# Development of a Driving Risk Model based on Speed Choice: A Case Study for Evaluating Safety Effects of In-Vehicle Traffic Warning Information

Wonchul KIM [a], Junyi ZHANG [b], Akimasa FUJIWARA [c]

[a] *Dept. of Regional & Urban Research, Chungnam Institute, Gongju, 314-140, Korea; E-mail: iwonchul@cni.re.kr*
[b,c] *Graduate School for International Development and Cooperation, Hiroshima University, Higashi-Hiroshima, 739-8529, Japan;*
[b] *Email: zjy@hiroshima-u.ac.jp*
[c] *Email: afujiw@hiroshima-u.ac.jp*

**Abstract:** This study focuses on the development of a driving risk model based on speed deviation. Speed data were collected via an on-site driving experiment on Sanyo expressway in Hiroshima prefecture in Japan, 2009, focusing on examining the impacts of in-vehicle traffic warning information (IVTWI) on traffic safety. Three driving scenarios, i.e. without IVTWI provision, voice-based and voice & image-based information provision, were examined to compare the impacts of IVTWI provision on traffic safety. Driving risk defined by three levels (i.e., low, medium and high) based on the magnitude speed deviation is modeled by an Ordered Response Probit (ORP) model. Analysis results show that traffic safety could be improved by IVTWI provision. Defined high driving risk derived from the proposed method could explain the occurrence of traffic accidents up to 38%. The results of the constructed model confirm that the probability of driving risk could be reduced by IVTWI provision.

*Keywords*: Traffic Accident; Driving Risk; Homogeneous Road Section; In-Vehicle Traffic Warning Information; Ordered Response Probit Model

## 1. INTRODUCTION

Speed is one of the important factors in road safety, affecting not only severity of crash but also the risk of being involved in a crash (Elvik *et al.*, 2004). The literature shows that the relationship between speed and road safety is usally examined by using the absolute speed or speed deviation (Aarts, 2006). For example, some researchers found that, as the absolute speed increases, the crash rate increases (Baruya, 1998; Finch *et al.*, 1994; Nilsson, 1992) and the severity of crash increases (Rosén and Sander, 2009; Bowie and Walz, 1994; Joksch, 1993; O'Day and Flora, 1982). In other studies (Harkey *et al*. 1990; Hauer, 1971; West and Dunn, 1971; Cirillo, 1968; Solomon, 1964) that used speed deviation, traffic safety (i.e., risk involved in a crash) has been evaluated based on the notion that the likelihood of traffic accidents increases, i.e., traffic safety decreases as the speed deviation increases.

In this case for using speed instead of traffic accidents as surrogate measure to measure traffic safety, the using of speed deviation would be appropriate as findings in the previous studies. In this background, it could be very useful for transportation safety researchers or engineers when making countermeasures, if an evaluation model which is able to econometrically evaluate the level of traffic safety with vehicle speed data is suggested. As a novel approach, the present study aimed at developing a *driving risk* (DR) model to evaluate the level of road safety based on driving speed choice, which is formulated by applying an ordered response probit (ORP) modeling approach. It is expected that the proposed model is applicable to evaluate the impacts of new traffic countermeasures on traffic safety prior to their implementation in practice without requiring accident records. To examine this research expectation, the influence of in-vehicle traffic warning by a DSRC system on the level of road safety (i.e., *driving risk*) is evaluated. The data for the study were obtained via an on-site driving experiment with an instrument vehicle that was conducted along Sanyo expressway in Hiroshima City, Japan in 2009. A comparative analysis between the *driving risk* and accident risk is conducted to validate the proposed *driving risk* concept.

The present study is organized as follows: Section 2 explains the concept of the proposed *driving risk* model. In Section 3 the process of data collection is described. Section 4 presents the results including the relation between the proposed *driving risk* and traffic accident frequency, and estimated results of the proposed model. The study is concluded with a brief discussion in Section 5.

## 2. A DRIVING RISK MODEL FRAMEWORK

The finding of the previsou studies that the increase of speed deviation (i.e., the difference between a driver's driving speed and the average speed of traffic at a road section) could lead to the increase of the likelihood of accident occurrence supports us to adopt the magnitude of speed deviation as a traffic safety indicator. We propose to use the term of *driving risk* to describe the level of road safety in terms of driver's speed choice (i.e., speed choice behavior) at a homogeneously small road section. The concept of *driving risk* is represented in Figure 1. The risk reduces when the chosen driving speed falls within a range of one standard deviation at a road section; otherwise the risk increases. The reason for adoption of standard deviation is based on studies of TRB(1998) and Garber *et al*. (2000), which suggesting that drivers driving in speed under average speed are the same with the ones above as long as the difference are the same. For example, in case of driver *i* (i.e., driver *i*'s line in Figure 1) travelling on the given roadway, the level of *driving risk* of individual speeds #1 and #2 at section *m* could be evaluated to be low and high *driving risk*, respectively.

