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Injury severity models for motor vehicle accidents: a review

1 **Randa Oqab Mujalli** MSc Engg
PhD student, TRYSE Research Group. Department of Civil Engineering, University of Granada, Granada, Spain

2 **Juan de Oña** PhD
Associate Professor, TRYSE Research Group. Department of Civil Engineering, University of Granada, Granada, Spain

Modelling of traffic accidents injury severity is a complex task. In the last few years the number and variety of studies that analyse injury severity of traffic accidents have increased considerably. In this paper 19 modelling techniques used to model injury severity of traffic accidents where at least a 4-wheeled vehicle is involved have been analysed. The analysis and the comparison between models was performed based on seven criteria (modelling technique, number of records, number of variables, area type, features, injury level and model fit). In general, it is not possible to recommend a method that could be identified as the best one. Each modelling technique has its own limitations and characteristics, awareness of which will help analysts to decide the best method to be used in each particular modelling problem. However, some general conclusions can be established: in most cases the results of models' fits are found to be satisfactory, though not excellent; in the case of data mining models, accuracy improves with balanced datasets; and no correlation was found to exist between the number of accident records and the number of analysed variables.

1. Introduction

Road accidents constitute a major public health problem worldwide, causing around 1·2 million deaths and over 50 million injuries each year (WHO, 2004). Identifying the main factors that are related to injury severity of traffic accidents, especially to fatalities, has therefore been a primary interest to injury severity analysts. Figure 1 shows that the number of studies about injury severity of traffic accidents has been increasing with time, with the largest number in the last five years.

Many techniques have been used to analyse the injury severity of traffic accidents. The methods that have been used most include ordered probit models, binary logit models, ordered logit models and hierarchical logit models. However, in recent years other types of models have appeared: artificial neural networks, Bayesian networks, trees and genetic programming.

Knowledge of the advantages and disadvantages of each method would help safety analysts decide the most appropriate method for each particular analysis. The scope of this paper is to provide insight on each of the methods already used to analyse injury severity of traffic accidents where at least a motorised 4-wheeled vehicle is involved, excluding traffic accident studies that analyse injury severity from a medical point of view, or those that discuss the vehicle design and equipment and their relation to the injury outcome and those studies that analyse accidents in urban areas only.

The analysis of the different models is based on the following aspects: type of modelling technique; number of crashes considered in the analysis; number of variables used for analysing the severity; area type of the road (urban, suburban or rural); features considered in the analysis (basic segment and/or intersection); type and number of categories for injury levels; and model fit.

This paper is organised as follows. Section 2 briefly describes the techniques used in the literature to analyse and/or model injury severity. A discussion of the studies found in literature is presented in Section 3. Summary and conclusions are given in Section 4.

2. Modelling techniques

In this section the modelling techniques used to analyse injury severity of traffic accidents are classified into four groups: discrete outcome models, data mining techniques, soft computing techniques and other techniques.

2.1 Discrete-outcome models (DOMs)

DOMs are used to represent probabilities of having an outcome based on certain factors or characteristics. In general, these

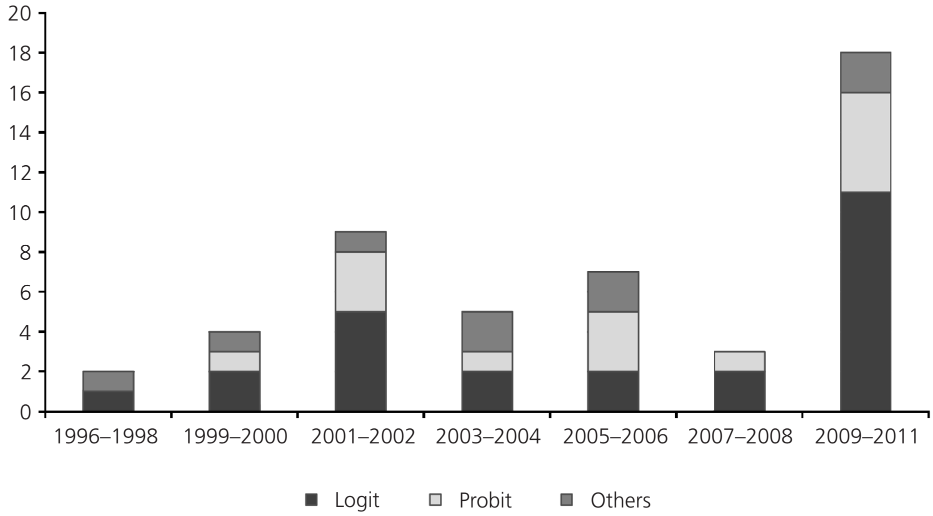

Figure 1. Case studies by type of model analysed from 1996 to 2011

models cannot be calibrated using standard curve-fitting techniques, such as least squares, because their dependent variable is an unobserved probability (between 0 and 1) and the observations are the individual outcomes (either 0 or 1) (Ortúzar and Willumsen, 2001).

2.1.1 Logit models (LMs)

A special case of general linear regression is the logistic regression or logit model, which assumes that the response variable follows the logit-function. The logistic model is an approach used to describe the relationship of single or several independent variables to a binary outcome variable. This modelling approach is usually preferred by researchers, since the logistic function must lie in the range between 0 and 1, and this is not usually the case with other possible functions (Kleinbaum and Klein, 2002).

The simplest form of the LM is the binary form, where the outcome variable is one of two outcomes. The binary logit model (BLM) and other extensions of it were found to be mostly used in the literature of accidents injury severity analysis.

A brief description of these extensions is the following (Keele and Park, 2004; Kleinbaum and Klein, 2002; Ortúzar and Willumsen, 2001; Train, 2009; Washington *et al.*, 2011).

