A STRUCTURAL EQUATION MODEL FOR ROAD ACCIDENT ANALYSIS

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ABSTRACT

In this paper a tool for effecting road accident analysis is proposed. Specifically, a structural equation model is introduced. Structural equation modelling (SEM) is a multivariate technique combining regression, factor analysis and analysis of variance in order to estimate interrelated dependence relationships simultaneously. This approach allows the modelling of a phenomenon by considering both the unobserved "latent" constructs and the observed indicators that describe the phenomenon. Structural equation models are made up of two components: the first describes the relationship between endogenous and exogenous latent variables, and permits the evaluation of both direction and strength of the causal effects among these variables (*latent variable model*); the second component describes the relationship between latent and observed variables (*measurement model*).

Although SEM methodology is well-known and widely applied in several fields of research, nowadays there are not many practical applications in the field of road safety.

The proposed model permits an exploration of the impact of the relationship between the accident severity and some accident characteristics. The data used for the model calibration relate to the accidents happened in 2003 in Cosenza province. For each accident some information was available. This information relates to different factors, such as environmental context, road characteristics and driver characteristics. In the proposed structural equation model the observed variables are the road accident characteristics, and two indicators of the road accident severity (number of injured and vehicles involved in the accident). The latent variables are the unobserved road accident aspects that can be explained by the observed variables.

Model results were statistically significant and showed that "Road classification" observed variable has the greatest effect through the "Road characteristics" latent variable on accident severity; while, through the "Environmental context" latent variable, "Atmospheric condition" variable has the greatest effect. The proposed model can be useful in order to analyze the correlation between accident characteristics and identify the attributes which influence the severity of road accidents.
Keywords: road safety, structural equation model, accident severity

1. INTRODUCTION

Generally, road safety is seen as the reduction of the number of road accidents and/or accident severity. In order to reduce the accident risk, the knowledge of crash causes is necessary.

Over the last few decades, some researchers have tried to determine what causes crashes and the relationships between the accident causes and occurrence. Therefore, there is a large number of theorical and experimental studies based on different methodologies.

As an example, there are some studies in which a single accident cause (Brenac 1996; Baruya 1998) or a single road typology (Council and Harwood 1999) are considered, and other studies in which several causes and some policies for each cause of accident risk are identified (Rumar and Stenborg 1995; Bryer 1999; Cascetta et al. 1999).

There are also some studies in which previsional models are proposed. In these models the relationship between a road safety indicator and the accident causes are investigated; examples of indicators are accident rates (calculated as the ratio between the number of road accidents and a parameter representing the risk exposure like the kilometres of covered road), numbers of road accidents, numbers of injured or dead persons, relating to a certain time period.

Traditionally, linear regression models have been introduced (Wright and Burnham 1985; Wright et al. 1988). As road accidents are rare events, Poisson regression models were considered more appropriate for investigating on accident risk, even if experimental data dispersion makes often the Poisson distribution hypoteses improper; for this reason, Negative Binomial regression models were considered more suitable (Saccomanno and Buyco 1988; Miaou and Harry 1993; Miaou 1994). Recently, interest in the Empirical Bayesian approach to crash data anlysis has increased significantly in order to improve the model forecasting (Persaud 1988; Hauer 1996; Hauer 2002; Saccomanno et al. 2007).

The aim of this research is the exploration of the relationship between road accident severity, in terms of number of injured and vehicles involved, and some factors characterizing accidents. In order to investigate this relationship, the Structural Equation Modelling (SEM) was adopted. This technique is useful to researchers as a multivariate technique combining regression, factor analysis and analysis of variance in order to estimate interrelated dependence relationships simultaneously. SEM was applied in several fields of research and generalized by Joreskog and Wiley (Joreskog 1973; Wiley 1973).

Some applications were proposed, for example, in the field of Psychology and Social Science (MacCallum and Austin 2000; Muthén et al. 2006), in the field of Natural Science (Mitchell 1992; Grace and Pugesek 1997), and especially in the field of Economy and Statistics (MacLean and Gray 1998; Eskildsen and Dahlgaard 2000).

