



Transportation Research Forum

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Source: *Journal of the Transportation Research Forum*, Vol. 49, No. 1 (Spring 2010), pp. 5-22

Published by: Transportation Research Forum

Stable URL: <http://www.trforum.org/journal>

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Contributing Factors to Older-Driver Injury Severity in Rural and Urban Areas

by Loshaka Perera and Sunanda Dissanayake

Older drivers tend to be involved in more severe crashes compared to middle-aged drivers, and U.S. Census Population statistics indicate that the older-driver population is rapidly increasing. Therefore, an improvement in older-driver safety is both important and necessary. In this analysis, a statistical modeling technique was used to identify factors contributing to older-driver injury severity. Two separate models were developed for rural and urban locations, which incorporated several potential explanatory variables. Speed, gender, presence of passengers, road type and street-lighting conditions were found to be important factors affecting injury severity of older drivers on both rural and urban roads.

BACKGROUND

The number of people 65 years and over in the United States is estimated to increase from 35 million in 2000 to 40 million in 2010, and then to 55 million in 2020. This is a 15% and 40% increase for each decade, respectively. Moreover, those 85 years and over are projected to increase from 4.2 million in 2000 to 6.1 million in 2010, and then to 7.3 million in 2020. As a percentage, this is a 40% and 44% increase for those decades, respectively (The U.S. Administration on Aging 2009). Kansas has similar trends to the U.S. statistics.

Since older drivers—considered in this study as those who are older than 65 years—are a subgroup of the older population, an increase in the older population means an increase of older drivers (Baker et al. 2003). According to past research studies, older drivers tend to be involved in more severe crashes compared to middle-aged drivers relative to their population and miles driven (McGwin and Brown 1999; Lyman et al. 2002; Mercier et al. 1997). On the other hand, advancement in technology and many other factors have led to an increase in life expectancy of the average person. According to the U.S. Administration on Aging and Centers for Disease Control and Prevention, in 2004 persons reaching age 65 had an average life expectancy of an additional 18.7 years (20 years for females and 17.1 years for males), compared to only 11.86 years for a person reaching age 65 in 1900 (Center for Disease Control and Prevention). However, as a result of natural aging, older drivers experience physical difficulties such as loss of vision, slower reaction times, decrease in depth perception and peripheral vision, and deterioration of physical strength and concentration. These may directly affect older drivers' driving capabilities and skills, which may increase the possibility of this group being involved in motor vehicle crashes. From a safety point of view this has a direct impact on safety aspects for all road users.

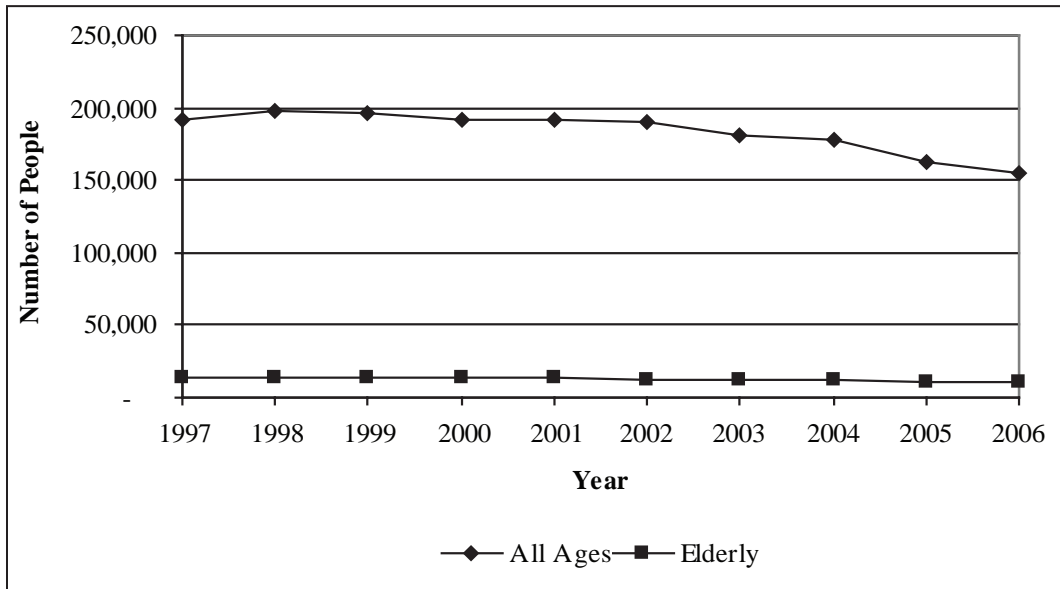
When analyzing crash data in Kansas for the 1997-2006 period, a decreasing trend in all people involved in crashes can be observed. Figure 1 depicts the comparison between the older population and all ages (including older group) involved in crashes; it is important to note that older people represent older drivers, older occupants and older pedestrians in this chart. However, a majority of older people involved in crashes are older drivers, not occupants or pedestrians.

Over the last decade, a decrease in the total number of people involved in crashes can be observed, whereas there is no such clear variation among the elderly population. This could be mainly due to two reasons. The first possibility is that there was no improvement in the elderly population with respect to involvement in crashes, and as a result the same number of crashes seemed to occur each year. Or, there was an improvement in driving among the elderly population and a reduction in involvement in crashes, but it was offset by an increased number of the elderly

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population so no differences can be observed. As statistics show positive elderly population growth rates over the last decade, the latter assumption is more appropriate, which can logically explain the situation. For example, according to the U.S. Census Bureau statistics, there was an increase of 13,658 elderly people in Kansas from 1990 to 2000.

Figure 1: Comparison of Number of People Involved in Crashes Based on Age: Older People (age 65 and above) vs. All Ages



Data Source: Kansas Accident Reporting System (KARS) Database (Kansas Department of Transportation)

The people involved in crashes presented in Figure 1 can be further classified into five different categories based on the severity of injuries.

