Statistical Modeling of User Perceptions of Infrastructure Condition: Application to the Case of Highway Roughness

Kevan Shafizadeh[1] and Fred Mannering[2]

Abstract: In determining certain infrastructure rehabilitation needs, it is sometimes important to consider user perceptions along with physical measures of infrastructure condition. Pavement roughness is one such case. A critical determinant of public satisfaction, user perception of pavement roughness can potentially play a critical role in the allocation of resources to competing highway resurfacing projects. In this paper, to gain a better understanding of user perceptions of pavement roughness, users were placed in real-world driving conditions and asked to rank the roughness of specific roadway segments. Coupled with individual-specific, pavement-specific, and vehicle-specific data, users' roughness rankings were modeled using a random effects ordered probit specification. The model identified a number of key factors influencing user roughness rankings. The results indicate that, while physical roadway-roughness measurements, such as the measured International Roughness Index, provided a strong indication of user roughness rankings (as one might expect), other factors such as the type of vehicle used, vehicle speed, individual's age, individual's gender, and interior vehicle noise levels were also significant. This study fills an important gap in the literature by linking physical infrastructure measurements with individual perceptions of infrastructure condition.

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Introduction

Physical measurements of infrastructure condition have long been used as a basis for determining rehabilitation needs and resource allocation. For highways, road roughness has traditionally played a significant role in highway resource allocation and forecasting highway needs. Road roughness has great appeal to state and federal agencies because it has been traditionally correlated to both structural deterioration and some estimated sense of public satisfaction with roadway conditions. As a result, many states collect detailed information on pavement condition including measurements relating to rutting, faulting, cracking, patching, and scaling. Among the various condition measures, the International Roughness Index is widely used by the Federal Highway Administration and has gained wide acceptance as a means of assessing changes in the condition of highways and to forecast highway investment needs. However, the relationship between physical measurements of pavement roughness and the public's actual perception of roughness has not been adequately modeled, statistically, and thus is not well understood. Many have argued that the public's perceptions of roughness should play an important role in resource allocation because of the influence that such perceptions can have on governmental agencies and political entities. As a result, perhaps the role that actual physical measurements play in resource allocation should be appropriately modified, particularly when structural integrity and safety (for example diminished skid resistance) are not in question.

The study of the relationship between physical roughness measures and user perceptions of roughness began in earnest in the late 1950s when AASHTO (1993) conducted a study, in which 100 individuals subjectively rated segments of pavements in three states (Illinois, Indiana, and Minnesota) on a scale from 0 to 5 (Carey and Irick 1960). That study established the concept of pavement serviceability with the present serviceability rating defined as the mean individual ratings made by the members of a panel intended to represent all highway users. This performance measure was widely accepted in the highway engineering community and became one of the study's most notable contributions.

To establish uniformity of the physical measurement of roughness, the World Bank commissioned an experiment in Brazil to establish a roughness measurement standard, which resulted in the development of the International Roughness Index (IRI) (Sayers et al. 1986). The IRI is used to define a characteristic of the longitudinal profile of a traveled wheel track and constitutes a standardized roughness measurement. It is based on a filtered ratio (referred to as the average rectified slope) of a standard vehicle's accumulated suspension motion (m) divided by the distance traveled by the vehicle during the measurement (km). Thus, commonly recommended measurement units are m/km. The IRI has been shown to correlate well with vertical passenger acceleration (a measure of ride quality) and tire load (a measure of controllability and safety). The IRI is now considered the international standard for comparing roughness measurements. However, since the 1950s, the adequacy of any physical roughness measurement (the IRI now included) to act as a proxy for user perceptions of roughness has been questioned.

[1]Assistant Professor, Dept. of Civil Engineering, California State Univ., Sacramento, CA 95819-6029. E-mail: kevan@csus.edu

[2]Professor, School of Civil Engineering, 550 Stadium Mall Dr., Purdue Univ., West Lafayette, IN 47907. E-mail: flm@ecn.purdue.edu

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The relationship between users' subjective ratings of roughness and any physical measurement of roughness is understandably complex. The early work of Carey and Irick (1960) showed good correlation between subjective ratings and physical measurements, but Janoff et al. (1985) noted that there were a number of factors that could potentially affect this correlation, such as vehicle characteristics, vehicle operating speed, and individual characteristics such as gender and age. Since the mid-1980s, several studies have explored the relationship between physical roadway measurements and user perceptions of roughness using slightly modified experimental procedures and/or different or updated road-roughness measuring devices (Janoff et al. 1985; Nair and Hudson 1986; Moore et al. 1985; Garg et al. 1988). The findings of these studies have varied widely in terms of the factors found to significantly impact road-roughness perceptions. Overall, our survey of the extant literature indicates that the link between physical measurements of roadway roughness and user perceptions is in need of further study—particularly in light of comparatively recent developments in the statistical modeling of ordered discrete data, such as those typically gathered during roadway-roughness perception surveys.