1. The multinomial logit model (MNL) is used when the outcome variable has more than two unordered categories.
2. The hierarchical logit, nested logit or multi-level logit model (HL) is used when certain assumptions valid for the MNL are violated, for example when the outcomes are not independent or when there are variations among individuals.
3. The mixed logit model (MXL) is a generalised extreme value (GEV) model where this distribution allows for correlations over outcomes, and it is a generalisation of the univariate extreme value distribution that is used for the standard LM. This model alleviates the three limitations of the standard LM by allowing for random variation, unrestricted substitution patterns and correlation in unobserved factors over time. MXLs are actually the integrals of the standard logit probabilities over density parameters.
4. The ordered logit model (OLM), also known as the proportional odds model, has an observed ordinal variable (Y), where Y is a function of another latent continuous unmeasured variable (Y^*). Values of Y^* determine the values of the resulting Y. Y^* has various threshold or cut points, where the value of Y depends on these thresholds. The random disturbance or the error term here follows a logistic distribution (Washington *et al.*, 2011).
5. The heteroskedastic logit model (HKL) is also a GEV model; however, instead of capturing correlations among outcomes, it allows the variance of unobserved factors to differ over outcomes.
6. The heterogeneous model (HM) is used when dealing with categorical dependent variables. If the variants of the error term are non-constant, the standard error will be incorrect and the parameters will be biased and inconsistent. In order to deal with unequal error variances, the HM is used.
7. Generalised estimating equations (GEEs) are an extension of the logistic model to handle outcome variables that have binary correlated outcomes. GEEs take into account the correlated nature of the outcome.

Twenty-five studies of accident injury severity used one or more of these LMs. These studies are listed in detail in Table 1.

Study authors (publication year)	Objectives of the study	Model type	No. records	No. variables	Area type	Features	Injury level	No. injury levels	Model fit test
Shanker *et al.* (1996)	To analyse severity on rural highways	HL	1505	21	Rural	SEG	KABCO	5	$\rho^2 = 0{\cdot}52$ (probably McFadden's)
Donelson *et al.* (1999)	To predict fatality for occupants of light-duty trucks in single-vehicle rollover crashes	BLM	55 000	11	Mixed	SEG	K	1	Kendall's tau (τ) coefficient *c* statistic = [0·882–0·916] for all models concordance = [88·4–85·5%] for all models discordance = [6·4–9·8%] for all models tied pair of a fatal crash = [4–5·6%] for all models
Krull *et al.* (2000)	To explore the effect of rollover crashes for single vehicles	BLM	59 743	16	Mixed	SEG	K + A, B + C + O	2	$\rho^2 = 0{\cdot}147$ (McFadden's)
Abdelwahab and Abdel-Aty (2001)	To analyse the injury severity of crashes of two vehicles that occurred at signalised intersections	OLM	1168	14	n.a.	INT	A, C + B, O	3	Accuracy = 58·9%
Dissanayake and Lu (2002)	To analyse injury severity of young drivers for single vehicles–fixed objects crashes	BLM	8382	16	Mixed	SEG	KABCO	5	Accuracy = 89·2%
Bédard *et al.* (2002)	To determine the independent contributions of driver, vehicle and accidents characteristics on fatalities in single vehicles–fixed objects crashes	BLM	109 837	12	n.a.	n.a.	K	1	n.a.
Srinivasan (2002)	To model injury severity	OMXL, OLM	3492	6	Mixed	BOTH	KACO	4	OMXL against OLM: $\chi^2 > \chi^2$ critical (60·86 > 28·86 at 0·05) for the observed data, $\chi^2 > \chi^2$ critical (31·92 > 28·86 at 0·05) for the predictive data
Ouyang *et al.* (2002)	To study the simultaneity of injury severity outcomes in two-vehicles crashes of car–truck combination	BLM	2986	24	Mixed	BOTH	A + K, O + C	2	$\rho^2 = 0{\cdot}172$ (probably McFadden's)
Khattak and Rocha (2003)	To study the influence of various vehicles platforms on rollover single-vehicle crashes and driver injuries	OLM	4552	5	n.a.	n.a.	AIS	7	$\rho^2 = 0{\cdot}1040$ (McFadden's)
Dissanayake (2004)	To identify roadway, environmental, vehicle and driver-related characteristics affecting the injury severity for single-vehicles crashes by young and older drivers	BLM	n.a.	15	Mixed	SEG	KABCO	5	n.a.

(*continued*)

Study authors (publication year)	Objectives of the study	Model type	No. records	No. variables	Area type	Features	Injury level	No. injury levels	Model fit test
Wang and Kockelman (2005)	To study the effects of various vehicle, environmental, roadway and occupant characteristics on the severity of injuries sustained by vehicle occupants in one- and two-vehicle crashes	HKL	n.a.	25	n.a.	SEG	KABCO	5	ρ^2 (McFadden's) for one vehicle: HOP = 0·237, OP = 0·235 for two vehicles: HOP = 0·257, OP = 0·251
Lenguerrand *et al.* (2006)	To classify severity of occupant into dead or not dead for car accidents	GEE, HL, BLM	12 030	9	n.a.	INT	K, not K	2	n.a.
Awadzi *et al.* (2008)	To model injury severity of younger and older drivers	MNL	n.a.	18	Mixed	BOTH	KBO	3	n.a.
Milton *et al.* (2008)	To study the variation that the influence of variables has on injury severity by the roadway segments	MXL	22 568	26	Mixed	BOTH	K + A, BO	2	$\rho^2 = 0{\cdot}1145$ (calculated McFadden's)
Malyshkina and Mannering (2009)	To analyse injury severity of accidents for two vehicles or fewer	MNL	81 172	16	Mixed	SEG	KBO	3	*p*-value for $\chi^2 = 0{\cdot}20$–$0{\cdot}50$
Schneider *et al.* (2009)	To assess driver injury severity resulting from single-vehicle crashes on rural two-lane highways in Texas	MNL	10 029	24	Rural	SEG	ABCO	4	ρ^2 (probably McFadden's) for small radius model: $\rho^2 = 0{\cdot}258$ for medium radius model: $\rho^2 = 0{\cdot}230$ for large radius model: $\rho^2 = 0{\cdot}253$
Jung *et al.* (2010)	To assess the effects of rainfall on the severity of single-vehicle crashes on Wisconsin interstate highways	OLM, BLM	255	30	n.a.	n.a.	K + A, B + C, O	3	Accuracy = 88% for the KA Accuracy = 68% for the B + C
Haleem and Abdel-Aty (2010)	To analyse crash injury severity at three- and four-legged un-signalised intersections	HL	2043	21	Mixed	INT	K + A, B + C + O	2	AIC = 34 040
Jin *et al.* (2010)	To analyse the factors affecting right-angle crash injury severity on four-legged signalised intersections	OLM	13 218	7	n.a.	INT	KABCO	5	$\rho^2 = 0{\cdot}0542$
Daniels *et al.* (2010)	To investigate which factors might explain the severity of crashes or injuries on roundabouts	HL	1491	7	n.a.	INT	K + A, K	2	χ^2 for K + A = 10·88 (DF = 8, *p*-value = 0·21) for K = 4·86 (DF = 6, *p*-value = 0·56)