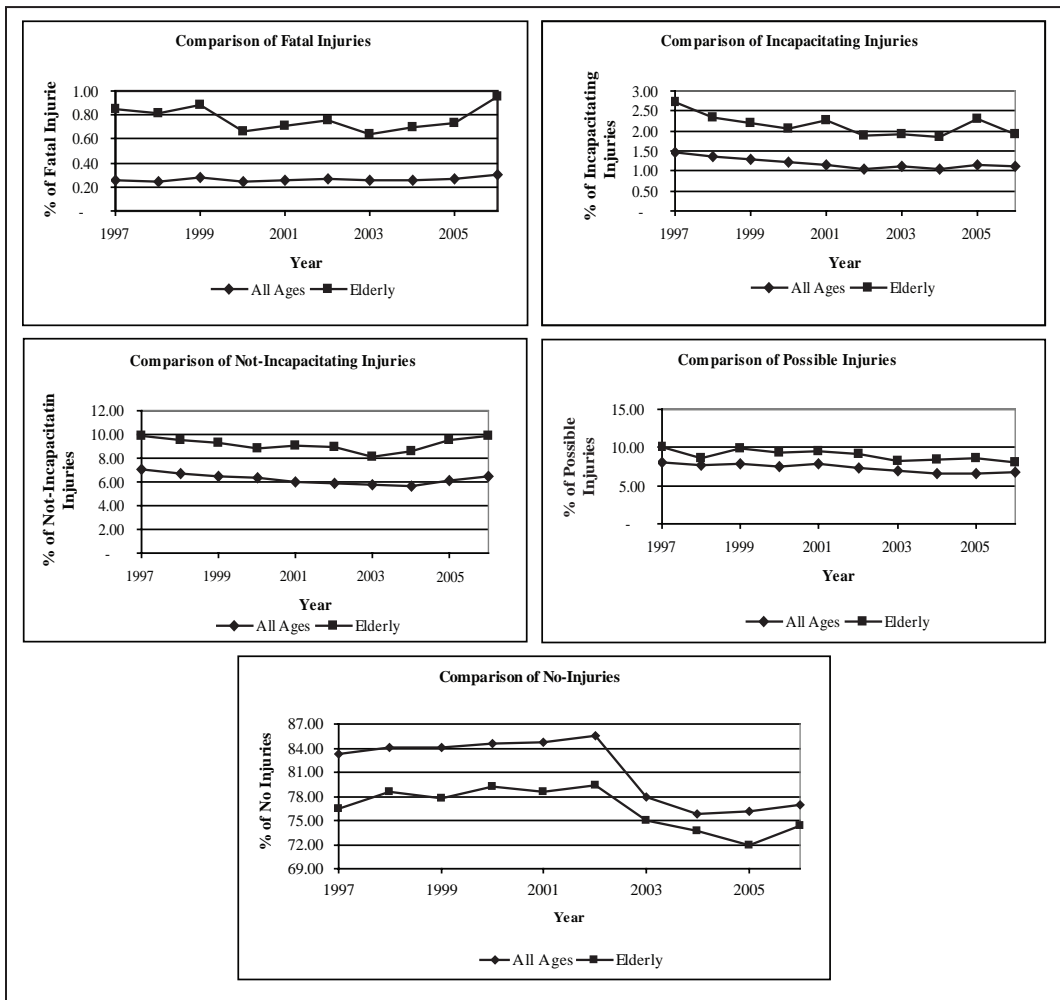
Figure 2 depicts injury severity levels as a result of crashes. By considering the figures, it is evident that older people (age 65 and above) experience more severe injuries when they are involved in crashes as compared to others, and the percentage of older people remaining uninjured as a result of crashes is lower compared to all ages.

Many past researchers have found that older-driver injury severity was high in crashes occurring on rural roads (Dissanayake and Lu 2002; Khattak et al. 2002; Zwerling et al. 2005). From 2002 to 2006, a total of 43,290 older-driver-involved crashes were reported in Kansas (KARS database).

When looking at public road miles in Kansas, there are about 123,694 rural highway miles and 11,768 urban highway miles, according to the U.S. Department of Transportation reports for the year 2005 (U.S. Department of Transportation 2008). All places of 5,000 or more inhabitants, as well as the towns, townships and other areas classified as urban by the U.S. Census Bureau are considered as urban or urban areas in this study.

A majority of those crashes occurred in urban areas. Despite the number of crashes, when looking at injury severity levels, rural road crashes were more severe compared to urban road crashes, according to the KARS database. Synthesizing these findings created an interest to elaborate more on older-driver-involved crashes, mainly classified under rural and urban areas and concentrating more on injury severity to identify contributing factors that could be used to improve safety of older drivers.

Figure 2: Comparison of Injuries to People Involved in Crashes Based on Age: Older People (age 65 and above) vs. All Ages



Data Source: Kansas Accident Reporting System (KARS) Database (Kansas Department of Transportation)

LITERATURE REVIEW

Older driver, safety-related research studies have an extended history in addressing different safety aspects using a variety of databases and surveys. Past researchers have used various statistical modeling techniques to predict or explain the nature of older-driver crashes or injuries, and there are many findings listed under this area.

Lyman et al. (2002) calculated driver involvement rates for all police-reported crashes in the U.S. per capita, per licensed driver and per vehicle-mile traveled for 1990 and 1995. Driver involvement rates were also calculated for fatal crashes, and based on those rates, projections were made for years 2010, 2020 and 2030. Using projections of population growth, it was estimated that for all ages there would be a 34% increase in the number of drivers involved in police-reported crashes and a 39% increase in the number of drivers involved in fatal crashes between 1999 and 2030. For older drivers alone, police-reported crash involvements are expected to increase by 178%, and fatal involvements are expected to increase by 155% by 2030.

Baker et al. (2003) studied special characteristics of fatal crashes involving females older than 70 years in the United States (from 1982 to 2001) and found that senior women are overrepresented in crashes that occur under what is generally considered the “safest” conditions in daylight, when traffic is low, when the weather is good and when the road is dry.

Dissanayake and Lu (2002) carried out a study to identify factors influencing injury severity of older drivers involved in fixed-object passenger car crashes in the state of Florida. Three years of crash data were used from 1994 to 1996 for the modeling process. Among their findings, older males had a higher probability of generating less severe injuries when involved in crashes compared to others, and, conversely, rural locations and locations with curves or grades had a higher probability of generating more severe injuries to older drivers.