In the field of Transportation Planning, SEM was adopted above all for activity participation and travel behaviour simulation (Lu and Pas 1999; Golob, 2000; Kuppam and Pendyala 2001). Also in public transport some authors proposed SEM applications, such as Bamberg and Schmidt (1998), Stuart et al. (2000), Fillone et al. (2005), and Tam et al. (2005).

There are some applications also in the field of safety. As an example, in Ulleberg and Rundmo (2003) a structural equation model suggested that the relation between the personality traits and risky driving behaviour is mediated through attitudes; in Vance et al. (2006) SEM was adopted in order to examine causal models of driving avoidance and exposure among older adults; in Fullarton and Stokes (2007) a structural equation model linking injury rates to the safety climate measure was proposed; in Paul and Maiti (2007) SEM was adopted in order to examine the role of behavioral factors on the occurrence of mine accidents and injuries.

The structural equation model proposed in this paper permits the investigation of the impact of some accident aspects on accident severity. The accidents analysed happened in Cosenza province (Southern Italy) in 2003. The paper is organized as follows: in the first section, a brief theoretical framework on structural equation models is introduced; in the second, a statistical-descriptive analysis of the data is reported; in the third, the general structure of the proposed model is described and finally, in the last section, the model results are briefly discussed.

2. THE STRUCTURAL EQUATION MODELS

SEM methodology spread fast as a consequence of the development of specific packages, like LISREL (Joreskog and Sorbom 1988, 1989, 1995) and AMOS (Arbuckle and Wothke 1995); the availability of these packages has encouraged several applications in different contexts. This approach allows the modelling of a phenomenon by considering both the unobserved “latent” constructs and the observed indicators that describe the phenomenon.

Structural equation models are made up of two components: the first describes the relationship between endogenous and exogenous latent variables, and permits the evaluation of both direction and strength of the causal effects among these variables (*latent variable model*); the second component describes the relationship between latent and observed variables (*measurement model*).

The basic equation of the *latent variable model* is the following (Bollen 1989):

$$\eta = B\eta + \Gamma\xi + \zeta \qquad \text{(Eq. 1)}$$

in which η (eta) is an ($m \times 1$) vector of the endogenous latent variables, ξ (xi) is an ($n \times 1$) vector of the exogenous latent variables, and ζ (zeta) is an ($m \times 1$) vector of random variables. The elements of the B (beta) and Γ (gamma) matrices are the structural coefficients of the model; the B matrix is an ($m \times m$) coefficient matrix for the latent endogenous variables; the Γ matrix is an ($m \times n$) coefficient matrix for the latent exogenous variables.

The basic equations of the *measurement model* are the following:

$$x = \Lambda_x \xi + \delta \qquad \text{(Eq. 2)}$$

for the exogenous variables,

$$y = \Lambda_y \eta + \varepsilon \qquad \text{(Eq. 3)}$$

for the endogenous variables,

in which x and δ (delta) are column q-vectors related to the observed exogenous variables and errors, respectively; Λ_x (lambda) is a ($q \times n$) structural coefficient matrix for the effects of the latent exogenous variables on the observed variables; y and ε (epsilon) are column p-vectors related to the observed endogenous variables and errors, respectively; Λ_y is a ($p \times m$) structural coefficient matrix for the effects of the latent endogenous variables on the observed ones.

The structural equation system is generally estimated by using the Maximum Likelihood method (ML). In other cases, the structural equation model parameters can be estimated by using other estimation methods, such as Unweighted Least Squares (ULS), Weighted Least Squares (WLS), Generalized Least Squares (GLS), and so on. These estimation methods are described in Bollen and Washington (Bollen 1989; Washington et al. 2003).

For a more detailed discussion on structural equation models one should refer to Joreskog (1973), Bollen (1989), Bagozzi (1994) and Golob (2003).

3. THE DATA

The data analysed relate to 1,880 accidents happened in Cosenza province in 2003. For each accident some information was available. This information relates to different factors, such as road characteristics, environmental context, and driver characteristics.