Paleti *et al.* (2010)	To capture the moderating effect of aggressive driving behaviour while assessing the influence of a comprehensive set of variables on injury severity	HKL	6950	15	n.a.	n.a.	KABCO	5	$\rho^2 = 0{\cdot}1188$ (calculated McFadden's)
Quddus *et al.* (2010)	To explore the relationship between the severity of road crashes and the level of traffic congestion using disaggregated crash records and a measure of traffic congestion while controlling for other contributory factors	OLM, HM	3998	17	n.a.	SEG	KAC	3	ρ^2 (McFadden's) $\rho^2 = 0{\cdot}096$ for the OLM $\rho^2 = 0{\cdot}099$ for the HM
Dupont *et al.* (2010)	To predict the chances for occupants involved in traffic accidents to end among the survivors given that the accident was fatal and to examine the features of the road users or of the vehicles that are positively or negatively associated with survival chances risk factor	BLM	1296	14	n.a.	BOTH	K	1	n.a.
Peek-Asa *et al.* (2010)	To identify driver and crash characteristics associated with increased odds of fatal or severe injury among urban and rural crashes	BLM	87 185	12	Mixed	BOTH	KA	2	n.a.
Kononen *et al.* (2011)	To predict the probability that a crash-involved vehicle will contain one or more occupants with serious or incapacitating injuries	BLM	n.a.	7	n.a.	n.a.	A	1	Sensitivity = 40% Specificity = 98% ROC area = 0·84

n.a., data not available; KABCO (K = killed, A = incapacitating, B = non-incapacitating, C = possible injury, O = no injury); AIS (0 = no injury, 1 = minor, 2 = moderate, 3 = serious, 4 = severe, 5 = critical; 6 = unsurvivable); SEG, basic segment only; INT, intersection only; BOTH, intersection + segments.
Probably McFadden's: ρ^2 value was given in the study, and was found to apply to McFadden's formula; calculated McFadden's: ρ^2 value was not given, but was calculated using log-likelihoods given in the study

Table 1. Studies that analyse injury severity of traffic accidents using logit models

2.1.2 Probit models (PMs)
PMs deal with the three limitations of LM: they can handle random variation; they allow any pattern of substitution; and they are applicable to panel data with temporally correlated errors (Train, 2009).

The most used type of PM in the analysis of accident severity is the ordered probit model (OPM). The OPM is a generalisation of the PM to the case of more than two outcomes of an ordinal dependent variable. If the model cannot be estimated using the ordinary least squares, it is usually estimated using the maximum likelihood (Train, 2009).

Other PMs used are the following.

- Heteroskedastic probit model (HOP): this is used when the error terms are not homoskedastic and their variance may be parametrised as a function of covariates. HOPs offers more flexibility than OPMs, since they capture the effect of the independent variables on the variance or uncertainty in the outcome (Lemp *et al.*, 2011).
- Bayesian ordered probit model (BOP): this is an extension of the Bayesian inference into the OPM, in which the parameters to be estimated are assumed to follow certain prior distributions. Based on the data, the likelihood function is used to update the prior distribution and obtain the posterior distribution (Xie *et al.*, 2009).

Fourteen studies of accident injury severity used one or more of these PMs. These studies are listed in detail in Table 2.

2.2 Data-mining techniques
Data mining is defined as the process of discovering patterns in data. The patterns discovered must be meaningful in that they lead to some advantages (Witten and Frank, 2005). Many data-mining techniques are being used in different fields of science, economy, engineering and so on. Decision trees and Bayesian networks have been also used to analyse the injury severity of traffic accidents.

2.2.1 Decision trees
Decision trees are non-linear predictive models that use the tree to represent the recursive partition. Within the literature of accident injury severity studies, two types have been used (see Table 3).

1. Classification and regression trees (CART): this procedure constructs binary trees, in which each internal node has exactly two outgoing edges. CART can consider misclassification costs in the tree induction. It also enables users to provide prior probability distribution. An important feature of CART is its ability to generate regression trees, where the leaf predicts a real number and not a class (Rokach and Maimon, 2008).
2. Chi-squared automatic interaction detection (CHAID): this is a procedure used to generate decision trees. For each input variable, CHAID finds the pair of values that is least significantly different with respect to the target variable (Rokach and Maimon, 2008).

2.2.2 Bayesian networks (BNs)
BNs are graphical models of interactions among a set of variables, where the variables are represented as nodes of a graph and the interactions as directed links between the nodes. Any pair of unconnected/nonadjacent nodes of such a graph indicates (conditional) independence between the variables represented by these nodes under particular circumstances (Mittal and Kassim, 2007).

Two studies were found to use BNs to analyse injury severity of accidents (see Table 3).

2.3 Soft computing techniques
Soft computing is a mix of distinct methods that in one way or another cooperate in their fundamentals. The principal objective of soft computing is to exploit the tolerance for imprecision and uncertainty in order to achieve manageability, robustness and solutions at low cost (Zadeh, 1994).