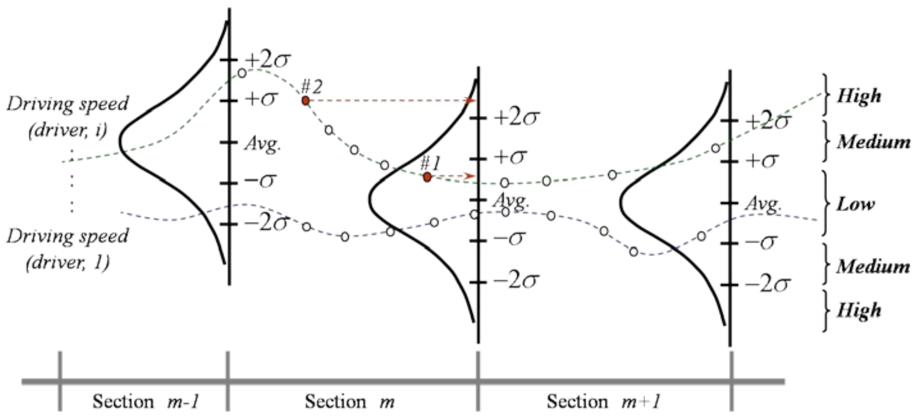


Figure 1. Concept of Driving Risk

By measuring the magnitude of speed deviation, one could see that the level of *driving risk* can be expressed with a discrete variable that the dangerousness of driving behavior will increase with larger values of $y_n$. To represent this concept, an ordered response probit (ORP) model is applicable. The ORP model can be built by first defining the following latent variable. Here, sample *n* refers to values of individual speeds collected by a speed detection system (e.g., GPS system recently).

$$y_n = \begin{cases} 1, & if\ \Delta V_n \le \sigma & \rightarrow \text{Low driving risk} \\ 2, & if\ \sigma < \Delta V_n \le 2\sigma & \rightarrow \text{Medium driving risk} \\ 3, & if\ \Delta V_n > 2\sigma & \rightarrow \text{High driving risk} \end{cases} \quad (1)$$

$$\Delta V_n = \left| \overline{V} - V_n \right|$$

$$y_n^* = \beta' x_n + \varepsilon_n \quad (2)$$

where,

$y_n$ : level of *driving risk* of sample *n*,
$V_n$ : operating speed of sample *n*,
$\overline{V}$ : average speed of a road section under study,
$\Delta V_n$ : speed deviation between $\overline{V}$ and $V_n$,
$\sigma$ : standard deviation,
$y_n^*$ : latent variable capturing the *driving risk* of sample *n*,
$x_n$ : vector of explanatory variables,
$\beta$ : vector of parameters to be estimated, and
$\varepsilon_n$ : error term assuming to follow a standard normal distribution.

The observed speed deviation variable $y_n$ can be expressed using the above-defined latent variable $y_n^*$ as follows:

$$y_n = \begin{cases} 1 & \text{if } -\infty \le y_n^* \le \mu_1 & \text{(Low driving risk)} \\ 2 & \text{if } \mu_1 < y_n^* \le \mu_2 & \text{(Medium driving risk)} \\ 3 & \text{if } \mu_2 < y_n^* \le \infty & \text{(High driving risk)} \end{cases} \quad (3)$$

Where $\mu_j$ (j=1,2) indicates a threshold to identify the category of *driving risk*. The probability associated with each category of *driving risk* can be specified as follows:

$$\begin{aligned} P_n(y_n = 1) &= \Pr(\varepsilon_i \le \mu_1 - \beta x_i) = \Phi(\mu_1 - \beta x_i) = \Phi(-\beta x_i) \\ P_n(y_n = 2) &= \Pr(\varepsilon_i \le \mu_2 - \beta x_i) - \Pr(\varepsilon_i \le \mu_1 - \beta x_i) = \Phi(\mu_2 - \beta x_i) - \Phi(-\beta x_i) \\ P_n(y_n = 3) &= 1 - \Phi(\mu_2 - \beta x_i) \end{aligned} \quad (4)$$

where $P_n(y_n = k)$ indicates the probability that sample *n*'s driving speed belongs to category *k*, and $\Phi(\ )$ represents the standard normal cumulative distribution function. Note that, $\mu_1 = 0$ is assumed for ease of interpretation without loss of generality (of course, any real value can be assumed).

To estimate equation (4), the following log-likelihood function is adopted in order to apply the maximum likelihood estimation method.

$$L = \sum_{n=1}^{N} \sum_{k=1}^{3} \delta_n^k \, ln\left(P_n(\, y_n = k\,)\right) \tag{5}$$

Here, $\delta_n^k$ is a dummy variable with a value of 1, if $y_n$ belongs to category k, otherwise 0; and $N$ is the sample size. When interpreting the estimation results, a positive sign of parameter ($\beta$) means that *driving risk* will increase with increasing value of the corresponding variable, and vice versa.