As reported in table 1, the configurations of the road geometric characteristics are straight stretch, climb down/climb up, bridge, tunnel, curve, and crossing; the road classification includes local and provincial way, state way, motorway, and built-up area; the configuration of the road signposting are relating to the presence/absence of road markings and signs; the street can be one-way or not; the atmospheric condition are serene, cloudy, rain, fog, snow, and hail; the road bed can be dry, slippery, snowy, wet, or icy; the drivers are classified in terms of gender, and in terms of age (younger than 30 years, between 30 and 60 years, or older than 60 years); the driver length of driving licence is equal to the number of years of driving licence; the driver can use the safety belt or not and can be in state of drunkenness or not.

A statistical-descriptive analysis of the accident characteristics was carried out. Table 1 reported the characteristics diversifying accidents, and for each configuration the corresponding number and percentage of accidents are reported.

The data were analysed also in terms of accident typology; specifically, 44.3% of the happened accidents are head-on or angled collisions, 21.2% are crashes against fixed obstacles, 17% are rear-end, the remaining 16.9% is divided into other typologies such as plunging off the road and crashing against accidental obstacles.

In case the accident is due to the driver behaviour we can have many causes, such as losing control of the vehicle, exciding speed limits and signposting violation.

Table 1. Road accident characteristics

Accident characteristic	Configuration	Number of accidents	Percentage of accidents
Road geometric characteristics	straight stretch	1085	57.7%
	climb down/climb up	26	1.4%
	bridge	3	0.2%
	tunnel	26	1.4%
	curve	422	22.4%
	crossing	318	16.9%
Road classification	local way	106	5.6%
	provincial way	90	4.8%
	state way	496	26.4%
	motorway	545	29.0%
	built-up area	643	34.2%
Road signposting	road markings and signs	1281	68.1%
	road signs	177	9.4%
	road markings	186	9.9%
	no signposting	236	12.6%
One-way street	yes	658	35.0%
	no	1222	65.0%
Atmospheric condition	serene	1230	65.4%
	cloudy	356	18.9%
	rain	284	15.1%
	fog	2	0.1%
	snow	7	0.4%
	hail	1	0.1%
Road bed condition	dry	1436	76.4%
	slippery	16	0.9%
	snowy	2	0.1%
	wet	420	22.3%
	icy	6	0.3%
Driver age	< 30 years	618	32.9%
	between 30 and 60 years	1068	56.8%
	> 60 years	194	10.3%
Driver gender	female	290	15.4%
	male	1590	84.6%
Driver length of driving licence	cardinal variable		
Driver use of safety belt	yes	1870	99.5%
	no	10	0.5%
Driver state of drunkenness	yes	10	0.5%
	no	1870	99.5%

4. THE PROPOSED MODEL: GENERAL STRUCTURE

In the proposed structural equation model the observed variables are the road accident characteristics described in table 2, and two indicators of the road accident severity, number of injured and vehicles involved in the accident. The latent variables are the unobserved road accident aspects that can be explained by the observed variables.

The general structure of the model includes 3 latent variables (figure 1). The first variable, named "Road characteristics", is linked to "Road geometric characteristics", "Road classification", "Road signposting", and "One-way street" observed variables.

Table 2. Road accident variables

Variable	Level of variation
Road geometric characteristics	Straight stretch/climb down/climb up (0), bridge/tunnel/curve (1), crossing (2)
Road classification	Local way (0), provincial way (1), state way (2), motorway (3), built-up area (4)
Road signposting	Road markings and signs (0), road signs (1), road markings (2), no signposting (3)
One-way street	Yes (0), no (1)
Atmospheric condition	Serene (0), cloudy (1), rain (2), fog (3), snow (4), hail (5)
Road bed condition	Dry (0), slippery (1), snowy (2), wet (3), icy (4)
Age	< 30 years (0), between 30 and 60 years (1), > 60 years (2)
Gender	Female (0), male (1)
Length of driving licence	Cardinal variable
Use of safety belt	Yes (0), no(1)
State of drunkenness	No (0), yes (1)

The second variable, named "Environmental context", is linked to "Atmospheric condition" and "Road bed condition" observed variables. The third variable, named "Driver characteristics", is linked to "Age", "Gender", "Length of driving licence", "Use of safety belt", and "State of drunkenness" observed variables.