2.3.1 Artificial neural networks (ANNs)
A neural network is an interconnected assembly of simple processing elements, units or nodes. The processing ability of the network is contained in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns (Gurney, 1997). Neural networks are composed of neurons, which in turn are composed of a number of inputs, and each input comes with a connection that has a weight and a threshold value.

A number of ANN types have been used by researchers of accident severity analysis (see Table 3).

- Multi-layer perceptron ANN (MLP): this usually consists of three layers – input layer, hidden layer and output layer. The connections in an MLP are feed-forward type in which they are allowed from an index to layers of a higher index. To train an MLP, the back-propagation algorithm is used (Rumelhart *et al.*, 1986).
- Fuzzy Artmap ANN (Artmap): this is based on adaptive resonance theory. It is a clustering algorithm that maps a set of input vectors to a set of clusters. Models built by fuzzy Artmap have fast, stable learning in response to binary input patterns (Carpenter *et al.*, 1992).

2.3.2 Evolutionary algorithms (EAs)
EAs mimic natural evolution in order to optimise a solution to a problem (Brameier and Banzhaf, 2007). These algorithms exploit differential fitness advantages in a population of solutions to gradually improve the state of that population.

Genetic programming (GP) is defined as any direct evolution or breeding of computer programs for the purpose of inductive learning. Unlike other EAs, GP can complete missing parts of an existing model.

Linear genetic programming (LGP) is a GP variant that evolves sequences of instructions from an imperative programming language or from a machine language. Linear refers to the structure of the imperative program representation, where the nodes do not have to be linearly listed nor need the method itself be linear.

Das and Abdel-Aty (2010) used LGP to classify injury severity according to the accident type in order to find the geometric and environmental factors that are related to this classification (see Table 3).

2.4 Generalised linear models (GLMs)

The log-linear model (LLM) is one of the specialised cases of GLMs for Poisson-distributed data. In log-linear models, there is no distinction between independent and dependent variables; all variables are treated as response variables. Chen and Jovanis (2000) used LLMs to identify significant variables that contribute to the occurrence of a specific injury severity for bus drivers (see Table 3).

3. Discussion

Figure 1 shows the different models that have been used in the field of traffic accident injury severity analysis. The most used are the logit and probit models, followed by other models. However, Tables 1, 2 and 3 show that there is a large dispersion in the principal magnitudes used for the models.

It should be taken into account that the following sections are not intended to make a comparison among different modelling techniques or different studies; the sections are presented as guidance for analysts, since a comparison is not possible due to the differences that exist in data sources, study objectives and certain conditions that might apply to a given study but not to others.

3.1 Number of records considered in the analysis

The number of records considered in the analysis ranges between 255 and 622 432. However, four extreme outliers were identified (Montgomery and Runger, 2003). Table 4 shows the statistical analysis results without extreme outliers.

Table 4 shows that the number of records (without extreme outliers) for all the studies ranges between 255 and 81 172, with a median value of 3955. PMs present the lowest median, with 3136 crashes, followed by LMs with 4552 records. The other models present the highest median (4713) for the number of records considered in the analysis.

All the values are very similar and no significant statistical difference was observed between the three groups (logit, probit and others) based on the Mann–Whitney *U* test.

3.2 Number of variables for analysing severity

The number of variables used in the modelling of injury severity ranges between 5 and 58. However, one extreme outlier was identified, which was not considered in the statistical analysis.

Table 4 shows that the number of variables (without extreme outliers) for all the studies ranges between 5 and 36, with a median value of 15. PMs present the highest median with 16 variables, followed by LMs with 15 variables. The other models present the lowest median (14) for the number of variables used for analysing severity.

All the values are very similar and no significant statistical difference was observed between the three groups (logit, probit and others) based on the Mann–Whitney *U* test.

No correlation was found to exist between the number of variables for analysing severity and the number of records considered in the analysis.

3.3 Focus of the study

There is a relatively high dispersion in the type of roadway segment analysed. Figure 2 shows that 14 studies analysed only basic segments, 9 studies analysed only intersections and 13 studies analysed both intersections and roadway segments in the same study. However, Moore *et al.* (2010) recommend that intersections and road segments should not be analysed together, since the factors related to accidents occurring on intersections are different from those occurring on roadway segments.

Regarding the area type in which the roadway or the intersection exists, only six studies analyse rural areas, while 22 studies mixed the data for rural, urban and/or suburban highways, keeping in mind that the characteristics of the roadways and intersections differ significantly between urban and rural areas.

3.4 Type and number of categories for injury levels

The definition of the injury severity might refer to the emphasis of the study (Krull *et al.*, 2000), either for convenience (Ouyang *et al.*, 2002) or because of the small counts of certain categories with respect to other categories (Peek-Asa *et al.*, 2010).

Most of the studies used the KABCO scale, which is the scale used in police observed accident records (Morgan, 2009). Others have combined one or more categories into one.

Table 4 shows that the number of injury levels for all the studies ranges between 1 and 7, with a median value of 3. In this case no extreme outliers were identified. PMs present the highest median, with 5 levels, followed by LMs with 3 levels. The other models present the lowest median (2) for the number of injury levels.