## 3. DATA COLLECTION

### 3.1 Participants

To recruit test drivers for the on-road driving experiment, a notice was put on information boards around campus of Hiroshima University. Finally, ten young test drivers (Male: 8, Female: 2) were involved in for five days from March 28 (Saturday) to April 1 (Wednesday), 2009. All of them were in their twenties (mean age: 22.2 years old, standard deviation: 1.25) and had inexperienced knowledge about the experiment driving route. Efforts of the participants were compensated after completing the driving task.

### 3.2 Study Area

The test course was about 3.3km distance which is composed of three continuous downgrade curves (i.e. small horizontal curve radii and steep grades) of the Sanyo expressway located in Hiroshima prefecture, Japan. For this abnormal geometry, drivers should be faced with a limited sight visibility. In the driving experiment, drivers had to travel from Shiwa interchange to Hirhoshima-higashi interchange (11km distance). This roadway consists of a two-lane (3.75m lanes) cross-section, in each direction, with 3.05m shoulders and 80km/h speed limit. Actually no change in travel lane and shoulder, shoulder widths, and speed limit exists in the study area (see Figure 2).

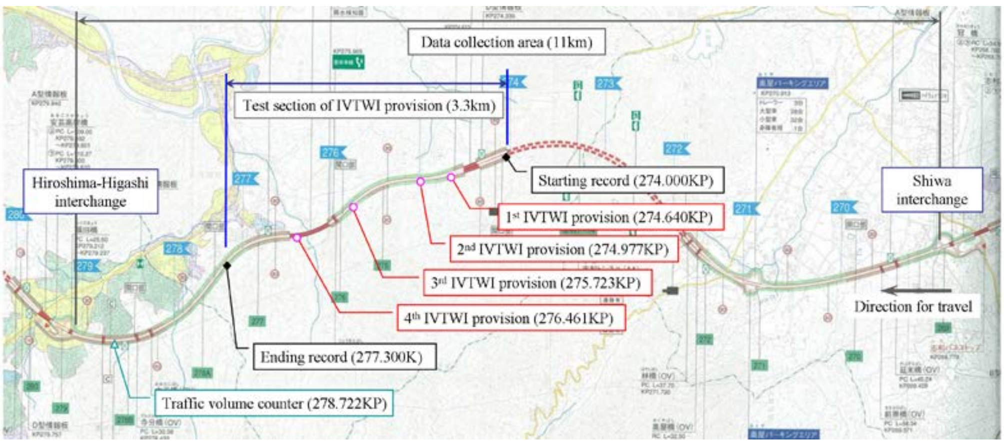


Figure 2. Study area

### 3.3 Experiment Scenario

To improve road safety of the study area, In-Vehicle Traffic Warning Information (IVTWI: “Please! Reduce your speed”) was provided to the test drivers, which is designed by West Nippon Expressway Company. Provision of the IVTWI was implemented through a dedicated short range communication (DSRC) beacon installed at the 274.000 kilometer post (KP) from the driving start point. Once communication between the DSRC beacon and the navigation system of the test vehicle was established at the 274.000 KP, the IVTWI was provided four times along the roadway for 5 seconds before the driver entered each curve section. Figure 2 shows the procedure in detail. With various driving scenarios, two drivers were tested every day, i.e., one drove the test vehicle in the morning (10:00-12:30) and the other did in the afternoon (13:00-15:30). These timeslots were intentionally planned to eliminate external effects of traffic congestion during morning and evening peak times. Given the timeslots, test drivers were informed that they should drive the test vehicle on the driving course three times as usual. At their first traversal, drivers did not get IVTWI, but they received voice-based IVTWI at the second traversal and voice & image-based IVTWI at the third traversal.

### 3.4 Apparatus

For the purpose of providing the IVTWI communicated by the DSRC beacon, a novel navigation system was installed on dashboard (Figure 3) of the test vehicle. A Global Positioning System (GPS) sensor in the navigation system automatically recorded driving speed, acceleration, and deceleration over time and space every 0.1 seconds.

(i) Test vehicle | (ii) Voice & image-based IVTWI | (iii) Test driver

Figure 3. Apparatus under the study

### 3.5 Obtained Data

To evaluate the level of traffic safety, the homogeneous-segment method was used to control the effects of geometry features on *driving risk*. This assumes that the average speed would be a constant within a homogeneous segment. For this application, two methods are generally suggested: the homogeneous-segment method (Kweon and Kockelman, 2005) and the fixed-length method (Shankar *et al.*, 1995). To tightly control geometric features, the former method has been the prevailing approach. Given this, the roadway was first divided according to the characteristics of vertical and horizontal alignments (i.e., horizontal curves and radius, and veritical grades) and then the average and standard deviations were computed at each divided road section.