Data

The data used in this study originated from three sources: (1) a mailed survey; (2) an in-vehicle user survey; and (3) the Washington State Department of Transportation's pavement management system. The mail survey was sent to over 2,500 registered vehicle owners in the Seattle, Washington metropolitan area. The purpose of the preliminary mail survey was to gather general public opinions about roadway roughness along with relevant sociodemographic information, as well as create a pool of potential participants for an in-vehicle study [see Shafizadeh et al. (2002)].

For the in-vehicle study, selected participants were told that they would be driving over predetermined highway test segments on a 40-km circular loop of Seattle-area freeways. As they drove over the test segments, they were asked: "How would you rank the roughness of the road on a scale from 1 to 5—with one being the smoothest (or the best) and five being the roughest (or the worst)?" Participants were not provided additional instructions. They were informed that during the driving experiment they would be notified when each segment started and ended and could provide their response at any point along the segment. To control for factors likely to influence user perceptions, the type of vehicle being used (minivan, pickup, etc.) and starting locations within the 37-segment test route were randomized. In addition, on each of the 37 segments, data were gathered on in-vehicle-cabin noise (dB), vehicle speed (km/h), weather conditions (clear, overcast, raining), and pavement conditions (wet or dry) as each participant traversed the segment [see Shafizadeh et al. (2002); Shafizadeh and Mannering (2003)].

Finally, the Washington State pavement management system provided physical data on each segment and was instrumental in the segment selection process by providing information about terrain, shoulder widths, number of lanes, and lane width, all of which were required to be homogeneous within each segment as part of the roadway segment selection criteria. Also, data relating to pavement defects were available from this source, including the IRI measurement, age of the roadway surface, information on patching, and the pavement structural condition (PSC). This last term is calculated separately for flexible and rigid pavements based on the amount and severity of various distresses and its values range from 100 (excellent pavement condition) to zero (completely deteriorated pavement).

Table 1. General Summary Statistics of Respondents, Segments, and Vehicles

Variables	Values
Individual-specific variables	
Percent of male/female respondents	64.5/35.5
Average household size (standard deviation)	2.7 (2.11)
Average household annual income category (U.S. dollars)	55,000–64,999
Average respondent age category (years)	41–45
Pavement-specific variables	
Average test segment IRI measurement (m/km) (standard deviation)	1.94 (0.89)
Average roadway segment surface age (years) (standard deviation)	17.43 (13.48)
Pavement structural condition (PSC) index of roadway (standard deviation)	90.78 (9.64)
Percent of segments by surface type: rigid/flexible	35.1/64.9
Percent of segments with/without patch work	18.9/81.1
Percent of segments with/without visible wear	32.4/67.6
Percent of segments with/without joints or abutments	37.8/62.2
Vehicle-specific variables	
Percent of test vehicles by type (sedan/sport-utility/pickup/minivan)	29.7/24.3/18.9/10.8

In total, 31 participants evaluated each of the 37 highway segments for a total of 1,147 roughness assessment observations. For each of these observations, there were associated quantitative sociodemographic data for the individual from the preliminary mailed survey, physical segment-specific data from the pavement management system, and in-vehicle survey data from the driving experiment. The sample statistics are summarized in Table 1.

Past research suggests that a number of factors will play a role in participants' perception of roughness. As mentioned above, one critical factor that we attempt to control for in this study is the type of vehicle. With the diversity of vehicles (with sizable market shares) currently populating the U.S. vehicle fleet, we gave consideration to four vehicle types as indicated in Table 1: midsized sedan, sport-utility vehicle, pickup truck, and minivan. To get some initial idea of the potential relationship between vehicle type and road roughness, we graphed the relationship between the IRI and percent of observations by perceived roughness ranking for each vehicle type (see Figs. 1–4). These figures show some very general trends with regard to vehicle type. For example, at high IRI values, above about 2.00 m/km, Fig. 2 shows that participants in sport-utility vehicles tended to have lower percentage of observations ranked as 5 (rough) relative to those respondents in other vehicle types. Also, Fig. 4 suggests that respondents using minivans had a higher percentage of observations with Roughness Rankings 1 and 2 (smooth), relative to respondents using midsized sedans and pickups, in the mid-IRI range of about 1.18 to 1.89 m/km. These figures suggest some interesting suspension or possibly perception/expectation differences that may vary by vehicle type. However, statistically defensible statements in this regard cannot be made until a full multivariate analysis is undertaken.