In this case, significant statistical differences were observed ($p < 0{\cdot}05$), based on the Mann–Whitney *U* test, between the

Study authors (publication year)	Objectives of the study	Model type	No. records	No. variables	Area type	Features	Injury level	No. injury levels	Model fit test
Renski *et al.* (1999)	To analyse effect of speed limit on occupant injury in single-vehicle crashes. Excluding pedestrian, bicyclist or motorcycle crashes	OPM	2729	7	Mixed	SEG	KABCO	5	$\rho^2 = 0{\cdot}116$ (probably McFadden's)
Khattak (2001)	To analyse the effect of information and vehicle technology on injury severity in rear-end crashes in two and three vehicles crashes	OPM	3912	36	Mixed	SEG	KABCO	5	ρ^2 (McFadden's) $\rho^2 = 0{\cdot}0319$, $0{\cdot}0671$, $0{\cdot}0660$ for drivers 1, 2, 3 respectively
Kockelman and Kweon (2002)	To analyse the injury severity of all crashes, two-vehicles crashes, single-vehicle crashes	OPM	n.a.	13	n.a.	n.a.	KACO	4	$\rho^2 = (0{\cdot}0451{-}0{\cdot}0868)$ (McFadden's)
Khattak *et al.* (2002)	To isolate factors that contribute to injuries to older drivers involved in crashes	OPM	17 045	16	Mixed	BOTH	KABC	4	$\rho^2 = 0{\cdot}057$ (probably McFadden's)
Abdel-Aty and Abdelwahab (2004)	To investigate the viability and potential benefits of using the ANN in predicting driver injury severity conditioned on the premise that a crash has occurred	OPM	7891	12	Mixed	SEG	K + A, BCO	2	Accuracy = 61·7%
Abdel-Aty and Keller (2005)	To analyse crashes' injury severity on signalised intersections, where the ordinal probit model was used to find the expected injury severity level	OPM	21 371	34	n.a.	INT	KABCO	5	$\rho^2 = 0{\cdot}24$ (calculated McFadden's)
Oh (2006)	To establish a statistical relationship correlating crash severity with weather, traffic manoeuvres and specific roadway geometrics at four-legged signalised intersections in rural areas. Four models were built: single-vehicle, two-vehicle, three- or more vehicle, multiple-vehicle	OPM	449	16	Rural	INT	KACO	4	$\rho^2 = 0{\cdot}176$ for all crashes model $\rho^2 = 0{\cdot}480$ for three or more vehicles $\rho^2 = 0{\cdot}197$ for two vehicles $\rho^2 = 0{\cdot}378$ for single vehicle
Gårder (2006)	To analyse the statistical association between head-on crash severity and potential causal factors	OPM	3136	7	Rural	SEG	KABCO	5	n.a.
Gray *et al.* (2008)	To study accidents for young male drivers	OPM	622 431	13	Mixed	BOTH	KACO	4	LL = −33 665·05 for London model LL = −267 706·85 for UK
Xie *et al.* (2009)	To analyse the relationship between accident injury severity and factors such as driver's characteristics, vehicle type and roadway conditions	OPM, BOP	76 994	14	n.a.	INT	KABCO	5	Accuracy: for BOP for small data size = [55–68%] for OP for small data size = [58–68%] for BOP for predicted rest of the data = [61·8–65·4%] for OP for predicted rest of the data = [59·9–62·9%]

Wang *et al.* (2009)	To identify factors contributing to injury severity at freeway diverge areas and to evaluate impacts of the factors	OPM	10 946	17	n.a.	INT	KABCO	5	$\rho^2 = 0{\cdot}0273$
Haleem and Abdel-Aty (2010)	To analyse crash injury severity at three- and four-legged un-signalised intersections	OPM, PM	2043	21	Mixed	INT	For the OPM: KABCO For the PM: K + A, BCO	5, 2	AIC = 17 091 (OPM + 3-legged) AIC = 9423 (OPM + 4-legged) AIC = 3804 (PM + 3-legged) AIC = 2100 (PM + 4-legged)
Lemp *et al.* (2011)	To study the impact of vehicle, occupant, driver and environmental characteristics on injury outcomes for those involved in crashes with heavy-duty trucks	OPM, HOP	1849	27	Mixed	n.a.	KABCO	5	LL: for OPM = −1993 for HOP = −1896
Zhu and Srinivasan (2011)	To analyse the empirical factors affecting injury severity of large trucks. Two measures of severity were used: PAR, determined from police accident reports; RES, determined by researchers	OPM	953	28	Mixed	BOTH	KA, B + C	2	ρ^2: for PAR model = $0{\cdot}1780$ for RES model = $0{\cdot}1827$

n.a., data not available; KABCO (K = killed, A = incapacitating, B = non-incapacitating, C = possible injury, O = no injury); SEG, basic segment only; INT, intersection only; BOTH, intersection + segments.
Probably McFadden's: ρ^2 value was given in the study, and was found to apply to McFadden's formula; Calculated McFadden's: ρ^2 value was not given, but was calculated using log-likelihoods given in the study

Table 2. Studies that analyse injury severity of traffic accidents using probit models

Study authors (publication year)	Objectives of the study	Model type	No. records	No. variables	Area type	Features	Injury level	No. injury levels	Model fit test
Trees									
Council and Stewart (1996)	To analyse severity of accident of single vehicles with fixed objects (for occupants)	Cart	n.a.	7	Mixed	BOTH	KBO	3	n.a.
Chen and Jovanis (2000)	To identify significant variables that contribute to the occurrence of a specific injury severity for bus drivers	Chaid	408	24	Rural	BOTH	KB	2	n.a.
Chang and Wang (2006)	To model the injury severity of an individual involved in a traffic accident	Cart	26 831	14	Mixed	BOTH	KBO	3	Accuracy: for fatal (0%) for injury (94%) for no injury (68%)
Bayesian networks									
Simoncic (2004)	To model two-car accident injury severity	BN	17 558	12	Mixed	n.a.	K + A, other	2	n.a.
De Oña *et al.* (2011)	To classify crashes according to their injury severity	BN	1536	18	Rural	SEG	K + A, C	2	Accuracy = 60% Sensitivity = 73% Specificity = 45% ROC area = 61%
Neural networks									
Abdelwahab and Abdel-Aty (2001)	To analyse the injury severity of crashes of two vehicles that occurred at signalised intersections	MLP, Fuzzy Artmap	1168	14	n.a.	INT	A, B + C, O	3	Accuracy = 65·6%
Abdel-Aty and Abdelwahab (2004)	To investigate the viability and potential benefits of using the ANN in predicting driver injury severity conditioned on the premise that a crash has occurred	MLP, Fuzzy Artmap	7891	12	Mixed	SEG	K + A, BCO	2	Accuracy: for MLP = 73·5% for fuzzy Artmap 40·6%
Delen *et al.* (2006)	To model the potentially non-linear relationships between the injury severity levels and accident-related factors	MLP	30 358	13	n.a.	n.a.	KABCO	5	Accuracy = 40·73%
Linear genetic programming									
Das and Abdel-Aty (2010)	To understand the relationship of geometric and environmental factors with injury-related crashes as well as with severe crashes	LGP	104 952	58	mixed	BOTH	B + O, A + C	2	Accuracy = 60·4%
Others									
Chen and Jovanis (2000)	To identify significant variables that contribute to the occurrence of a specific injury severity for bus drivers	LLM	408	24	Rural	BOTH	KB	2	$R^2 = 0{\cdot}95$