To put this assumption into analysis, the study stretch with 3.3km distance was first divided into 18 sections according to vertical and horizontal alignments. Table 1 shows the road profiles about divided 18 segments. Except section 3, all sections are composed of curve shapes with various radii (i.e., degree of curvature) and vertical grades. Table 1 presents the average values. The figures of vertical grades indicate that the roadway proflile is composed of largely three sections, with -2.177 in sections 1~7, -4.0 in sections 8~15 and +2.0 in sections 16~18. This means that drivers experience continuous downgraded driving before reaching section 16. Other factors (e.g., driver, road environments, traffic operation, etc.) affecting *driving risk* were also collected to acknowledge their simultaneous effects on driving speed choice. Also, traffic volume data were collected from a vehicle detector system (VDS) installed at 278.722 KP (see Figure 2) of the roadway.

Given varying driving scenarios, drivers were requested to drive the test roadway three times for five days, and in total 30 traversals (=10 drivers × 3 traversals) were recorded. Since the movements of the test vehicle were measured by 0.1 second, a total sample size of 37,740 (i.e., driving speed) was obtained.

Table 1. Profile of the study area

| No. | KP (274.000~) | Type | Length (m) | Degree of curvature (°) | Vertical grades (%) | Samples |
|---|---|---|---|---|---|---|
| 1 | 274.144.611 | Left curve | 144.611 | 3.745 | -2.177 | 155 |
| 2 | 274.342.323 | Left spiral | 197.712 | 1.881 | -2.177 | 2306 |
| 3 | 274.366.681 | Tangent | 24.358 | 0.000 | -2.177 | 290 |
| 4 | 274.511.324 | Right spiral | 144.643 | 2.071 | -2.177 | 1706 |
| 5 | 274.791.536 | Right curve | 280.212 | 4.093 | -2.177 | 3365 |
| 6 | 275.048.679 | Right spiral | 257.143 | 2.036 | -2.177 | 3048 |
| 7 | 275.120.000 | Left spiral | 71.321 | 1.129 | -2.177 | 839 |
| 8 | 275.277.085 | Left spiral | 157.085 | 4.715 | -4 | 1877 |
| 9 | 275.327.006 | Left curve | 49.921 | 7.207 | -4 | 595 |
| 10 | 275.622.595 | Left curve | 295.589 | 7.162 | -4 | 3542 |
| 11 | 275.822.595 | Left spiral | 200.000 | 3.606 | -4 | 2395 |
| 12 | 276.022.595 | Right spiral | 200.000 | 3.570 | -4 | 2415 |
| 13 | 276.360.709 | Right curve | 338.114 | 7.162 | -4 | 4131 |
| 14 | 276.560.709 | Right spiral | 200.000 | 3.590 | -4 | 2433 |
| 15 | 276.760.709 | Left spiral | 200.000 | 3.572 | -4 | 2432 |
| 16 | 276.880 | Left curve | 119.291 | 7.162 | 2 | 1468 |
| 17 | 277.173.867 | Left curve | 293.867 | 7.162 | 2 | 3673 |
| 18 | 277.300 | Left sprial | 126.133 | 6.171 | 2 | 1070 |

## 4. RESULTS

### 4.1 Relationship between Driving Risk and Traffic Accident Occurrence

Prior to apply the proposed model, the effectiveness of the proposed method should be confirmed by validating the relationship between the *driving risk* and the traffic accident occurrence. For this, a total of 84 traffic accidents records with more than serious injury were collected for 2002–2006.

For the comparison, 987 high *driving risk* cases (i.e., risk level 3; see the equation (1)) were used. These 987 high driving risk were measured through the 1$^{st}$ traversal, i.e., without any taffic safety information provision. The relation between high *driving risk* and traffic accident records is presented to Figure 4. Higher numbers of accidents (i.e., more than 5) are observed at section 4, 9, 10, 12, 13, 14, 15, and 17. Except for section 9, in all these cases the number of high *driving risk* cases also tends to be higher. Based on this tendency, the relation between *driving risk* and traffic accident occurrence is shown in Figure 5. The result indicates that the level of traffic safety could be examined by the *driving risk*, as 38% of the variance in traffic accident occurrences could be explained by the number of high *driving risk* cases.

