-value	Significance
Threshold 0	–1.039	0.184	–5.637	0.000	***
Threshold 1	–0.960	0.180	–5.330	0.000	***
Threshold 2	–0.611	0.174	–3.521	0.000	***
Threshold 3	–0.189	0.171	–1.108	0.268	
Threshold 4	0.093	0.170	0.550	0.582	
Threshold 5	0.556	0.170	3.275	0.001	**
Threshold 6	0.853	0.171	4.980	0.000	***
Threshold 7	1.116	0.171	6.508	0.000	***
Threshold 8	1.620	0.173	9.354	0.000	***
Threshold 9	1.867	0.173	10.787	0.000	***
Sidewalk characteristics[b]	1.569	0.125	12.527	0.000	***
Surrounding[b]	0.222	0.047	4.768	0.000	***
Bicyclist (yes=1/no=0)	–0.250	0.096	–2.601	0.009	**
Sidewalk characteristics[b]	**Estimate**	**Standard error**	***t* statistic**	***p*-value**	**Significance**
Surrounding[b]	0.176	0.030	5.883	0.000	***
Externalities[b]	–0.125	0.026	–4.858	0.000	***
Discomfort[b]	–0.131	0.046	–2.875	0.004	**
Age (years)	0.005	0.001	3.699	0.000	***
Potholes (yes=1/no=0)	–0.201	0.048	–4.208	0.000	***
Sidewalk width (m)	0.152	0.026	5.908	0.000	***
Surrounding[b]	**Estimate**	**Standard error**	***t* statistic**	***p*-value**	**Significance**
Externalities[b]	–0.194	0.038	–5.145	0.000	***
Discomfort[b]	–0.392	0.074	–5.331	0.000	***
Driveway length (m)	–0.010	0.003	–3.540	0.000	***
Buffer width (m)	0.112	0.025	4.445	0.000	***
Discomfort[b]	**Estimate**	**Standard error**	***t* statistic**	***p*-value**	**Significance**
Externalities[b]	0.277	0.030	9.129	0.000	***
Externalities[b]					
Bicyclist (yes=1/no=0)	0.284	0.102	2.788	0.005	**
Median strip presence (yes=1/no=0)	–0.373	0.103	–3.627	0.000	***
Buffer width (m)	–0.099	0.030	–3.261	0.001	**

Note: MIMIC = multiple indicator and multiple cause; QoS = quality of service. Significance codes: $^{***}p < 0.001$, $^{**}p < 0.010$, $^{*}p < 0.050$, $\cdot p < 0.100$.
[a]Pedestrian perception responses in situ from 0 to 10.
[b]Inferred latent variable.

$$z = 0.008^{*}A - 0.365^{*}BP - 0.315^{*}PP + 0.151^{*}MSP + 0.238^{*}SW + 0.096^{*}BW - 0.005^{*}DL \quad (6)$$

where

A: average *age* of pedestrians using the sidewalk (years)
BP: *Bicyclist* presence on the sidewalk (yes = 1/no = 0)
PP: *Potholes* presence on the sidewalk (yes = 1/no = 0)