Abdel-Aty (2003) analyzed driver injury severity levels using the ordered probit modeling methodology. Three different models were developed for roadway sections, signalized intersections and toll plazas in central Florida using 1996 and 1997 crash data. Results showed that several factors were common in all three models, such as driver age, gender, seat belt use, vehicle type, point of impact and speed ratio, which was the ratio between running speed and posted speed. Further results revealed that wherever a crash occurred, older drivers, male drivers and those not wearing seat belts had a higher chance for severe injuries. Results from the roadway section model showed crashes at curves and those in rural areas were more likely to cause injuries.

Boufous et al. (2008) carried out a study based on a past finding that “older people are more likely to be seriously injured or to die as a result of a traffic crash.” This study was carried out using data gathered from 2000–2001 in New South Wales, Australia. Multivariate analysis was carried out and various factors were found to be independent predictors for injury severity among older people. In addition, they found that intersection configuration could explain over half of the observed variation in injury severity and concluded that intersection treatments might help to reduce injury severity in crashes.

Khattak et al. (2002) carried out a study to identify factors contributing to severe injuries among older drivers involved in traffic crashes using crash data from the years 1990–1999 in the state of Iowa. According to their study, older male drivers experienced more severe injuries when compared to older female drivers, and unprotected older drivers incurred more severe injuries irrespective of gender. Further, the model revealed that crashes occurring on horizontal curves on level terrain were more injurious compared to crashes occurring at other locations. The model also showed that older drivers under the influence of alcohol experienced more severe injuries when compared with older drivers who were not under such influence. Injury levels were found to be more severe on higher-speed-limit roadways and older drivers tended to be more severely injured if the crash occurred on a rural road.

Older drivers’ maneuvering difficulties compared with younger drivers were studied by Chandraratna and Stamatiadis (2003) using Kentucky crash data from 1995–1999. It was found that the risk of an older driver being involved in a left-turn crash increased after the age of 65, with higher tendencies in rural areas. Light conditions were also a contributing factor for left-turn crashes and females had a higher chance of being involved in left-turn crashes compared to males. However, younger females also had a higher propensity to be involved in left-turn-related crashes, just not as high as elderly females. Similar results were obtained for gap acceptance (acceptance of gaps available for crossing non-limited-access highways) and again older females were at a greater risk, but light conditions were found to be insignificant. Lane changing was also found to be a difficulty among older drivers. Presence of a passenger in the vehicle was found to lower the crash-involvement risk, especially in the case of left-turn crashes.

Mercier et al. (1999) studied broadside and angle vehicular collisions using Iowa crash data from 1986–1993. They found gender to be a predictor of injury severity on rural highway crashes, and age was also found to be a significant predictor of injury severity for both sexes, being slightly greater for females than males. Use of seat belts did reduce injury severity, but results were less certain for females.

McKelvey and Stamatiadis (1989) studied highway accident patterns in Michigan (1983 to 1985) and found that older drivers were more likely to be involved in multi-vehicle crashes and head-on, angle crashes on non-interstate highways than were other drivers. Cited violations among older drivers were found to be failing to yield right of way, illegal turns and improper lane use.

Mercier et al. (1997) studied the influence of age and gender on injury severity as a result of head-on crashes on rural highways using Iowa crash data from 1986–1993. The initial hypothesis was that due to a variety of reasons, older drivers and passengers would suffer more severe injuries than others when involved in head-on collisions. Logistic regression analysis methodology was used and variables included age of both the driver and passenger, position in the vehicle and form of protection (seat belts and air bags) used. Age was identified as an important factor predicting injury severity for both men and women, and use of seat belts appeared to be more beneficial for men than for women. Deployed air bags were more beneficial for women than for men.

Many researchers studied older-driver involvement in intersection-related crashes and found that elderly drivers were more susceptible to head-on crashes while turning left and in angle and rear-end crashes than middle-aged drivers (Stamatiadis et al. 1991a). Braitman et al. (2007) identified the factors that led to older drivers' intersection crashes using crash data from Connecticut for the years 2003 to 2004. Based on the study they found that failure to yield the right of way increased with age and occurred mostly at stop-controlled intersections, generally where drivers were turning left. Further, they found that the age group from 70–79 years made more evaluation errors after seeing the vehicle and were unable to judge the available gaps, while drivers above 80 years failed to see or detect the other vehicle. Stamatiadis et al. (1991b) examined the relationship between accidents of elderly drivers and intersection traffic control devices (using Michigan data from 1983 to 1985) and found that older drivers were overrepresented in head-on crashes while turning left. The predominant violations were failing to yield the right of way, following too closely and improper turns; the leading types of crashes were head-on while turning left, and right-angle and rear-end collisions.

Preusser et al. (1998) calculated fatal crash involvement risk for older drivers relative to drivers aged 40–49 years in the United States during the years 1994–1995. Results indicated that drivers aged 65–69 years were 2.26 times more at risk for multiple-vehicle crashes at intersections and 1.29 times more at risk in all other situations. Comparable figures for drivers aged 85 and older were 10.62 for multiple-vehicle crashes at intersections and 3.74 for all other situations. Also, the relative crash risk was particularly high for older drivers at uncontrolled and stop-controlled locations.

Johnson (1995) conducted a study to see what factors were involved in rural older adults' decisions to stop driving. The study found that the majority of the participants had been involved in some sort of an accident while driving, and for most of them this experience influenced the decision to stop driving. Health problems were also identified as a key factor in the decision to stop driving. Feelings of insecurity about driving made some participants give up driving, and, more importantly, the study found that influence from family and friends was a significant factor, though this was not consistent with past findings.

Indike Ratnayake (2004) carried out an analysis using Kansas crash data consisting of all ages that experienced a crash from 1999 to 2002. Ordered probit modeling was used to investigate the critical factors contributing to higher crash severity in rural/urban highway crashes. According to the author, most of the contributing factors towards high-severity crashes were common for both rural and urban areas. Among the research findings, alcohol involvement, excessive speed, driver ejection and curved and graded roads were contributory factors for high-severity crashes.

Duncan et al. (1998) analyzed injury severity in truck-passenger car, rear-end collisions using ordered probit modeling. Based on their model, they concluded that darkness, high speeds, grades, alcohol and being a female were factors that increased passenger vehicle occupant severity.