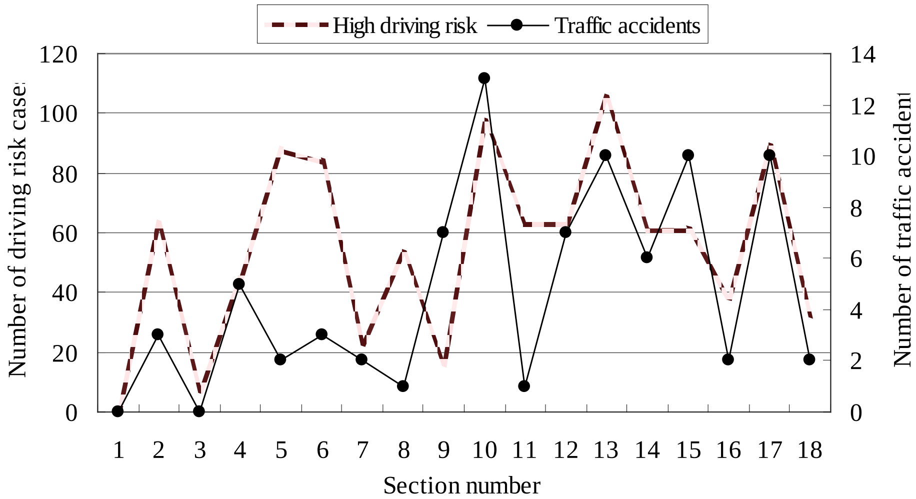


Figure 4. Relationship between high driving risk and traffic accident occurrence

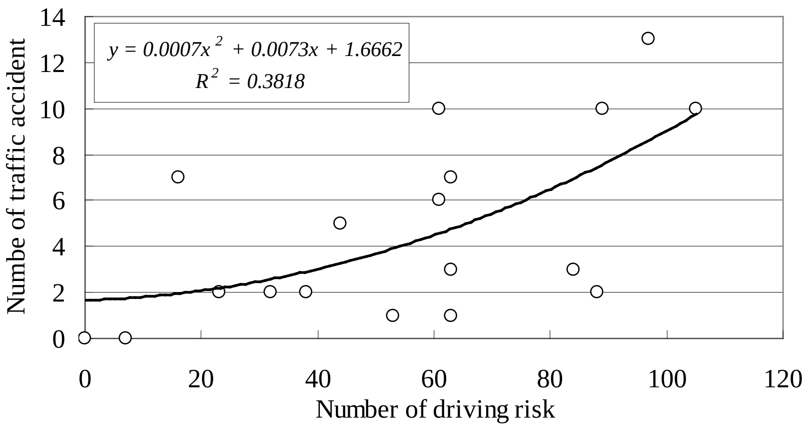


Figure 5. Regression of number of traffic accident and driving risk

## 4.2 The Driving Risk Model

4.2.1 Employed variables

To evaluate the level of traffic safety based on speed data, various influential factors, such as, characteristics of drivers, the road environment, road geometry, and the two formats of IVTWI provision, are incorporated into the *driving risk* model (Table 2). The summary statistics in Table 2 show that participants of the on-site driving experiment were composed of 20% female and 80% male drivers with an average age of 22.2 years old. Moreover, it indicates that the drivers had a likelihood of traffic accidents of 0.5 time per two and half years (=31.8 months) in average. As mentioned, half of the experiment was conducted in the morning and half in the afternoon. During the on-site experiment, road surface condition was dry in nine out of ten cases (=0.892 in average). Note that the wet road condition was recorded in light rain cases (e.g., a little shower). The observed traffic volume helps us to infer that there was no traffic congestion during the experiment periods, as the maximum value of traffic volume (19.8 veh/min/lane) is about half of the criterion of level of service E (=2200veh/hour/lane) on expressways. Because the study area is composed of various horizontal curves and vertical grades, the test drivers faced with various drving geometery. Two types of IVTWI, i.e., the voice-based and voice & image-based IVTWI, were provided in 4.5% and 3.8% of all cases, respectively.

Table 2. Definitions of employed variables and summay statistics

| Variables | Mean | S.D. | Minimum | Maximum |
|---|---|---|---|---|
| Dependent variable | | | | |
| Y = Homogeneous-segment based driving risks | 1.306 | 0.568 | 1.000 | 3.000 |
| Independent variables | | | | |
| ***Drivier factors*** | | | | |
| X1=Gender (0:female; 1:male) | 0.789 | 0.408 | 0.000 | 1.000 |
| X2=Age | 22.198 | 1.249 | 21.000 | 24.000 |
| X3=Duration of driving license ownership (month) | 31.811 | 19.446 | 9.000 | 60.000 |
| X4=Accident Experience (number of accident experienced) | 0.480 | 0.665 | 0.000 | 2.000 |
| ***Road environment factors*** | | | | |
| X5=Driving period (0:am; 1:pm) | 0.480 | 0.500 | 0.000 | 1.000 |
| X6=Road surface condition (0:wet; 1:dry) | 0.892 | 0.311 | 0.000 | 1.000 |
| X7=Traffic volume (veh/min/lane) | 13.769 | 3.834 | 8.400 | 19.800 |
| ***Geometry factors*** | | | | |
| X8=Vertical grades (absolute value, %) | 3.105 | 0.943 | 2.000 | 4.000 |
| X9=Road length (m) | 228.178 | 73.878 | 24.358 | 338.114 |
| X10=Tangent × Vertical grades (%) | 0.017 | 0.190 | 0.000 | 2.177 |
| X11=Left curve × Vertical grades (%) | 0.720 | 1.342 | 0.000 | 4.000 |
| X12=Right curve × Vertical grades (%) | 0.632 | 1.332 | 0.000 | 4.000 |
| X13=Left spiral × Vertical grades (%) | 0.949 | 1.565 | 0.000 | 4.000 |
| X14=Right spiral × Vertical grades (%) | 0.788 | 1.425 | 0.000 | 4.000 |
| X15=Tangent × Road length (m) | 0.187 | 2.127 | 0.000 | 24.358 |
| X16=Left curve × Road length (m) | 62.363 | 115.736 | 0.000 | 295.589 |
| X17=Right curve × Road length (m) | 61.994 | 125.186 | 0.000 | 338.114 |
| X18=Left spiral × Road length (m) | 50.635 | 82.050 | 0.000 | 200.000 |
| X19=Right spiral × Road length (m) | 52.998 | 92.821 | 0.000 | 257.143 |
| X20=Tangent × Degree of curvature (°/100m) × Road length (m) | 0.000 | 0.000 | 0.000 | 0.000 |
| X21=Left curve × Degree of curvature (°/100m) × Road length (m) | 444.529 | 827.823 | 0.000 | 2116.417 |
| X22=Right curve × Degree of curvature (°/100m) × Road length (m) | 367.176 | 789.825 | 0.000 | 2420.896 |
| X23=Left spiral × Degree of curvature (°/100m) × Road length (m) | 175.217 | 340.088 | 0.000 | 1436.000 |
| X24=Right spiral × Degree of curvature (°/100m) × Road length (m) | 147.794 | 317.761 | 0.000 | 1430.000 |
| ***IVTWI provision factors*** | | | | |
| P1=Voice-based IVTWI (0:no, 1:provision) | 0.045 | 0.207 | 0.000 | 1.000 |
| P2=Voice & image-based IVTWI (0:no, 1:provision) | 0.038 | 0.109 | 0.000 | 1.000 |