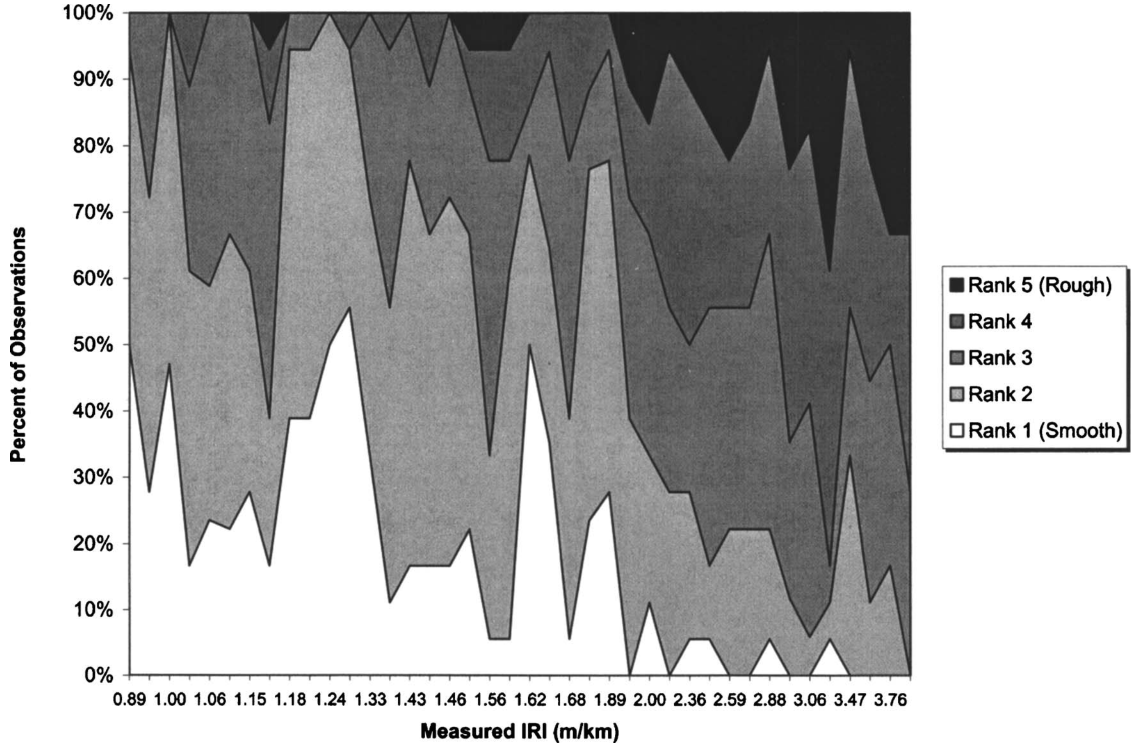

Fig. 1. IRI measurements versus driver roughness rankings for drivers using midsized sedan test vehicle

Methodology

We seek to model users' ratings of roadway roughness on a scale from 1 to 5—with 1 being the smoothest and 5 being the roughest. These roughness data are discrete and ordered (3 is worse than 2, 2 is worse than 1, and so on). Because the data are ordered, conventional discrete outcome models such as standard multinomial logit and probit models may not be appropriate and can result in the loss of estimation efficiency [see Washington et al. (2003) for a complete discussion of this point]. Ordered probability models have been developed to study such data. These models are derived by defining an unobserved variable z, which is