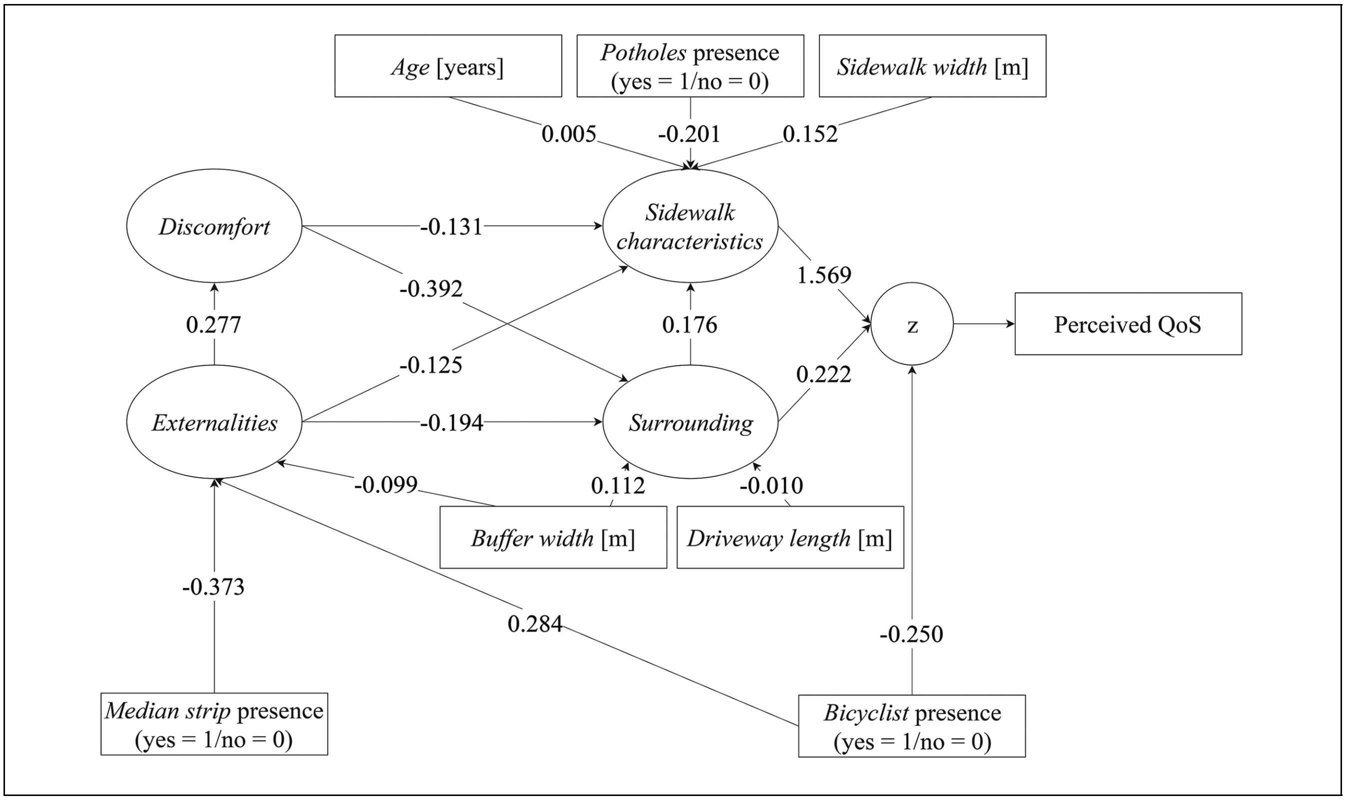


Figure 4. MIMIC model to forecast the pedestrian perceived QoS.

MSP: *Median strip* presence on the sidewalk right of way (yes = 1/no = 0)
SW: *Sidewalk width* (m)
BW: *Buffer width* (m)
DL: *Driveway length* on the sidewalk section (m)

Table 4 shows the measured QoS ($\overline{QoS}$) for each sidewalk ($\overline{QoS}$), the confidence intervals for the $\overline{QoS}$, and the estimated QoS ($\widehat{QoS}$).

For this study, the forecasted ($\widehat{QoS}$) value matches with the 95% confidence interval of the measured QoS in 26 out of 30 sidewalks. Considering the error dispersion obtained from the differences presented between the $\widehat{QoS}$ and the $\overline{QoS}$, the following were found: an error minimum value of –2.15, first quartile of –0.70, second quartile of –0.21, third quartile of 0.31, and a maximum value of 1.25. This shows that the model presents an error variance of around 0 with a median close to 0.

Finally, the χ^2 test was considered to prove whether the distribution of the frequencies obtained using the model is statistically similar to the distribution of the observed data frequency. The χ^2 test presents problems when the frequencies obtained using the models are less than 5. For this reason, to conduct this analysis, four different alternatives were generated for QoS forecasting (5 or less, 6, 7, 8 or more). The calculated test statistic for this model is 1.281 and must be compared with a statistical value of the χ^2 considering a significance level of 0.05 and three degrees of freedom (χ^2 = 7.815). Considering this result, it is clear that the frequencies obtained from the expected value of this model are statistically similar to the observed data frequency.