4.2.2 Estimated results

Table 3 shows the estimation results. All estimated parameters are significant at 1% confidence level. Parameters ($\beta$) and asymptotic *t*-statistics were calculated by using the maximum likelihood estimate by Time Series Processor (TSP) software (Hall, 1997). To assess the performance (i.e., the goodness-of-fit) of the estimated model, an adjusted Rho-squared ($\bar{\rho}^2$) is also presented (Long, 1997). Based on the estimated results, the $\bar{\rho}^2$(=0.348) of the homogeneous-segment based *driving risk* model is reasonably acceptable.

Since the latent variable in ORP model (see Equation 2) has a linear relationship with the explanatory variables, positive signs for the estimated parameters can be interpreted as an increase of *driving risk*. In this sense, Table 3 shows that the *driving risk* increases with accident experience (=X4), driving period (=X5), vertical grades at tangent and left curve (=X10~11) sections, and road length (=X16~19). For example, the likelihood that a driver who experienced traffic accidents before may get involved in another traffic accident increases. Driving in the afternoon also shows to be more dangerous than driving in the morning. Driving on inclined tangent and left curve sections also increases the *driving risk*.

As a negative parameter sign means that *driving risk* will decrease with increasing value of the corresponding variable, it is observed that the *driving risk* reduces with gender (=X1), duration of driving license ownership (=X3), road surface condition (=X6), traffic volume (=X7), inclined right curve (=X12), degree (=X21, 23, 24) of curve sections. For example, the *driving risk* decreases when a driver is male and experienced. Moreover, the *driving risk* is lower under dry road conditions and with lower traffic volumes. The *driving risk* for a driver travelling at right curve sections with a larger degree of curvature is also likely to be lower. The impacts of IVTWI provision on traffic safety as also presented in Table 3 are in line with what might have been expected. The signs of the estimated parameters related to IVTWI provision are negative, meaning that the *driving risk* could be reduced by providing IVTWI. By comparing the magnitude of estimated *t*-statictics of the two formats of IVTWI provision, it is inferred that the voice & image-based IVTWI is more effective in reducing the *driving risk* than the voice-based imformation.

Table 3. Estimation results of homogeneous-segment based driving risk model

| Explanatory Variables | Estimates | *t*-statistics |
|---|---|---|
| Constant | 5.4439 | 60.5700** |
| X1=Gender (0:female; 1:male) | −2.4583 | −60.5853** |
| X3=Duration of driving license ownership (month) | −0.0429 | −68.0798** |
| X4=Accident Experience (number of accident experienced) | 0.9922 | 72.8679** |
| X5=Driving period (0:am; 1:pm) | 1.9218 | 69.6701** |
| X6=Road surface condition (0:wet; 1:dry) | −0.7325 | −21.7953** |
| X7=Traffic volume (veh/min/lane) | −0.2768 | −72.4657** |
| X10=Tangent × Vertical grades (%) | 0.1175 | 2.6946** |
| X11=Left curve × Vertical grades (%) | 0.0795 | 6.0533** |
| X12=Right curve × Vertical grades (%) | −0.1875 | −6.4706** |
| X16=Left curve × Road length (m) | 0.0041 | 3.1869** |
| X17=Right curve × Road length (m) | 0.0024 | 6.6501** |
| X18=Left spiral × Road length (m) | 0.0024 | 9.4486** |
| X19=Right spiral × Road length (m) | 0.0011 | 4.9961** |
| X21=Left curve × Degree of curvature (°/100m) × Road length (m) | −0.0007 | −3.7443** |
| X23=Left spiral × Degree of curvature (°/100m) × Road length (m) | −0.0004 | −11.2249** |
| X24=Right spiral × Degree of curvature (°/100m) × Road length (m) | −0.0002 | −5.2134** |
| P1=Voice-based IVTWI (0:no, 1:provision) | −0.3994 | −11.3799** |
| P2=Voice & image-based IVTWI (0:no, 1:provision) | −0.6458 | −13.9485** |
| $\mu_2$ | 1.2930 | 68.4747** |
| Sample size | 37740 | |
| Log-likelihood with zero coefficients | −31154.978 | |
| Log-likelihood for estimated model | −20781.272 | |
| Adjusted Rho-squared ($\bar{\rho}^2$) | 0.332 | |