Summarizing the past findings, it can be stated that older driver involvement in crashes and injury severities are expected to rise considerably in the next two decades, and crashes that occurred in rural locations resulted in severe injuries. Older females are over represented in crashes, and

crashes occurring on high-speed-limit roads (non-interstate highways) are found to be more severe. Further, lack of seat belt usage and being under the influence of alcohol are also found to be significant factors causing high injury severities. Multi-vehicle crashes and head-on crashes involving older drivers are also found to be more severe as compared to other types of crashes.

DATA

Crash data obtained from the Kansas Department of Transportation were used in this study. This data set, Kansas Accident Reporting System (KARS), consists of all police-reported crashes in the state of Kansas. For the analysis in this study, crash data from 2002 to 2006 involving older drivers (age 65 and above) were considered. KARS data were initially classified under a rural/ urban classification. The classification was done based on the type of road on which the crash occurred, and if such data was not available, that particular data line was deleted from the analysis. In addition, some data lines were deleted where data were missing in at least one variable. About 11,636 older drivers involved in crashes on rural roads and 27,480 on urban roads remained for analysis.

Crash data were further analyzed based on various aspects, such as driver-related, crash-related, roadway-related and environment-related factors.

METHODOLOGY

The ordered probit model has the ability to recognize the indexed nature of various response variables (Kockelman and Kweon 2002). A variable can be considered as ordinal when its categories can be ranked from low to high, where distances between adjacent categories are unknown (Long 1997). Injury severity in motor vehicle crashes can also be ordered as fatal injury, disabling or incapacitating injury, non-incapacitating injury, possible injury or no injury, ranging from the highest severity level to the lowest according to the severity of injuries caused to occupants. According to Long (1997), simply because the values of a variable can be ordered, does not imply that the variable should be analyzed as ordinal. But in this study, the response variable that is injury severity can be analyzed as ordinal, because in reality the injury severity outcome of crashes could be arranged in order from lower injury severity (no injury) to higher injury severity (fatal). Further, Long has discussed the applicability of ordered logit and probit models in detail (Long 1997).

The ordered probit model can be derived from a measurement model in which a latent variable y^* ranging from $-\infty$ to ∞ is mapped to an observed ordinal variable y , injury severity in this case (Long 1997). The latent variable y^* is continuous, unobservable, and used to derive the measurement model as follows:

$$(1) \quad y_i = m \quad \text{if } \tau_{m-1} \leq y^* < \tau_m \quad \text{for } m = 1 \text{ to } J$$

The τ 's are called thresholds or cutoff points. The extreme categories 1 and J are defined by open-ended intervals with $\tau_0 = -\infty$ and $\tau_J = \infty$. The observed y is related to y^* , according to the measurement model:

$$(2) \quad y_i = \begin{cases} 1 \rightarrow \text{No injury} & \text{if } \tau_0 = -\infty \leq y^* < \tau_1 \\ 2 \rightarrow \text{Possible} & \text{if } \tau_1 \leq y^* < \tau_2 \\ 3 \rightarrow \text{Non-incapacitating} & \text{if } \tau_2 \leq y^* < \tau_3 \\ 4 \rightarrow \text{Incapacitating} & \text{if } \tau_3 \leq y^* < \tau_4 \\ 5 \rightarrow \text{Fatal} & \text{if } \tau_4 \leq y^* < \tau_5 = \infty \end{cases}$$

The structural form for the ordered probit model with binary response can be considered as

$$(3) \quad y_i^* = x_i \beta + \varepsilon_i$$

x_i is a row vector with a 1 in the first column for the intercept and the i^{th} observation for x_k in column $k+1$. β is a column vector of structural coefficients, with the first elements being the intercept β_0 . and ε_i is the error term.

In order to estimate the regression of y^* on x as in binary regression modeling, the maximum likelihood (ML) estimation can be used with an assumption. In ordered probit modeling, the error term ε_i is assumed to be distributed normally with a mean of 0 and variance of 1.

Once the distribution of the error is specified, the probabilities of observing values of y given x can be computed. For example, if the injury severity of an older driver, who is a victim of a motor vehicle crash that is fatal, the y value is 5 and y^* falls between τ_4 and $\tau_5 = \infty$. Accordingly, the probability formula will be

$$(4) \quad \Pr(y_i = 5 | x_i) = \Pr(\tau_0 \leq y_i^* < \tau_1 | x_i)$$

By generalizing the equation to compute the probability of any observed outcome $y = m$ given x , it becomes

$$(5) \quad \Pr(y_i = m | x_i) = \Phi(\tau_m - x_i \beta) - \Phi(\tau_{m-1} - x_i \beta)$$

Where Φ is the cumulative distribution function of the error term ε_i

Let β be the vector with parameters from the structural model, with the intercept β_0 in the first row, and let τ be the vector containing the threshold parameters. Either β_0 or τ_1 is constrained to 0 to identify the model. In this analysis, the SAS version of 9.1 was used, which considered the τ_1 value as equal to 0.

$$(6) \quad \Pr(y_i = m | x_i, \beta, \tau) = \Phi(\tau_m - x_i \beta) - \Phi(\tau_{m-1} - x_i \beta)$$

Using numerical methods, the equation can be maximized to find τ 's and β 's. The marginal effect from x factors can be determined by computing the partial changes in the equation in order to interpret the regression model.

According to the ordered regression model equation, explanatory variables are linearly related to the dependent variables through a link function transformation to the response variable, and thus they have an increasing effect on injury severity if the variable estimate has a positive value and a decreasing impact on injury severity if the estimate is negative. Model output under selected categories is as follows.

Goodness-of-Fit Measure

In linear regression models, the goodness of fit is usually measured by the R^2 value, whereas there is no such straightforward measure to evaluate model fitness of ordered probit models. McFadden suggested a likelihood ratio index (LRI) that is analogous to the R^2 in the linear regression model (SAS Institute Inc. 2008).

$$(7) \quad R^2_M = 1 - [\ln L / (\ln L_0)]$$

where

L = the value of the maximum likelihood function, and

L_0 = likelihood function when regression coefficients, except for the intercept term, are zero (SAS Institute Inc. 2008).

The R^2_M value is bounded by zero and one, where one denotes perfect fit of the model. Similarly, a few other values are given in the SAS output, such as Estrella, Adjusted Estrella, Veall-Zimmermann and McKelvey-Zovoina, which can also be used to evaluate goodness of fit of a model (SAS Institute Inc. 2008).