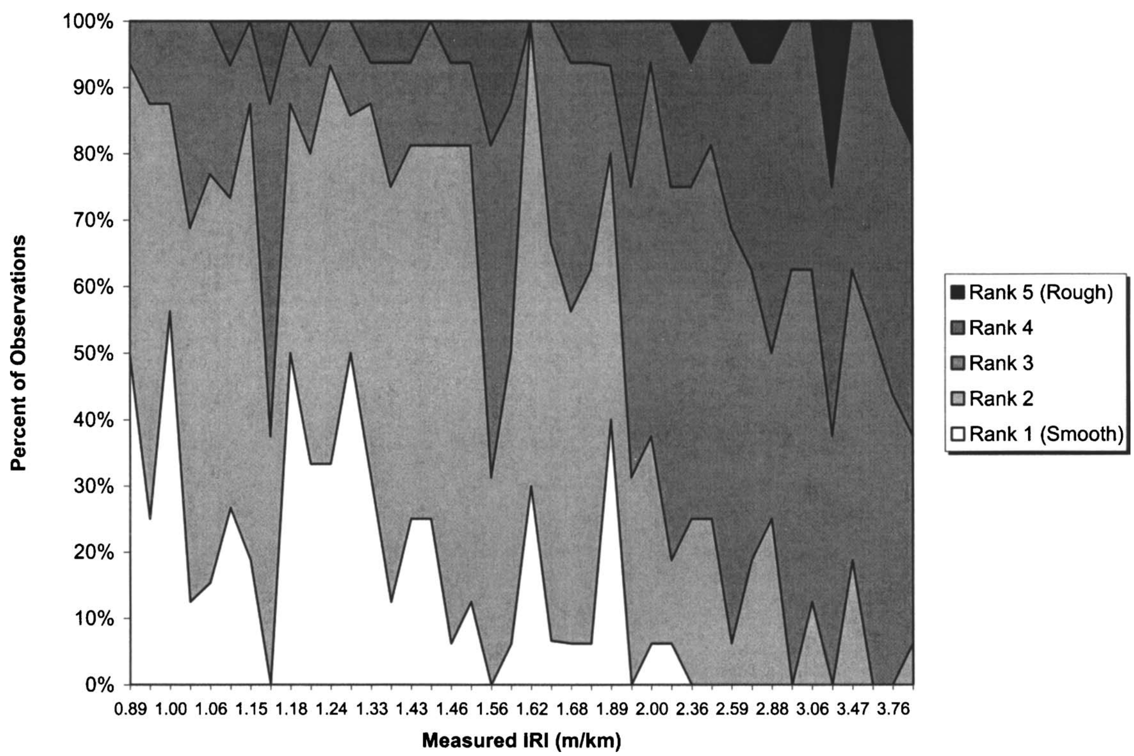

Fig. 2. IRI measurements versus driver roughness rankings for drivers using sport-utility test vehicle

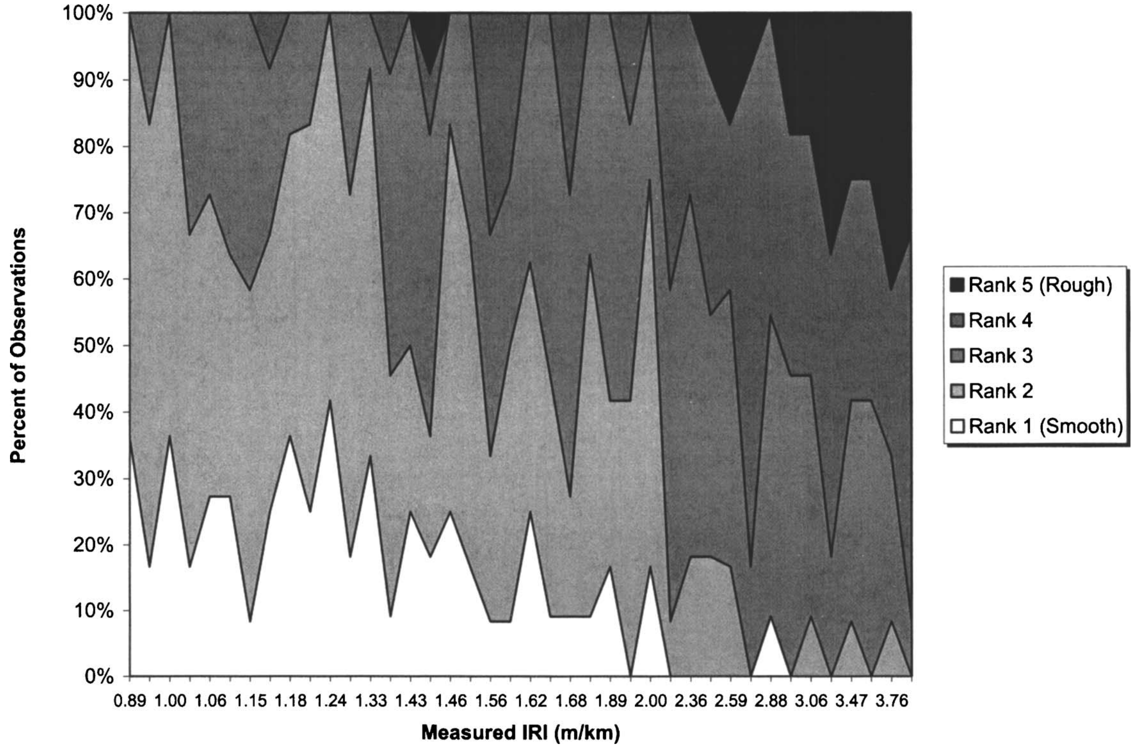

Fig. 3. IRI measurements versus driver roughness rankings for drivers using pickup test vehicle