n.a., data not available; KABCO (K = killed, A = incapacitating, B = non-incapacitating, C = possible injury, O = no injury); SEG, basic segment only; INT, intersection only; BOTH, intersection + segments.

Table 3. Studies that analyse injury severity of traffic accidents using other techniques

	No. of accident records	No. of variables	No. of injury levels
All studies			
Max.	81 172	36	7
Min.	255	5	1
Median	3955	15	3
Logit studies			
Max.	81 172	30	7
Min.	255	5	1
Median	4552	15	3[a]
Probit studies			
Max.	76 994	36	5
Min.	449	7	2
Median	3136	16	5[b]
Other studies			
Max.	30 358	24	5
Min.	408	7	2
Median	4713	14	2[a]

[a,b] Values with different superscript letters differ statistically significantly ($p < 0.05$), based on Mann–Whitney *U* test.

Table 4. Maximum, minimum and median for number of accident records, number of variables and number of injury levels

number of injury levels considered in the probit models with respect to the other two types of models (logit and others).

3.5 Model fit

In general, the statistical tests used to validate the performance of the model vary with the study. These tests indicate whether the model fits the data adequately or not, but they do not permit comparison of the results of one study with another.

In the following, descriptions of the fit parameters used for the analysed models are presented.

3.5.1 *R*-squared

R-squared (R^2) is a statistic that is generated in ordinary least-squares (OLS) regression that is often used as a goodness-of-fit measure. Its value ranges between 0 and 1, where 1 indicates a high level of explanation of the variance by the regression model and zero indicates a low level of explanation (Bruin, 2006).

Chen and Jovanis (2000) used R^2 to test LLM fit (see Table 3). The results indicated that the log-linear model fitted the data very well ($R^2 = 0.95$).

3.5.2 Pseudo *R*-square

When analysing data with a logistic regression, an equivalent statistic to R^2 does not exist. The model estimates from a logistic regression are maximum-likelihood estimates arrived at through an iterative process. However, to evaluate the goodness-of-fit of logistic models, several pseudo *R*-squareds (ρ^2) have been developed (McFadden, adjusted McFadden, Efron's, Cox and Snell, Negelkerke, Cragg and Uhler's, McKelvey and Zavoina, Count, adjusted count, etc.). These look like R^2 in the sense that they are on a similar scale, ranging from 0 to 1 (though some ρ^2 never achieve 0 or 1) with higher values indicating better model fit (Bruin, 2006).

In this survey (see Tables 1, 2 and 3) several studies used a ρ^2 to test the fit of their models. Others studies supplied the log-likelihood (LL) of the model. Thus, when information about LL

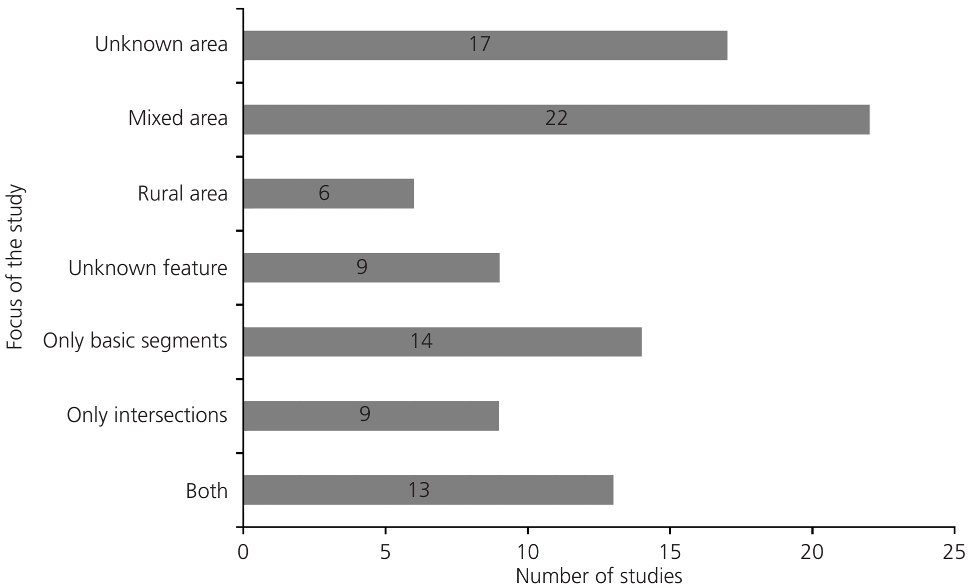

Figure 2. Number of case studies according to the focus of the study

was available, the McFadden ρ^2 was calculated in order to homogenise the model fit results.

However, Bruin (2006) indicated that ρ^2 cannot be interpreted independently or compared across datasets; a ρ^2 only has meaning when compared to another ρ^2 of the same type, on the same data, predicting the same outcome. Thus, it is only possible to indicate whether the results of a study are within the satisfactory range for such parameters for model fit. As indicated by McFadden (1979), the satisfactory range for the McFadden's ρ^2 lies between 0·2 and 0·4.