In regression modeling, statistical significance of individual factors is important, and overall goodness of fit also plays a vital role in that aspect. In SAS output for an ordered probit model, the number of goodness-of-fit measurements was given, because unlike other regression modeling, there is no such single value that can determine the model fitness consistently. As a result, various values given in terms of probabilities were considered when selecting models, and out of that, McFadden's LRI was used in this study. Similarly, the Estrella value is also desirable in discrete choice modeling (SAS Institute Inc. 2008).

RESULTS AND DISCUSSION

The ordered probit modeling technique was used to identify contributing factors for older-driver injury severity. Two separate models were developed to assess older-driver injury severity in rural and urban areas by considering nearly 50 explanatory variables using statistical modeling software, SAS version 9.1 (SAS Institute Inc. 2008). The dependent variable was injury severity of older-drivers. Variable names, description about how variables are determined and corresponding mean values are given in Table 1. For the categorical variables given in Table 1, there is no particular reference group considered. If the given condition is met, the variable takes the value one, otherwise it takes the value zero.

As the selection criteria of variables to be included in the model, a 95% confidence level was used in which the probability should be less than 0.05. Co-linearity of individual variables was also checked before including variables into the model, and if such a relationship existed, the correlated variable with the lower mean value was discarded.

Table 1: Variable Description for Older-Driver Injury-Severity Models

Variable Name	Description	Rural		Urban	
		Mean	Std.D	Mean	Std.D
Driver Related					
AGE_65-69	Age is between 65-69 years=1, o.w*=0	0.33	0.47	0.29	0.45
AGE_70-74	Age is between 70-74 years=1, o.w=0	0.25	0.43	0.25	0.43
AGE_75-79	Age is between 75-79 years=1, o.w=0	0.21	0.4	0.22	0.41
AGE_80-84	Age is between 80-84 years=1, o.w=0	0.13	0.34	0.16	0.36
GENDER_male	Male=1, o.w=0	0.64	0.48	0.54	0.50
PASSENGERS_no	No passengers=1, o.w=0	0.65	0.48	0.74	0.44
SEAT BELT_on	Wearing seat belt=1, o.w=0	0.89	0.31	0.96	0.19
ALCOHOL FLAG_yes	If yes=1, o.w=0	0.01	0.09	0.01	0.07
Crash Related					
VEHICLE_car	Car=1, o.w=0	0.56	0.50	0.70	0.46
VEHICLE_van	Van=1, o.w=0	0.09	0.29	0.09	0.28
VEHICLE_pick-up	Pick-up truck=1, o.w=0	0.24	0.43	0.14	0.35
VEHICLE_suv	SUV=1, o.w=0	0.05	0.21	0.05	0.21
MANEUVERING_straight	Going straight=1, o.w=0	0.69	0.46	0.50	0.50
MANEUVERING_left turn	Making a left turn=1, o.w=0	0.09	0.28	0.17	0.37
MANEUVERING_right turn	Making a right turn=1, o.w=0	0.02	0.15	0.05	0.22
MANEUVERING_stopped	Stopped or slowing down=1, o.w=0	0.05	0.22	0.17	0.37
MANEUVERING_backing	Backing=1, o.w=0	0.06	0.23	0.04	0.19
MANEUVERING_lane changing	Lane changing=1, o.w=0	0.01	0.12	0.03	0.18
ACCIDENT_other vehicle	Collided with other vehicle =1, o.w=0	0.52	0.50	0.91	0.29
ACCIDENT_parked vehicle	Collided with parked vehicle =1, o.w=0	0.04	0.20	0.04	0.19
ACCIDENT_animal	Collided with an animal =1, o.w=0	0.26	0.44	0.01	0.09
ACCIDENT_fixed object	Collided with a fixed object =1, o.w=0	0.12	0.32	0.03	0.17
COLLISION_head on	Head on collision=1, o.w=0	0.02	0.13	0.02	0.13
COLLISION_rear end	Rear end collision=1, o.w=0	0.11	0.31	0.27	0.45
COLLISION_angle	Angle collision=1, o.w=0	0.25	0.43	0.50	0.50
COLLISION_sideswipe	Sideswipe collision=1, o.w=0	0.08	0.27	0.08	0.28
NUMBER OF VEHICLES_multi	Multi vehicle crash=1, o.w=0	0.48	0.50	0.92	0.27
Roadway Related					
FUNCTION CLASS_interstate	Occurred on an interstate=1, o.w=0	0.08	0.27	0.09	0.28
FUNCTION CLASS_arterial	Occurred on an arterial=1, o.w=0	0.44	0.50	0.67	0.47
FUNCTION CLASS_collector	Occurred on a collector=1, o.w=0	0.26	0.44	0.08	0.27
FUNCTION CLASS_local	Occurred on a local street=1, o.w=0	0.22	0.41	0.16	0.37
LOCATION_intersection	Occurred at an intersection=1, o.w=0	0.30	0.46	0.57	0.49
LOCATION_roadway	Occurred on roadway=1, o.w=0	0.95	0.22	0.99	0.10
ROAD CHARACTER_straight	Road is straight=1, o.w=0	0.93	0.25	0.96	0.20
ROAD CHARACTER_curved	Road is curved=1, o.w=0	0.07	0.25	0.04	0.20
ROAD CHARACTER_grade	Road is on grade or at hillcrest=1, o.w=0	0.24	0.43	0.18	0.38
SURFACE_black top/ concrete	Road surface is blacktop/ concrete=1, o.w=0	0.89	0.31	0.99	0.12
POSTED SPEED_mph	Posted speed in mph	51.74	15.71	36.05	9.96

Table 1: (cont.)