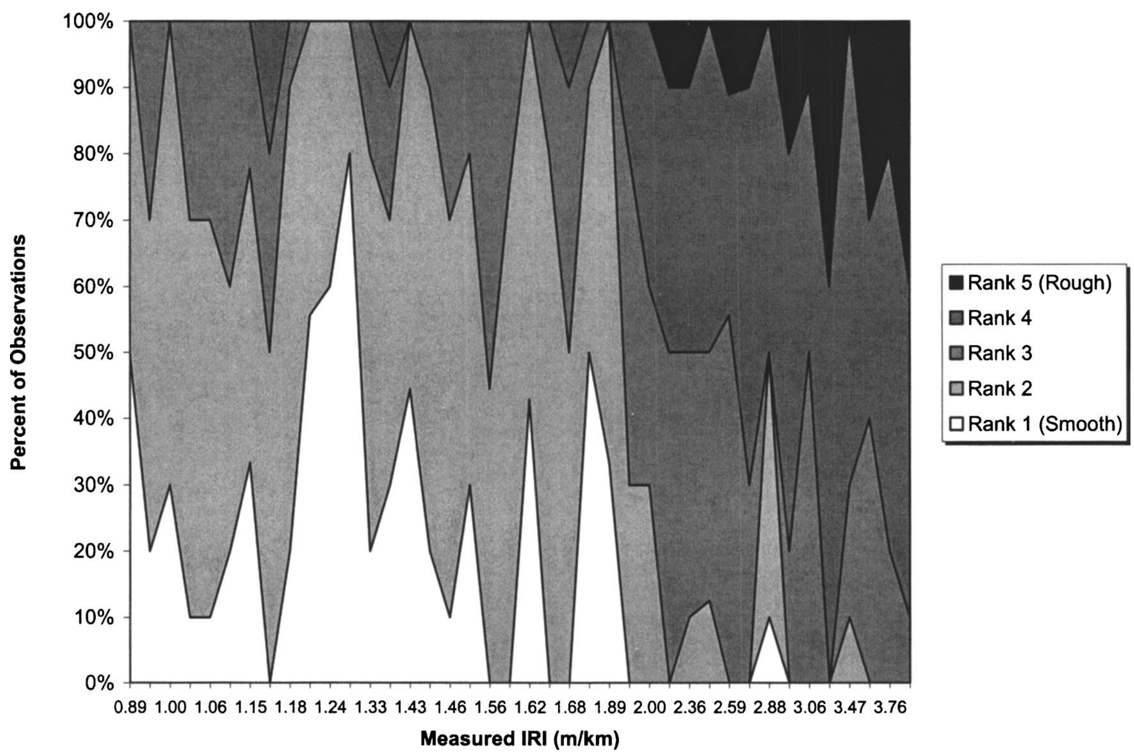

Fig. 4. IRI measurements versus driver roughness rankings for drivers using minivan test vehicle

used as a basis for modeling the ordinal ranking of data. This unobserved variable is specified as a linear function

$$z_n = \boldsymbol{\beta} X_n + \varepsilon_n \tag{1}$$

where X=vector of variables determining discrete ordering for observation n; $\boldsymbol{\beta}$=vector of estimable coefficients; and ε=random disturbance. Using this equation, the observed ordinal data y_n are defined as

$$y_n = \begin{cases} 1 & \text{if } z_n \leqslant \mu_0 \\ 2 & \text{if } \mu_0 < z_n \leqslant \mu_1 \\ 3 & \text{if } \mu_1 < z_n \leqslant \mu_2 \\ 4 & \text{if } \mu_2 < z_n \leqslant \mu_3 \\ 5 & \text{if } z_n \geqslant \mu_3 \end{cases} \tag{2}$$

where μ=estimable parameters (referred to as thresholds) that define y_n. The μ's are parameters that are estimated jointly with the model coefficients $\boldsymbol{\beta}$. The estimation problem then becomes one of determining the probability of the five specific ordered responses for each observation n, which is done by making an assumption on the distribution of ε_n in Eq. (1). If ε_n is assumed to be normally distributed across observations an ordered probit model results, and if ε_n is assumed to be logistically distributed an ordered logit model results. Note that without loss of generality μ_0 can be set equal to zero, thus requiring estimation of three thresholds μ_1, μ_2, and μ_3.