Discussion and Analysis

A methodology was used that allowed the incorporation of both objective and subjective attributes simultaneously to forecast the pedestrian perceived QoS. This approach has been used for other transport modes or pedestrians' choices, but the contribution of this research is to propose a new use of MIMIC models to identify the effects that objective and subjective attributes, and their interactions, have on the perceived QoS in pedestrians. This approach made it possible to quantify the effects of these attributes on the perceived QoS when a model that contemplates both objective and subjective attributes simultaneously is generated. The objective and subjective attributes used in this study were found in the literature as variables affecting PPSI. There were 11 independent variables identified that could contribute to the forecasting of the perceived QoS. Of these independent variables, seven are characteristics pertaining to the users and sidewalks, and four are LV.

Our results suggest that the LV *externalities* is the first to be perceived by pedestrians, negatively impacting the

Table 4. Forecasting for Sidewalk QoS using the Sidewalk Data

Location #	$\overline{\text{QoS}}$	$\overline{\text{QoS}}$ min.	$\overline{\text{QoS}}$ max.	$\widehat{\text{QoS}}$
1	7.18	5.76	8.60	5.93
2	6.45	4.78	8.13	6.61
3	8.00	6.43	9.57	6.47
4	7.00	5.65	8.35	8.15
5	5.36	4.33	6.40	5.35
6	5.91	3.84	7.98	5.36
7	7.27	5.82	8.72	7.52
8	8.00	7.08	8.92	5.85
9	7.70	6.39	9.01	6.34
10	3.55	1.79	5.31	4.46
11	7.18	5.92	8.44	6.56
12	7.36	6.17	8.55	8.33
13	8.09	6.76	9.42	6.98
14	8.27	6.73	9.82	7.59
15	5.09	3.39	6.79	5.16
16	6.40	5.09	7.71	6.99
17	5.82	4.03	7.61	6.15
18	5.50	4.48	6.52	5.99
19	5.50	3.72	7.28	6.75
20	4.73	3.46	6.00	4.46
21	6.36	4.98	7.74	6.14
22	8.55	7.62	9.47	7.54
23	6.90	5.52	8.28	5.75
24	7.27	6.68	7.87	7.07
25	7.20	5.97	8.43	6.82
26	5.50	3.74	7.26	5.45
27	6.70	4.72	8.68	5.99
28	3.73	2.85	4.61	4.68
29	8.80	7.44	10.16	8.16
30	5.45	3.95	6.96	5.64

Note: max. = maximum; min. = minimum; QoS = quality of service.

perceived QoS through the mediation of the other LVs (*discomfort, surrounding*, and *sidewalk characteristics*). To forecast the value of this LV, the model suggests that sidewalks with the presence of *bicyclists* increases the LV value, decreasing the perceived QoS. The literature has indeed established that the presence of bicycles on sidewalks negatively affects perceived PLOS (*27*, *37*). This model also suggests that sidewalks located in rights of way considering a *median strip* for vehicles and increasing the separation between pedestrians and motor vehicles can counteract the effect of *externalities* on the perceived QoS. This result is also supported in the literature (*8*). In addition, greater separation between pedestrians and motor vehicles has also been shown to improve PLOS (*40*, *41*).

According to the model, the second LV perceived by pedestrians is *discomfort*. This LV also negatively impacts the perceived QoS through the mediation of other LVs (*surrounding* and *sidewalk characteristics*), and is also impacted by *externalities*, meaning that the objective variables affecting *externalities* also indirectly affect *discomfort*. However, it was not possible to find which sidewalk or user characteristics had a direct impact on the value of *discomfort*.

The third LV perceived by pedestrians is *surrounding*. This LV positively impacts the perceived QoS both directly and through the mediation of *sidewalk characteristics*, and it is negatively impacted by *externalities* and *discomfort* (which means that the presence of *bicyclists, median strip*, and *buffer width* have an indirect impact on this LV). However, the model suggests that the *buffer width* impacts *surrounding* indirectly, and that an increase in the separation between pedestrians and motor vehicles directly impacts *surrounding* improving its value. The model also suggests that increasing the *driveway length* along the sidewalk decreases the perceived value of *surrounding* for pedestrians, negatively impacting the perceived QoS. This result is supported by the literature, as it has been established that the presence of driveway segments increases conflicts for pedestrians, creates potential dangers for them, and reduces their satisfaction, comfort, and safety (*6*, *14*, *27*, *29*, *38*).