Variable Name	Description	Rural		Urban	
		Mean	Std.D	Mean	Std.D
Environment Related					
LIGHT_day light	Daylight=1, o.w=0	0.69	0.46	0.89	0.31
LIGHT_dark-street lights on	Dark-street light on=1, o.w=0	0.04	0.20	0.07	0.26
LIGHT_dark-no street lights	Dark-no street lights=1, o.w=0	0.21	0.40	0.01	0.11
WEATHER_adverse	No adverse weather condition=1, o.w=0	0.88	0.32	0.88	0.32
WEATHER_rainy	Rainy weather condition=1, o.w=0	0.06	0.23	0.09	0.29
WEATHER_snowy	Snowy weather condition=1, o.w=0	0.02	0.13	0.01	0.12
ROAD SURFACE_dry	Road Surface is dry=1, o.w=0	0.87	0.34	0.85	0.35
DAY_week day	Week day=1, o.w=0	0.76	0.43	0.82	0.38
TIME_peak	Occurred during peak times=1, o.w=0	0.24	0.43	0.23	0.42

*- o.w refers to otherwise

Model results are given in Table 2 for rural roads and in Table 3 for urban roads. Coefficients were estimated using the maximum likelihood method, as explained in the methodology section. Likelihood ratio indexes (LRI) are presented for each model, along with Estrella values and log likelihood values. In the rural model, more explanatory variables were statistically significant. By looking at the two sets of values obtained for the two models, it can be stated that the injury-severity model for rural roads has a better fit compared to the injury-severity model for urban roads. The likelihood ratio index value for the rural injury-severity model is 0.1738 and 0.0653 for the urban injury-severity model. Thus, the injury-severity model for rural roads has a better capability of explaining injury severity caused to older drivers with a selected set of explanatory variables compared to the model for injury severity on urban roads.

Table 2: Estimation of Factors for Older-Driver Injury-Severity Model on Rural Roads

Parameter	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	-0.8288	0.1491	-5.56	<.0001
Driver Related				
AGE_65-69	-0.2723	0.0532	-5.12	<.0001
AGE_70-74	-0.2237	0.0538	-4.16	<.0001
AGE_75-79	-0.1785	0.0544	-3.28	0.0010
AGE_80-84	-0.1728	0.0576	-3.00	0.0027
GENDER_male	-0.1719	0.0323	-5.32	<.0001
PASSENGERS_no	0.0665	0.0317	2.09	0.0362
SEAT BELT_on	-0.8346	0.0390	-21.40	<.0001
ALCOHOL FLAG_yes	0.4444	0.1203	3.69	0.0002
Crash Related				
VEHICLE_car	0.3039	0.0629	4.83	<.0001
VEHICLE_van	0.3589	0.0759	4.73	<.0001
VEHICLE_pick-up	0.1636	0.0636	2.57	0.0101
VEHICLE_suv	0.3556	0.0855	4.16	<.0001
MANEUVERING_straight	(n.s)	(n.s)	(n.s)	(n.s)
MANEUVERING_left turn	-0.2571	0.0484	-5.32	<.0001
MANEUVERING_right turn	-0.5589	0.1078	-5.18	<.0001
MANEUVERING_stopped	-0.2967	0.0677	-4.38	<.0001

Table 2: (cont.)

Parameter	Estimate	Standard Error	t Value	Approx Pr > t
MANEUVERING_backing	-0.5939	0.1171	-5.07	<.0001
MANEUVERING_lane changing	(n.s)	(n.s)	(n.s)	(n.s)
ACCIDENT_other vehicle	-0.8819	0.0673	-13.11	<.0001
ACCIDENT_parked vehicle	-0.7868	0.1115	-7.06	<.0001
ACCIDENT_animal	-1.8224	0.0721	-25.28	<.0001
ACCIDENT_fixed object	-0.1501	0.0560	-2.68	0.0073
COLLISION_head on	1.5153	0.0903	16.79	<.0001
COLLISION_rear end	0.4804	0.0619	7.77	<.0001
COLLISION_angle	0.6353	0.0568	11.18	<.0001
COLLISION_sideswipe	(n.s)	(n.s)	(n.s)	(n.s)
NUMBER OF VEHICLES_multi	(n.s)	(n.s)	(n.s)	(n.s)
Roadway Related				
FUNCTION CLASS_interstate	(n.s)	(n.s)	(n.s)	(n.s)
FUNCTION CLASS_arterial	0.3743	0.0549	6.81	<.0001
FUNCTION CLASS_collector	0.3708	0.0615	6.03	<.0001
FUNCTION CLASS_local	0.2003	0.0692	2.89	0.0038
LOCATION_intersection	0.0892	0.0392	2.27	0.0229
LOCATION_roadway	-0.2484	0.0561	-4.42	<.0001
ROAD CHARACTER_straight	(n.s)	(n.s)	(n.s)	(n.s)
ROAD CHARACTER_curved	(n.s)	(n.s)	(n.s)	(n.s)
ROAD CHARACTER_grade	(n.s)	(n.s)	(n.s)	(n.s)
SURFACE_black top/ concrete	(n.s)	(n.s)	(n.s)	(n.s)
POSTED SPEED_mph	0.0208	0.0013	15.99	<.0001
Environment Related				
LIGHT_day light	(n.s)	(n.s)	(n.s)	(n.s)
LIGHT_dark-street lights on	(n.s)	(n.s)	(n.s)	(n.s)
LIGHT_dark-no street lights	0.1156	0.0471	2.45	0.0142
WEATHER_adverse	(n.s)	(n.s)	(n.s)	(n.s)
WEATHER_rainy	(n.s)	(n.s)	(n.s)	(n.s)
WEATHER_snowy	(n.s)	(n.s)	(n.s)	(n.s)
ROAD SURFACE_dry	0.1734	0.0411	4.22	<.0001
DAY_week day	(n.s)	(n.s)	(n.s)	(n.s)
TIME_peak	-0.0719	0.0335	-2.15	0.0319
τ_2	0.3732	0.0122	30.56	<.0001
τ_3	1.1510	0.0242	47.66	<.0001
τ_4	1.6850	0.0353	47.67	<.0001
Estrella		0.2496		
Adjusted Estrella		0.2439		
McFadden's LRI		0.1738		
Log Likelihood		-7230		
Number of Observations		11,636		

Note: (n.s) refers to "not significant" in the table

Table 3: Estimation of Factors for Older-Driver Injury-Severity Model on Urban Roads