A complication can arise with the maximum likelihood procedures of a standard ordered probability model, because, in this case, each of the 31 participants generated 37 observations (i.e., one observation for each of the 37 roadway segments) of perceived level of roughness. As a result, the 37 responses given by each participant will likely share unobserved effects. If these shared unobserved effects are not considered, and the model is estimated as though the 37 observations from each survey participant came from 37 independent participants, the standard errors of the model's coefficients may be underestimated, resulting in inflated t statistics, potentially misleading levels of significance, as well as potential biases in coefficient estimates (Washington et al. 2003; Choocharukul et al. 2004).

This complication can be addressed with a standard random effects model, which allows for an individual-specific error term (in addition to an overall error term) to account for random error within each individual. By rewriting Eq. (1), we can express the traditional error term as being comprised of two components: the traditional disturbance term unique to each observation, ε_{ic}, and an individual-specific random effect disturbance term φ_i (assumed to be normally distributed with mean 0 and variance σ^2)

$$z_{ic} = \boldsymbol{\beta} X_{ic} + \varepsilon_{ic} + \varphi_i \tag{3}$$

where the subscript i=individual participants (i=1,…,31); subscript c=roadway segments (c=1,…,37); and all other terms are as previously defined. A Hausman specification test for correlation between the errors and the regressors can be used to check if the random effects model is appropriate (Hausman 1978). The Hausman test statistic σ estimated as part of the random effects model determines the significance of the random effects formulation relative to the standard ordered logit model. See Greene (2003) or Washington et al. (2003) for additional details on ordered probability models or random effects models.

In terms of interpreting the effect of individual estimated coefficients in ordered probability models, a positive value of a coefficient implies that an increase in the variable will unambiguously increase the probability of the highest-ordered discrete category being selected (y=5) and unambiguously decrease the probability of the lowest-ordered discrete category being selected (y=1). The estimated coefficients, however, do not provide a clear indication of how changes in specific explanatory variables affect the probabilities of intermediate ordered categories (y=2, 3, or 4). Instead, marginal effects can be computed for each category to assess each variable's impact on the probability for each category threshold. For indicator variables, the effects are computed as the difference in the estimated probabilities with the indicator variable changing from zero to one, while all other variables are equal to their means. For continuous variables, the effects are computed from the partial derivatives

Table 2. Random Effects Ordered Probit Model of User-Perceived Roughness Rankings[a]

Independent variable	Estimated coefficient	t statistic
Constant	−8.257	−4.27
Individual-specific variables		
Gender indicator (1 if participant was female, 0 if male)	−0.791	−4.68
Older age indicator (1 if participant was over age 55, 0 otherwise)	−0.985	−5.07
Pavement-specific variables		
IRI measurement (m/km) of roadway segment	0.949	5.51
Age of roadway segment surface (years)	0.033	3.59
Patch indicator (1 if the segment appeared to have patch work, 0 otherwise)	0.801	3.39
Pavement structural condition (PSC) index of roadway	−0.033	−3.35
Vehicle-specific variables		
Noise (dB) inside test vehicle during evaluation	0.161	6.31
Noise increase indicator (1 if the noise inside test vehicle during evaluation increases by 3 dB or more between two adjacent test segments, 0 otherwise)	1.048	2.22
Sport-utility vehicle indicator (1 if sport utility, 0 otherwise)	−1.387	−6.35
Minivan vehicle indicator (1 if minivan, 0 otherwise)	−0.827	−3.35
Speed (km/h) of test vehicle during evaluation	−0.0215	−2.76
Model parameters		
Threshold parameter μ_1	2.939	18.65
Threshold parameter μ_2	5.502	30.08
Threshold parameter μ_3	7.861	28.16
Random effect (Hausman test) parameter σ	0.897	6.01
Number of observations	1,147	
Initial log-likelihood	−1,675.57	
Log-likelihood at convergence	−1,223.69	

[a]Dependent variable responses are integers between 1 (very smooth) and 5 (very rough).