** Significant at 1% confidence level.

4.2.3 IVTWI provision affecting distribution of driving speeds

Evidence in the literature indicates that driving speed and its deviation are important factors to measure the level of traffic safety. As one of the effects of IVTWI provision, it was expected that driving speed and its deviation would be reduced. To examine this, driving speed and its deviation are analyzed based on the observations with and without IVTWI provision.

The distributions of driving speed for each homogeneous section are presented in Figure 6. Based on the first driving result (Black colored bar), the average driving speed reduces in sections 1~4, it increases from section 5~15 with speeds of 90km/h and over, and it decreases again in sections 16~18. This can be explained by the vertical grades, as the speed increases with increase of vertical grades.

This tendancy of driving speed changed when IVTWI was provided. For example, at section 1~4 without IVTWI provision, the driving speed of 2nd and 3rd traversals are greater than that of 1st traversals. However, the driving speed of 2nd and 3rd traversals in sections 5~16 with IVTWI provision are less than that of 1st traversals. This indicates that the proposed IVTWI provision was effective in improving traffic safety by reducing driving speed.

The effectiveness of IVTWI provision on traffic safety is also confirmed by analyzing the standard deviation (SD) of driving speed at a road section. Based on the analyis results in Figure 7, at section 1~4 without IVTWI provision, the SD of 3rd traversals is greater than that of 1st traversals. Regarding the 4th IVTWI provision, the SD of 2nd and 3rd traversals in sections 5~13 with IVTWI provision are less than that of 1st traversals.