Parameter	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	-1.1555	0.1320	-8.75	<.0001
Driver Related				
AGE_65-69	(n.s)	(n.s)	(n.s)	(n.s)
AGE_70-74	(n.s)	(n.s)	(n.s)	(n.s)
AGE_75-79	(n.s)	(n.s)	(n.s)	(n.s)
AGE_80-84	0.0556	0.0260	2.14	0.0325
GENDER_male	-0.1816	0.0205	-8.85	<.0001
PASSENGERS_no	0.0609	0.0227	2.68	0.0073
SEAT BELT_on	-0.7992	0.0395	-20.25	<.0001
ALCOHOL FLAG_yes	0.2990	0.1144	2.61	0.0089
Crash Related				
VEHICLE_car	0.1460	0.0233	6.26	<.0001
VEHICLE_van	(n.s)	(n.s)	(n.s)	(n.s)
VEHICLE_pick-up	(n.s)	(n.s)	(n.s)	(n.s)
VEHICLE_suv	(n.s)	(n.s)	(n.s)	(n.s)
MANEUVERING_straight	0.1129	0.0248	4.55	<.0001
MANEUVERING_left turn	(n.s)	(n.s)	(n.s)	(n.s)
MANEUVERING_right turn	-0.4482	0.0580	-7.73	<.0001
MANEUVERING_stopped	0.0878	0.0378	2.32	0.0202
MANEUVERING_backing	-0.5545	0.0988	-5.61	<.0001
MANEUVERING_lane changing	-0.7700	0.1019	-7.56	<.0001
ACCIDENT_other vehicle	(n.s)	(n.s)	(n.s)	(n.s)
ACCIDENT_parked vehicle	-0.2700	0.1116	-2.42	0.0156
ACCIDENT_animal	-1.1851	0.1897	-6.25	<.0001
ACCIDENT_fixed object	0.4910	0.0993	4.95	<.0001
COLLISION_head on	1.0794	0.0723	14.92	<.0001
COLLISION_rear end	0.4653	0.0466	9.98	<.0001
COLLISION_angle	0.6075	0.0436	13.93	<.0001
COLLISION_sideswipe	(n.s)	(n.s)	(n.s)	(n.s)
NUMBER OF VEHICLES_multi	-0.7672	0.0981	-7.82	<.0001
Roadway Related				
FUNCTION CLASS_interstate	(n.s)	(n.s)	(n.s)	(n.s)
FUNCTION CLASS_arterial	0.0911	0.0220	4.14	<.0001
FUNCTION CLASS_collector	(n.s)	(n.s)	(n.s)	(n.s)
FUNCTION CLASS_local	(n.s)	(n.s)	(n.s)	(n.s)
LOCATION_intersection	0.1336	0.0224	5.96	<.0001
LOCATION_roadway	(n.s)	(n.s)	(n.s)	(n.s)
ROAD CHARACTER_straight	(n.s)	(n.s)	(n.s)	(n.s)
ROAD CHARACTER_curved	(n.s)	(n.s)	(n.s)	(n.s)

Table 3: (cont.)

Parameter	Estimate	Standard Error	t Value	Approx Pr > t
ROAD_CHARACTER_grade	0.0515	0.0248	2.08	0.0379
SURFACE_black top/ concrete	(n.s)	(n.s)	(n.s)	(n.s)
POSTED SPEED_mph	0.0131	0.0011	12.44	<.0001
Environment Related				
LIGHT_dark-no street lights	0.2125	0.0918	2.31	0.0206
LIGHT_dark-street lights on	(n.s)	(n.s)	(n.s)	(n.s)
LIGHT_dark-no street lights	(n.s)	(n.s)	(n.s)	(n.s)
WEATHER_adverse	0.3255	0.0660	4.93	<.0001
WEATHER_rainy	0.2637	0.0726	3.63	0.0003
WEATHER_snowy	(n.s)	(n.s)	(n.s)	(n.s)
ROAD SURFACE_dry	(n.s)	(n.s)	(n.s)	(n.s)
DAY_week day	(n.s)	(n.s)	(n.s)	(n.s)
TIME_peak	(n.s)	(n.s)	(n.s)	(n.s)
τ_2	0.4663	0.0098	47.71	<.0001
τ_3	1.3991	0.0253	55.23	<.0001
τ_4	2.0193	0.0497	40.61	<.0001
Estrella		0.0687		
Adjusted Estrella		0.0666		
McFadden's LRI		0.0653		
Log Likelihood		-13529		
Number of Observations		27,480		

Note: (n.s) refers to "not significant" in the table

Past studies based on ordered probit modeling have shown that the goodness-of-fit value is typically low. In the model developed by Ma and Kockelman (2004), it was approximately 0.05, and in the models developed by Kockelman and Kweon (2002), the highest LRI value was around 0.08. Many other studies in the past had similar results (Renski et al. 1999; O'Donnell and Connor 1996). Therefore, the reliability of the overall models is acceptable, since LRI values are high compared to past studies.

Variables considered in this analysis can be broadly classified under four sections: driver related, crash related, roadway related and environment related. Thus, the discussion of model results is also presented under the same sections for better understanding.

Driver Related

When looking at both models, most of the driver-related variables are statistically significant in affecting injury severity of older drivers. On rural roads, if a driver's age is less than 85 years, there is a tendency for reduction in injury severity as indicated by the negative coefficients, and on urban roads no such clear differentiation is indicated. Prior findings indicate similar results. For example, Preusser et al. (1998) studied the relative risk of older drivers and found that relative risk rises steadily with increasing driver age, and a significant increase is observed after the driver turns 85. Similarly, according to Li et al. (2003), fragility increases with advancing age and has contributed to excess death rates among older drivers.

The variable associated with gender has a negative estimate in both models, indicating that when older male drivers are involved in crashes, there is a tendency for low injury severity compared to older female drivers involved in crashes. In other words, older females are at higher risk compared to males, irrespective of occurring in a rural or urban area. Similar results were found in past studies as well (Baker et al. 2003, Li et al. 2003). This may be due to the fact that females are generally not as capable as males at bearing physical or mental trauma resulting from crashes (Ratnayake 2004).

According to Hing et al. (2003), drivers perform differently in the presence of passengers. In both models, if no passengers are present, there is a tendency towards having more severe injuries as a result of crashes, as indicated by positive coefficients in Table 2 and 3. When passengers are present, they might be active in adverse conditions providing extra support and information to drivers (Hing et al. 2003), and if a crash occurs, there is a higher chance for someone to remain uninjured who could then ask emergency services for help.