Table 3. Computed Marginal Effects of Random Effects Ordered Probit Model

Variable	Marginal effects $y=1$	$y=2$	$y=3$	$y=4$	$y=5$
Gender indicator (1 if participant was female, 0 if male)[a]	0.0451	0.0994	−0.0669	−0.0598	−0.0178
Older age indicator (1 if participant was over age 55, 0 otherwise)[a]	0.0620	0.1190	−0.0916	−0.0693	−0.0200
IRI measurement (m/km) of roadway segment	−0.0008	−0.0019	0.0011	0.0012	0.0004
Age of roadway segment surface (years)	−0.0017	−0.0043	0.0026	0.0026	0.0008
Patch indicator (1 if the segment appeared to have patch work, 0 otherwise)[a]	−0.0363	−0.1035	0.0462	0.0704	0.0232
Pavement structural condition (PSC)	0.0017	0.0043	−0.0026	−0.0026	−0.0008
Noise (dB) inside test vehicle during evaluation	−0.0085	−0.0209	0.0126	0.0128	0.0039
Noise increase indicator (1 if the noise inside test vehicle during evaluation increased by 3 dB or more between two adjacent test segments, 0 otherwise)[a]	−0.0410	−0.1326	0.0386	0.0993	0.0358
Sport-utility test vehicle indicator (1 if sport utility was test vehicle type, 0 otherwise)[a]	0.0892	0.1629	−0.1270	−0.0968	−0.0283
Minivan test vehicle indicator (1 if minivan was test vehicle type, 0 otherwise)[a]	0.0530	0.0995	−0.0791	−0.0571	−0.0163
Speed (km/h) of test vehicle during evaluation	0.0011	0.0028	−0.0017	−0.0017	−0.0005

[a]Marginal effects for indicator variables represent the change in the probability following a change in the variable from 0 to 1.

$$\frac{\partial P(y=1)}{\partial \boldsymbol{X}} = -\phi(-\boldsymbol{\beta X})\boldsymbol{\beta}'$$

$$\frac{\partial P(y=2)}{\partial \boldsymbol{X}} = [\phi(\mu_0-\boldsymbol{\beta X})-\phi(\mu_1-\boldsymbol{\beta X})]\boldsymbol{\beta}'$$

$$\frac{\partial P(y=3)}{\partial \boldsymbol{X}} = [\phi(\mu_1-\boldsymbol{\beta X})-\phi(\mu_2-\boldsymbol{\beta X})]\boldsymbol{\beta}'$$

$$\frac{\partial P(y=4)}{\partial \boldsymbol{X}} = [\phi(\mu_2-\boldsymbol{\beta X})-\phi(\mu_3-\boldsymbol{\beta X})]\boldsymbol{\beta}'$$

$$\frac{\partial P(y=5)}{\partial \boldsymbol{X}} = -\phi(\mu_3-\boldsymbol{\beta X})\boldsymbol{\beta}' \tag{4}$$

where $P(y=j)$=probability of response category j, $\phi(\cdot)$=standard normal density; and all other terms are as previously defined.

The marginal effects for each response category can be interpreted as the change in the outcome probability of each threshold category $P(y=j)$, given a unit change in a continuous variable x. In the context of user perceptions of roadway roughness, a large marginal effect (in absolute value terms) indicates that the coefficient has a relatively large effect on the users' roughness rankings, while a relatively small marginal effect indicates a relatively minimal effect on users' roughness rankings. A positive marginal effect for a specific roughness ranking indicates an increase in probability for that ranking, while a negative value would correspond to a decrease in probability for that ranking.

Estimation Results

Estimation results from the random effects ordered probit model are presented in Table 2, and the corresponding marginal effects are shown in Table 3. The model provides information on how pavement, vehicle, and user characteristics are associated with perceived roughness rankings. The sign of each coefficient estimate indicates the impact of the variable on the roughness ranking—with positive coefficients indicating that the pavement is more likely to be rated very rough and negative coefficients indicating that the pavement is more likely to be rated very smooth. The significance of the random effects parameter σ, with a t statistic of 6.21, indicates that a random effects element of the model is warranted.

Individual sociodemographic characteristics were found to influence perceptions of road roughness with women and older individuals (age 55 or over) found to be more likely to rank segments as smooth (Roughness Categories 1 and 2) and less likely to rank segments in Roughness Categories 3, 4, and 5, as indicated by the signs of the marginal effects shown in Table 3.

As expected, roadway characteristics were also highly significant. Roughness, measured through the IRI, was the third most statistically significant factor, with a high IRI measurement (indicating a more deteriorated pavement) making it less likely that the segment would be rated smooth (Roughness Categories 1 and 2) and more likely that the segment would be rated in Roughness Categories 3, 4, and 5. The increasing age of the roadway surface and the presence of patches also decreased the probability that the pavement would be considered smooth (Roughness Categories 1 and 2). Also, the better the pavement structural condition, the more likely the roadway is to be classified as smooth (Roughness Categories 1 and 2).

Increases in interior noise levels and increases in the noise level between adjacent roadway segments made it less likely that the segment was rated smooth (Roughness Categories 1 and 2) and more likely that the segment was rated in Roughness Categories 3, 4, and 5. The interior noise level captures the absolute effect of noise while the increase in noise level (a variable indicating a 3 dB increase or more) from the preceding highway section captures the important relative effect of abruptly changing noise conditions.