The fourth LV that the model suggests pedestrians perceive when walking is *sidewalk characteristics*. This LV positively impacts the perceived QoS but only directly and it is, at the same time, also affected by the other LVs (*surrounding, discomfort*, and *externalities*). This means that the attributes *buffer width, driveway length, median strip* presence, and *bike presence* have an indirect effect on this LV. The model suggests that some sidewalk attributes, such as the presence of *potholes*, can decrease the LV value, negatively impacting the perceived QoS. This finding is also supported in the literature, where it is mentioned that poor sidewalk conditions represented by the presence of *potholes* decrease infrastructure quality (*7, 9, 12–16, 20, 33*). According to the model results, increasing other sidewalk attributes such as *sidewalk width* represents an improvement in LV value and perceived QoS, which is also consistent with what has been shown in the literature through history (*40*, *41*). User characteristics such as *age* have a positive impact on this LV value, meaning that the older the user, the better the value for *sidewalk characteristics* and the perceived QoS.

All the previously mentioned, LVs affect perceived QoS both directly and indirectly, meaning that the user attribute *age* and the sidewalk attributes *potholes* presence, *sidewalk width, buffer width, driveway length, median strip* presence, and presence of *bicyclist* indirectly affect perceived QoS. The model also suggests that the presence of *bicyclist* on the sidewalk has a direct negative impact on perceived QoS. Also, that to improve the perception of the LVs *sidewalk characteristics* and *surrounding* generates a positive impact on perceived QoS. Finally, avoiding pedestrian irritation because of their perception of the LVs *discomfort* and *externalities* improves perceived QoS, and can be done easily by ameliorating the different sidewalk attributes previously analyzed and by considering Equation 6.

Conclusions and Further Investigation

Based on the forecasting model, it is possible to identify the role and impacts of some sidewalk attributes on the LV and perceived QoS (see Table 3 and Figure 4). Initially, it can be suggested that to decrease the negative effect of *externalities* and to improve the pedestrian perception of their QoS, bicyclists should not be allowed on the sidewalk. In addition, to further decrease the negative effect of *externalities*, the distance between pedestrians and the road would need to be increased, which also serves to improve the perception of *surrounding*. To design rights of way including the presence of a median strip decreases the negative effect of the perceived *externalities* on perceived QoS, and to design and build sidewalks reducing *driveway length* has a positive impact on the perception of *surrounding*. To provide a sidewalk with no *potholes* and increase the sidewalk width positively impacts pedestrian perception of *sidewalk characteristics*. In sum, it is possible to involve on-site measurable attributes with user perceptions to generate better pedestrian infrastructure, understanding the impacts of the sidewalk attributes on the users.

It was found that a model jointly considering objective and subjective variables and their interactions can explain pedestrian QoS with satisfactory fit indicators. The approach proved that proposing LVs allows an understanding of the effects of the objective attributes on the pedestrian cognitive process when evaluating their perceived QoS. In addition, although this study is based on forecasting pedestrians' perceived QoS on urban sidewalks, the model estimated in this study can also be used to enrich other related indices (e.g., walkability).

The proposed pedestrian QoS forecasting model presented in Equation 6 can be easily applied to evaluate the service provided by sidewalks, but it was designed only for Bogota. However, considering the structure of the ordered probit MIMIC model, it is possible and recommended to develop a methodology to calibrate a similar model for use in different contexts. An approach to developing this calibration methodology may consist, first, in understanding how the measurement model is generated in the new context (user perceptions) and then, by considering the differences between the proposed measurement model and that in the new context.

Finally, this study makes one of the first attempts to understand how pedestrians rate the sidewalk QoS from their perceptions, a topic that is as yet nascent. For this reason, information is only provided about pedestrians considering them as a transport mode. Future studies should consider the heterogeneous effects of pedestrian differences (e.g., sex, occupation, platoons, trip purpose, environmental conditions, slope, etc.) in their QoS perceptions.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J. Vallejo-Borda, A. Rodriguez-Valencia, J. Ortúzar; data collection: J. Vallejo-Borda; analysis and interpretation of results: J. Vallejo-Borda, H. Ortiz-Ramírez, A. Rodriguez-Valencia, R. Hurtubia, J. Ortúzar; draft manuscript preparation: J. Vallejo-Borda, H. Ortiz-Ramírez. All authors reviewed the results and approved the final version of the manuscript.

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