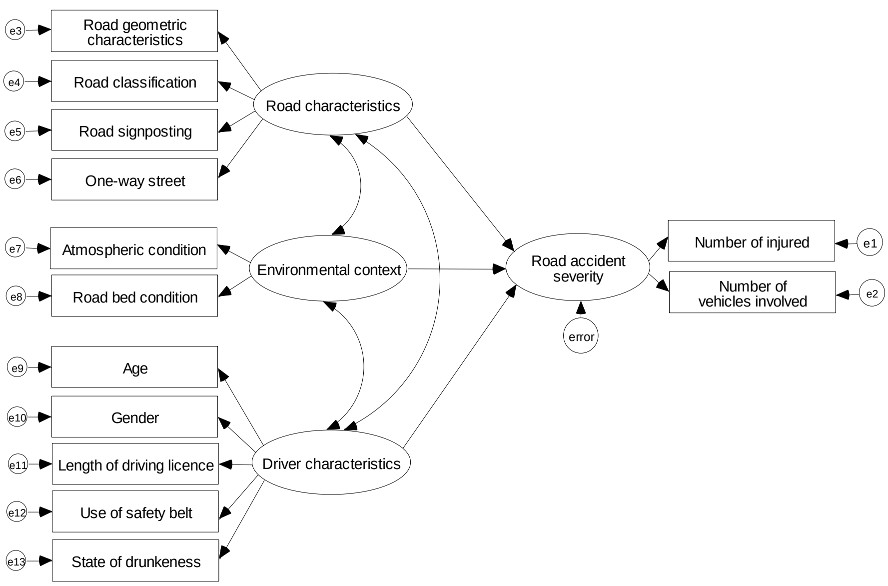

Figure 1. General structure of the model

The *latent variable model* relates the 3 exogenous latent variables to an endogenous latent variable, named “Road accident severity”; moreover, the exogenous variables are correlated among them. The *measurement model* relates each latent variable to the variables that characterize road accidents. Specifically, we supposed that the exogenous latent variables are measured by the 11 road accident characteristics and the latent variable “Road accident severity” is measured by the indicators “Number of injured” and “Number of vehicles involved”.

By effecting some preparatory calibrations, we propose the final model shown in figure 2.

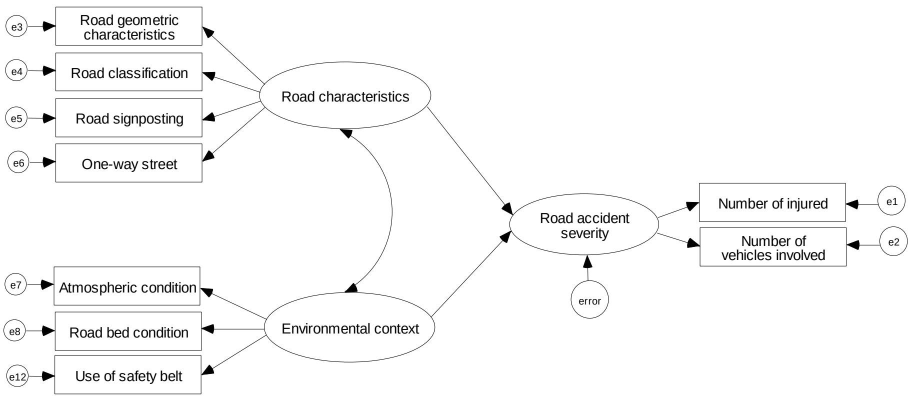

Figure 2. Final structure of the model

In the final model there isn’t the latent variable linked to the driver characteristics because it wasn’t statistically significant; only the “Use of safety belt” observed variable, linked to the “Driver characteristics” latent variable in the first specification of the model, was included in the latent variable linked to the environmental context.

5. THE PROPOSED MODEL: RESULTS

The model was calibrated by using the AMOS 4.0 package (SmallWaters Corporation) (Arbuckle, and Wothke 1995).

The model results are shown in tables 3 and 4. Specifically, the parameters estimated, the Standard Error (S.E.), the Critical Ratio (C.R.) and the level of statistical significance (P) of each variable are reported in table 3; some tests on the goodness of fit are reported in table 4.