Turning to vehicle-type variables, driving a sport-utility vehicle or a minivan resulted in pavements being perceived as smoother with higher probabilities of choosing Roughness Categories 1 and 2. In fact, Table 3 indicates that, when controlling for other factors influencing roughness ratings, an individual driving a sport-utility vehicle had their probability of rating the pavement as smooth (Roughness Category 1) increase by 0.0892 and their probability of selecting the next best smoothness category, Category 2, increase by 0.1629. Sport-utility vehicle drivers are also less likely to choose the middle category (Roughness Category 3 has a probability decrease by 0.127), and less likely to choose the "rough" Categories 4 and 5 with selection probabilities decreasing by 0.0968 and 0.0283, respectively. A similar trend, albeit with lower absolute values, is observed for the minivan marginal effects. Interestingly, midsized sedans and pickup trucks were statistically indistinguishable from each other in terms of their impact on roughness rankings. In general, the statistical findings are in agreement with the simple graphical comparisons made earlier with regard to Figs. 1–4.

Finally, estimation results indicated that increasing speed made it more likely that the roadway segment was rated smooth, with slight increase in the probabilities of selecting Roughness Categories 1 and 2 and slight increases in the probabilities of Roughness Categories 3, 4, and 5. This finding may reflect the physical reactions of vehicle suspension systems at speed and/or may be influenced by individuals' expectations of vehicle/pavement feedback as speed increases.

Based on the modeling results presented above, some interesting comparisons with previous studies can be drawn. For example, as with our study, Nair and Hudson (1986) and others dating as far back to the original 1950s road tests (AASHTO 1993) found that roughness, however measured, was among the most statistically significant factors associated with roughness rankings. Other factors that were found to be significant and in general agreement with Nair and Hudson (1986) included vehicle type and the presence of maintenance work (e.g., patch work). It is also noteworthy that pavement type was not statistically significant—a finding that conflicts with Nair and Hudson (1986). It is suspected that other variables in our model, such as the IRI or noise levels, are capturing the differences in pavement types.

Conclusions and Directions for Future Work

This study identifies some key factors associated with users' perceptions of road roughness. The factors associated with an increased probability of a roadway segment being ranked as rougher include higher values of the International Roughness Index, older pavement surface, higher in-vehicle noise, and increases in vehicle noise between successive roadway segments. Variables associated with an increased probability of a roadway segment being ranked smoother include whether the study participant was a female, whether the study participant was over 55 years old, better values of the pavement structural condition measure, the use of a sport-utility vehicle, the use of a minivan, and higher vehicle speeds.

The findings of this study are certainly suggestive and have fundamental implications for resource allocation to infrastructure maintenance, particularly when the structural integrity and/or functionality (in terms of highway safety, such as the loss of braking) are not in question. Public concerns, however, persist relating to subjective matters, such as roadway roughness. While subjective public assessments of infrastructure condition can sometimes be a critical element affecting resource allocation, it is important to recognize that our understanding of these assessments is still developing. This paper provides some initial evidence that suggests a complex interaction of variables influences public perceptions of highway roughness. A better understanding of such relationships could be the beginning of a more cost-effective allocation of limited infrastructure-rehabilitation resources by maximizing the increase in public satisfaction with infrastructure projects.

With regard to the specific problem of improving our understanding of the factors that affect user perceptions of highway roughness, there are at least two recommendations for future work. First, the range of the IRI values should be expanded from what was available in our study. Our IRI range was limited because of the need to restrict our study to Seattle-area freeways, which allowed reasonable time commitments for local-user participants. Second, our data are limited to a single, discrete response about a continuous test segment. Because test segments were not completely homogeneous, users had to exercise their best judgment when evaluating test segments. In an ideal testing scenario, it would be better if each test segment were completely homogeneous, but this goal was unrealistic in many instances.

Notation

The following symbols are used in this paper:

$P(\cdot)$ = probability;
$\boldsymbol{X}$ = vector of variables determining discrete ordering of data;
x = individual variable determining discrete ordering of data;
y = ordinal discrete data;
z = unobserved variable defined for modeling ordered data;
$\boldsymbol{\beta}$ = vector of estimable coefficients for ordered data modeling;
ε = random disturbance term;
μ = threshold parameter;
σ = random effects parameter;
$\phi(\cdot)$ = standard normal density; and
φ = individual-specific random disturbance term.

Subscripts

c = roadway segment;
i = individual participant;
j = response category; and
n = observation.

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