Most of the models in this paper that use McFadden's ρ^2 present values below 0·2. However, there are five studies that present values over 0·2: Shanker *et al.* (1996) ($\rho^2 = 0{\cdot}52$), Wang and Kockelman (2005) ($\rho^2 = 0{\cdot}235$–$0{\cdot}257$), Abdel-Aty and Keller (2005) ($\rho^2 = 0{\cdot}24$), Oh (2006) ($\rho^2 = 0{\cdot}378$–$0{\cdot}480$) and Schneider *et al.* (2009) ($\rho^2 = 0{\cdot}23$–$0{\cdot}258$).

3.5.3 Accuracy

Accuracy measures the percentage of cases in the accident data correctly predicted by the model. Therefore, accuracy is obtained at the case-specific level, that is, cases that are correctly classified as fatal or non-fatal according to their observed injury experience (Saccomanno *et al.*, 1996).

Most of the studies used this parameter to test the capability of their models to correctly classify the injury severity to a specific level (see Tables 1, 2 and 3). The global accuracy range lies between 0·41 and 0·89. The highest global accuracy achieved was for a BLM model built by Dissanayake and Lu (2002) and the lowest was obtained by Abdel-Aty and Abdelwahab (2004) when they constructed a fuzzy Artmap ANN model.

The results presented by Dissanayake and Lu (2002) indicate that the number of accidents classified under each severity level was homogeneous along all the levels. On the other hand, the lowest accuracy obtained for a specific level (fatal accidents) with a Cart model was practically zero (Chang and Wang, 2006). The authors referred this result to the fact that their dataset was imbalanced, such that the fatal accidents accounted only for about 0·4% of the whole sample used to build the model.

Delen *et al.* (2006) also obtained relatively low accuracy results (40·7%) for their model (MLP ANN). They explained their results by a multi-class classification problem. A possible solution would be reducing the multi-class problem into a series of binary classification problems. Applying such a solution, the complete dataset was separated into eight subsets with binary output variables, in which a top-down (more serious injury against the less serious injuries) and a bottom-up model (less serious injury against more serious injuries) were built. The method applied by Delen *et al.* (2006) could be compared to that applied by Dissanayake and Lu (2002) where, after developing two formats of binary logistic models (top-down and a bottom-up format with four models in each), they found that the method of selecting the models' format did not drastically affect model reliability; however, they chose to use the top-down format in their analysis since it achieved better model accuracies (73·4–98·0%).

3.5.4 Other measures

Other measures used to test the model fit are Akaike information criterion (AIC), log-likelihood (LL), chi-squared (χ^2) and Kendall rank correlation coefficient (Kendall's tau (τ) coefficient).

The likelihood is the probability of the data given the parameter estimates. The goal of a model is to find values for the parameters (coefficients) that maximise the value of the likelihood function. Many procedures use the log-likelihood because it is easier to work with (Bruin, 2006). Two studies used the LL as the fit test. However, only Lemp *et al.* (2011) used it to compare two models (OPM against HOP).

The Akaike information criterion is used only once (Haleem and Abdel-Aty, 2010) to select a model from a set of models. The chosen model is the one that minimises the Kullback–Leibler distance between the model and the truth (low AIC and high LL indicate good fit). AIC is a criterion that seeks a model that has a good fit to the truth with few parameters (Burham and Anderson, 2002).

The χ^2 test is used to verify whether a sample of data came from a population with a specific distribution. χ^2 is applied to binned data. However, the value of the χ^2 statistic is dependent on how the data are binned. Another disadvantage of χ^2 is that it requires a sufficient sample size in order for the χ^2 approximation to be valid (NIST/Sematech, 2003). Three studies (Daniels *et al.*, 2010; Malyshkina and Mannering, 2009; Srinivasan, 2002) were found to use χ^2 as the model goodness-of-fit test.

Only Donelson *et al.* (1999) used Kendall's tau (τ) coefficient, which is a statistic used to measure the association between two quantities. A τ test is a non-parametric hypothesis test that uses the coefficient to test for statistical dependence (Kruskal, 1958). The results indicated that the BLM fitted the data used.

3.6 Modelling techniques

The use of modelling techniques varied with time; thus DOMs continued to be dominant. From 2001 new methods started to be applied in the analysis of injury severity, such as neural networks, Bayesian networks and most recently genetic algorithms.

Table 5 shows the frequency of usage of each model. In this survey, 19 modelling techniques used to model injury severity of traffic accidents, applied in 58 case studies, have been analysed. The most used techniques are the DOM (46 cases), highlighting the BLM, OLM and OPM models over all the others. These three models were used in more than 54% of the cases.

Type of model	Family of models	Model	Frequency
Discrete model	Logit models	BLM	11
		OLM	6
		HL	4
		MNL	3
		HKL	2
		MXL	1
		GEE	1
		OMXL	1
	Probit models	OPM	14
		BOP	1
		HOP	1
		PM	1
Other models	Decision trees	CART	2
		CHAID	1
	Bayesian networks	BN	2
	Artificial neural networks	MLP	3
		Fuzzy Artmap	2
	Evolutionary algorithms	LGP	1
	Log-linear models	LLM	1

Table 5. Frequency of usage of each model

3.6.1 Logit models

Table 5 shows that the most-used logit models are BLMs followed by OLMs, while the least used types were MXL, GEE and OMXL (ordered mixed logit models).

The frequent use of BLMs to analyse accident severity might refer to the fact that most of the studies used the outcome variable as binary (Delen *et al.*, 2006; Dissanayake and Lu, 2002; Jung *et al.*, 2010). This refers to the fact that BLM is easily interpretable.

A restriction of OLMs is that regression parameters have to be the same for different accident severity levels, called proportional odds. However, it is not always clear whether the distances between accident severity levels are equal, and hence it is arbitrary to assume that all coefficients of ordered probability models are the same (Jung *et al.*, 2010).

Moreover, Srinivasan (2002) stated that the primary restriction of the ordered models comes from the assumption of deterministic thresholds that are often identical across all observations for each ordinal outcome level. Also, it is assumed that the outcome is homogeneous and independent of exogenous variables. In addition, these models disregard possible correlations across the thresholds of different outcomes.