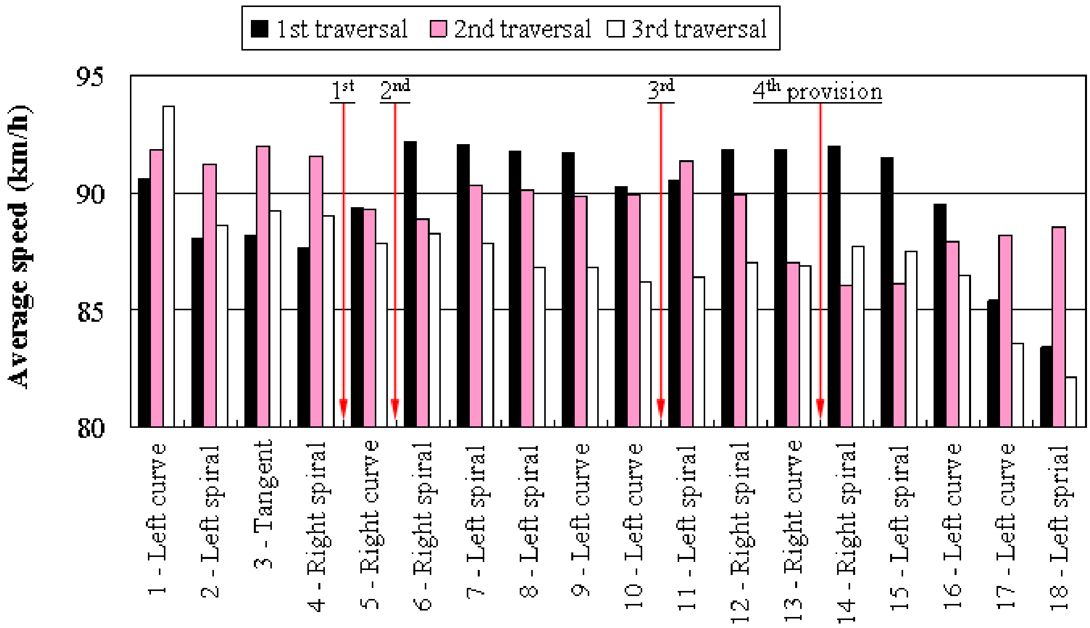


Figure 6. Speed profile along the roadway

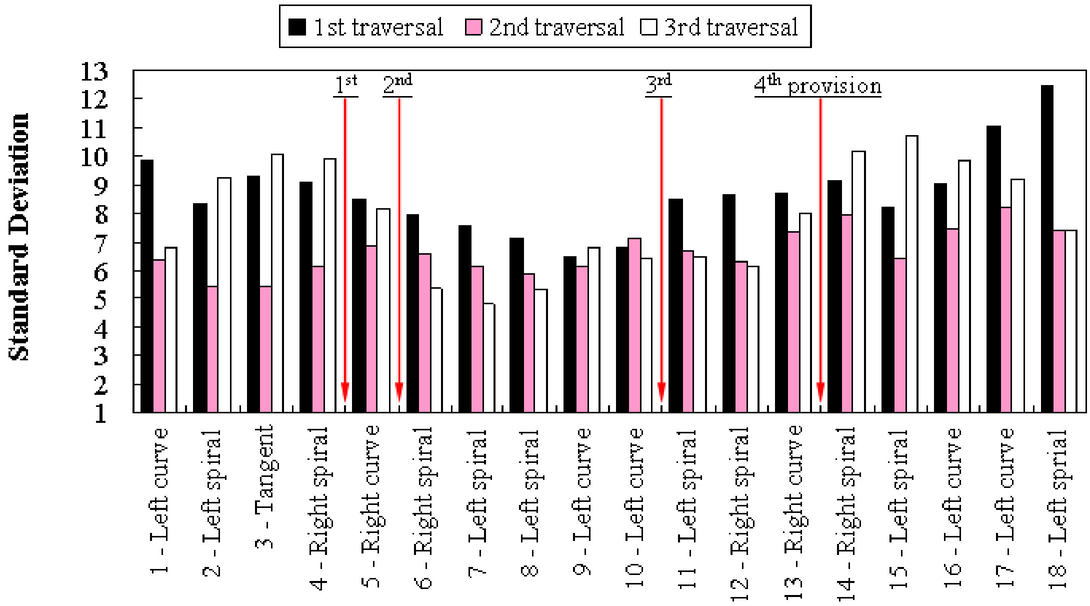


Figure 7. Distribution of speed deviation along the roadway

## 5. CONCLUSIONS

Traffic accident records have been frequently used to evaluate the level of traffic safety. This analysis method, however, is not applicable to road sections for which there is a shortage of accident data. Relying on this method in such cases could provide road users with imprecise information. As an alternative, the existing study suggests to use speed data as a surrogate of traffic accident data. The reason for this is that speed is governed by various factors simultaneously.

Measurement of speed is becoming versatile and data can nowadays be collected by a probe vehicle on a real-time basis, giving easy access to accurate speed data. Nevertheless, appropriate methodologies have been lacking to utilize these advancements. Hence, this paper proposed a *driving risk* model which can be applied to evaluate the level of traffic safety based on driving speed data measured by a probe vehicle.

*Driving risk* was defined here to represent the latent driving safety level based on the driving speed deviation. This definition is supported by the findings of existing studies, i.e., the larger the difference between driving speed and the average speed is, the more traffic accidents or conflicts will occur. This incites us to assume that larger speed deviation could cause dangerous driving behavior. As such, *driving risk* is further specified into three levels: low, medium and high risks. To describe the *driving risk* levels as a categorical variable, an ordered response probit (ORP) model is applied.

To examine the usability of the proposed model, an on-site driving experiment was conducted on Sanyo expressway for five days in Hiroshima prefecture in Japan, 2009. The data collection was focused on a 3.3km long section of the Sanyo expressway which is the most dangerous road section due to including three continuous downgrade curves (i.e. small horizontal curve radii and steep grades). Ten young drivers participated in the experiment and three scenarios of IVTWI provision were tested. The scenarios were set to cover both voice-based and voice & image-based information.

To compare the difference between scenarios, detailed speed analysis was conducted.

Because it was assumed that, at their first traversal, drivers had no knowledge of the driving scenario, the IVTWI was not provided. At second and third traversals, the voice-based and voice & image-based IVTWI were provided. For this analysis, the study area was first divided by the homogeneity feature of roadway. By comparing these differences, it was observed that the value and standard deviation of driving speed reduced after IVTWI provision.

To validate the relationship between *driving risk* and traffic accident occurrence, 84 traffic accidents with more than serious injury for the years 2002–2006 and 987 high *driving risk* cases at first traversals were used. It was confirmed that higher *driving risk* is associated with higher accident occurrence, given that nearly 38% of variance could be explained.

Model estimations indicate that *driving risk* can be reduced by providing IVTWI, and that providing voice & image based information is more effective than providing voice-only information. Concerning the influences of other variables on *driving risk*, this study shows that the average *driving risk* increases with accident experience, driving period, vertical grades at tangent and left cruve sections, and road length. And it reduces with gender, duration of driving license ownership, road surface, traffic volume, inclined right curve, degree of curve sections. In summary, when accident records are lacking, the proposed *driving risk* model can be used to evaluate the level of road safety.

In the progress of this study, largely two study limitations have been found. One is that it was ignored that driver's distraction of IVTWI in making an interpretation of safety its impacts. For example, it could reduce the positive efficacy of IVTWI as side effect. The other is that an investigation of the proportional odds assumption before estimating an ordered probit model doesn't show clearly. These two items, therefore, should be further studied for the better understanding.

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