Seat belt usage reduces injury severity in both models, while presence of alcohol has raised injury severity among older drivers, as indicated by the positive coefficients. Use of a restraint device was found to be an important factor capable of reducing injury-severity levels (Li et al. 2003; Dissanayake and Lu 2002; Khattak et al. 2002). This result is confirmed by the large negative coefficients in Table 2 and 3. Drunk older drivers do not take evasive maneuvers to prevent crashes most of the time (Khattak et al. 2002), and this could lead to higher injury severity among them. A careful observation of estimates gives more specific details about how far alcohol involvement affects injury severity.

Crash Related

Among different types of vehicles used by older drivers such as cars, vans, SUVs, pick-up trucks, farm equipment, campers and many other types of vehicles, variables associated with cars, vans and SUVs indicate a statistically significant increasing influence towards injury severity in the rural model. Pick-up trucks also had a statistically significant effect at a very low level, as expressed by the low positive coefficient in Table 2. However, in the urban injury-severity model, only cars have a statistically significant influence on injury severity. Variables associated with left turn, right turn, stopping and backing were statistically significant in the rural injury-severity model, indicating a negative impact on older-driver injury severity. In the urban injury-severity model, no such consistent pattern is observed. The variables going straight and stopped had positive relationships to injury severity, while right-turn, backing and lane changing had a negative relationship to older driver injury severity.

It was found that all four variables related to accident class had negative coefficients in the rural model. This was due to other possibilities, such as overturned vehicles and collision with other objects resulting in more severe injuries compared to the ones considered in the model. Similar types of results can be observed in the urban injury severity model, except for the positive impact on injury severity when older-driver vehicles hit fixed objects. Similar to many other prior findings (Stamatiadis et al. 1991a; Hing et al. 2003), head-on crashes, rear-end crashes and angle crashes are statistically significant in both rural and urban models, with positive parameter estimates indicating these crashes are associated with high injury severity.

According to the model findings, the number of vehicles involved in a crash was not significant in the rural model; but in the urban model, multi-vehicle crashes showed significant results. The negative coefficient revealed that injuries in single-vehicle crashes are more severe than in multi-vehicle crashes on urban roads.

Roadway Related

According to the model estimates, intersection-related crashes involving older drivers on rural roadways are associated with high severe injuries, whereas on-road type crashes have an opposite

effect compared to off-road type crashes. Similarly on urban roads, intersection-related crashes have a positive relationship with injury severity, but whether the crash is on-road or off-road is not statistically significant in the urban model. This is quite obvious because there are higher chances for rural crashes to end up on off-roads causing severe injuries due to lesser traffic in connection with higher speed limits (mean of 52 mph) and lack of facilities available on the roadside, such as guard rails, shoulder lanes and lighting. But on urban roads where speeds are lower (mean of 36) and with better facilities, the chances are lower for such type of crashes.

Rural arterials, collectors and local roads are statistically significant in the rural model, all of which are associated with higher injury severity. The rural interstate variable is not statistically significant, according to the model output. In the urban model, only arterials are statistically significant and had a positive effect on injury severity.

Speed is a major determinant of injury severity based on the laws of physics. Verifying that, model results indicated that speed has a positive relationship with injury severity, and estimates further explain that the rate is a little higher on rural roads compared to urban roads. Prior researchers have also found that speed is one of the most important parameters capable of generating different levels of injury severity (Dissanayake and Lu 2002).

Environment Related

In both models, streets that are dark and without streetlights are significant contributors to crashes resulting in increased injury severity. Crashes occurring during peak times (considered in this study as between 7 a.m. to 9.30 a.m. and 4 p.m. to 6.30 p.m.) on rural roads have negative effects with respect to injury severity compared to off-peak-time crashes. Different weather conditions showed no significance in the rural injury severity model, but in the urban injury severity model, absence of adverse weather conditions and rainy weather conditions showed significant positive impacts on injury severity.

CONCLUSIONS

The ordered probit model was used in this study to identify contributing factors towards higher injury severity on rural and urban roads. The objective of this type of modeling was to see the combined effect of variables contributing towards higher injury severity.

In both cases, older males had a tendency for reduced injury severities compared to older females, and usage of seat belts and presence of passengers led to a reduction in injury severity among older drivers. On the other hand, alcohol involvement increased injury severity among older drivers. Accordingly, awareness of such implications by older drivers would in general be helpful in improving the overall safety situation. Encouraging them to travel with passengers when it is possible and reducing drunk driving for example, could lead to reduction in injury severities. Older drivers above the age of 85 are among the high-risk category in rural areas, therefore from the safety point of view, encouraging the discontinuation of driving is more appropriate for them at such age. However, it is necessary to have access to alternative options and lack of availability of public transportation in rural areas could be a concern. Further, the validity period of driver license needs to be re-evaluated for older drivers, since older driver impairments could grow rapidly.

Head-on, rear-end and angle crashes are related to elevated injury severities in rural and urban areas. Cars, vans and SUVs were positive and statistically significant in the rural road model relative to other types of vehicles, whereas in the urban road model, only cars were significant in increasing injury severity of older drivers. Single-vehicle crashes resulted in more severe injuries on urban roads, causing higher injury severity for older drivers; but on rural roads, the number of vehicles involved in crashes did not contribute to injury severity.

Crashes occurring on both rural and urban arterials caused higher injury severity to older drivers, and speed was also found to be a major contributing factor toward injury severity. In both

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models, intersection-related crashes and crashes occurring under no-streetlight conditions resulted in a higher tendency towards increasing injury severity among older drivers. Exact reasons pertaining to older driver involvement in intersection-related crashes need to be identified in order to suggest countermeasures, but providing more street lighting would reduce number of crashes and the injury severities.

Off-road-type crashes and crashes occurring during off-peak times in rural areas had a tendency to cause more severe injuries to older drivers. Better roadside facilities, such as guardrails, wide shoulders and safer off-road conditions (this includes an increase of clearance distance without any objects like light poles and safe elevation transitions), would improve safety in rural areas. Further, an improvement in emergency response services, as well as a high tech notification system (such as an integrated unit in vehicles that sends a message when a crash occurs to authorities) could also reduce the injury severities in rural areas.

Acknowledgements

Authors would like to acknowledge the Kansas Department of Transportation (KDOT) for funding this research, as well as for providing necessary data.

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