Consequently, these assumptions could lead to significant bias and inconsistency in ordered outcome models. Therefore, Srinivasan (2002) used an OMXL, where she compared OMXL to OLM using a χ^2 test. The results indicated that the χ^2 test rejected the restrictive OLM.

Lenguerrand *et al.* (2006) compared different models (BLM, HL and GEE). HLs were found to be more suitable for problems with correlated data than BLM and GEE, and for clusters and sub-clusters, since BLM and GEE models both underestimate parameters and confidence intervals. Thus, they recommended the use of HLs when the number of vehicles per accident or the number of occupants per accident is high.

3.6.2 Probit models

The most frequently used probit model is the OPM (see Table 5). OPMs have been used to model injury severity of accidents on roadways and intersections. Some researchers have used models that combined accidents occurring at intersections with accidents off intersections (Gray *et al.*, 2008; Xie *et al.*, 2009; Zhu and Srinivasan, 2011).

OPMs proved to be a good choice for modelling injury severity of accidents. Even when compared with other models such as the BOP, the OPM still performed as well (Xie *et al.*, 2009). BOP and OPM produced similar results for large data size; the authors recommended using BOPs for smaller data sizes, as they can produce more reasonable parameter estimation and better prediction performance. In contrast, when comparing OPMs with HOPs, the HOP was preferred over the OPM in terms of log-likelihoods (Lemp *et al.*, 2011).

Haleem and Abdel-Aty (2010) used OPM, PM and HL methods to analyse accident injury severity at intersections. The results indicated that the PM fits the data better than the OPM.

3.6.3 Other modelling techniques

Cart procedures were used by Council and Stewart (1996) and Chang and Wang (2006) to model the injury severity of accidents. The results presented by Chang and Wang (2006) indicated that Cart can effectively handle multi-collinearity problems, and they could handle the outliers that exist in the data by isolating them into a node.

However, Chang and Wang (2006) indicated that one of the problems with applying Cart methods is that they do not provide confidence intervals for the risk factors (splitters) and predictions. Also, there is difficulty in applying the sensitivity analysis, which does not permit examination of the marginal effects of the predictors on the response variable. In addition the Cart models are unstable; the structure and the accuracy alter if different strategies are followed to create learning and test sets.

BNs were used by Simoncic (2004) and De Oña *et al.* (2011) to model injury severity of accidents. The work presented by Simoncic (2004) based the conclusion upon a single network, which was not validated using a test set. De Oña *et al.* (2011)

built several BNs to model injury severity of accidents. These networks were compared to each others in terms of complexity, accuracy, sensitivity and specificity. Each of the networks was validated using a test set.

MLP and fuzzy Artmap ANNs have been compared twice to analysis of injury severity on road segments and on intersections (Abdel-Aty and Abdelwahab, 2004; Abdelwahab and Abdel-Aty, 2001). Both studies indicated that MLP ANN performance is superior to fuzzy Artmap ANN. Delen *et al.* (2006) also used MLP ANN to model injury severity on roadways. They used more injury levels and their results (in terms of accuracy) were worse than those of previous studies (Abdel-Aty and Abdelwahab, 2004; Abdelwahab and Abdel-Aty, 2001).

Abdelwahab and Abdel-Aty (2001) compared the performance of MLP ANN and fuzzy Artmap ANN with the performance of OLM. Their results indicated that the best in terms of accuracy was the MLP ANN followed by OLM, and finally by fuzzy Artmap. Thus, OLM was superior in performance with respect to certain types of ANNs. Abdel-Aty and Abdelwahab (2004) used MLP ANN, fuzzy Artmap ANN and OPM. The results once again showed the superiority of MLP ANN over all the other techniques, but this time OPM did not perform better than the fuzzy Artmap.

4. Summary and conclusion

This review of several studies on models used in the modelling of traffic accident injury severity indicates that each method has its advantages and disadvantages. Many modelling techniques have been in use to analyse the injury severity of accidents. The most-used models are the logit and probit. However, in recent years, methods based on data-mining techniques, as well as other models based on soft computing techniques, have appeared.

Within the discrete outcome models, the most used are OPM, BLM and OLM. BLMs are commonly used when the study uses a binary variable for severity. When the severity is ordered (killed, severe injury, slight injury, possible injury or property damage only), OPMs and OLMs are commonly used.

There is a large diversity in the number of accident records and the number of variables used. However, no significant statistical difference was found between logit, probit and other models. The number of records and the number of variables are found to be mostly dependent upon the availability of data.

Most of the studies use the KABCO scale or a modification. Based on the studies analysed, the probit models use a higher number of injury levels (5) than the logit models (3 levels) or the rest of the models (2 levels). In this case, significant statistical differences were observed ($p < 0{\cdot}05$) between the probit models and the other types of models.

The model fit results are satisfactory in most cases (e.g. global accuracy in the range 0·41–0·89; McFadden's pseudo R-square values between 0·2 and 0·4), although some exceptional results can be observed (e.g. Chen and Jovanis (2000) obtained $R^2 = 0{\cdot}95$), while others were not so satisfactory (e.g. many studies with McFadden's pseudo R-square below 0·2).

Different factors affect the accuracy obtained by data mining and soft computing models, such as the balance of cases among the different categories that lie under the injury severity levels. If the numbers of observed cases classified among the different levels do not differ greatly, this identifies a balanced dataset; and accuracy would improve since the classification will not be biased towards a specific injury severity level.

In general, it is not possible to identify which is the best method to use. Use of a given model might be suitable under certain circumstances, but not under others. Many examples are available in the literature (Lenguerrand *et al.*, 2006; Xie *et al.*, 2009). This is probably one of the main reasons why, in recent years, the number of studies that analyse injury severity of traffic accidents has greatly increased. Documentation of the characteristics and limitations of each modelling technique will help analysts to decide the best method to use in each particular modelling problem.

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