In order to estimate the model, the constriction of two parameters to a value equal to 1 was necessary. Afterwards, the estimated coefficients were standardized. All parameters assume a value statistically different from zero, at a good level of significance. Only one parameter is less statistically significant than the others (level of significance of 22.2%).

The minimum value of the discrepancy function is 102.099; this value is statistically significant according to the chi-squared test. The tests on the goodness of fit are quite satisfactory: the Goodness of Fit Index (GFI) is at 0.988, the Adjusted Goodness of Fit Index (AGFI) is 0.977, and the Comparative Fit Index (CFI) is 0.971. The best value can obtain with these indexes is unit; therefore, the indexes obtained from the model are very good.

Table 3. Parameter estimation and levels of statistical significance

			No stand. weight	S.E.	C.R.	P	Stand. weight
Road accident severity	⇐	Road characteristics	-1.083	0.160	-6.785	0.000	-0.307
Road accident severity	⇐	Environmental context	0.001[c]	0.001	1.220	0.222	0.037
Road geometric characteristics	⇐	Road characteristics	0.215	0.076	2.813	0.005	0.092
Road classification	⇐	Road characteristics	2.062	0.260	7.928	0.000	0.597
Road signposting	⇐	Road characteristics	1.000[d]				0.301
One-way street	⇐	Road characteristics	-0.806	0.100	-8.088	0.000	-0.551
Atmospheric condition	⇐	Environmental context	-0.022	0.008	-2.749	0.006	-0.870
Road bed condition	⇐	Environmental context	-0.039	0.014	-2.853	0.004	-0.941
Use of safety belt	⇐	Environmental context	0.001	0.001	2.038	0.042	0.071
Number of injured	⇐	Road accident severity	1.000[d]				0.972
Number of vehicles involved	⇐	Road accident severity	0.188	0.070	2.705	0.007	0.273

(c) Not statistically significant at a level of 5%
(d) Constrained value

The Root Mean square Residual (RMR) index has a value of 0.025, and the Root Mean Square Error of Approximation (RMSEA) has a value of 0.042; the values of these indexes are low and therefore are quite good. For a more detailed discussion on the indexes one should refer to Arbuckle and Wothke, and Bollen (Arbuckle and Wothke, 1995; Bollen, 1989).

Table 4. Goodness of fit indexes

Indexes	Values
Chi-Square	102.099
Goodness Of Fit Index (GFI)	0.988
Comparative Fit Index (CFI)	0.971
Adjusted Goodness Of Fit Index(AGFI)	0.977
Root Mean square Residual (RMR)	0.025
Root Mean Square Error of Approximation (RMSEA)	0.042

The model offers empirical findings and practical implications; it can be used for identifying the characteristics which influence road accident severity in order to improve the safety on the road by taking into account the strength of the relationship between the variables introduced.

The latent variable with a major effect on road accident severity is “Road characteristics”, which have a coefficient value of -0.307 (standardized weight). The “Environmental context” latent variable has a minor impact (0.037).

The “Road classification” observed variable has a major impact on the “Road characteristics” exogenous latent variable (0.597); similarly, the “Road bed condition” factor has a major impact on the “Environmental context” latent variable (-0.941).

The endogenous latent variable, indicating road accident severity, is best explained by the indicator of the number of injured, whose coefficient has a value of 0.970; on the other hand, the indicator of the number of vehicles involved in the accident has a lower value (0.273).

Each exogenous observed variable, linked to the endogenous latent variable through an exogenous latent variable, has an indirect effect on the endogenous latent variable; direct effects were not included in the model structure (table 5).

Table 5. Indirect effects of observed variables on endogenous latent variable

Observed exogenous variable	Indirect effect (through Road characteristics)	Indirect effect (through Atmospheric condition)
Road geometric characteristics	0.092*(-0.307) = -0.028	
Road classification	0.597*(-0.307) = -0.183	
Road signposting	0.301*(-0.307) = -0.092	
One-way street	-0.551*(-0.307) = 0.169	
Atmospheric condition		-0.870*0.037 = -0.032
Road bed condition		-0.941*0.037 = -0.035
Use of safety belt		0.071*0.037 = -0.003

By considering the observed variables linked to the “Road characteristics”, we can observe that “Road geometric characteristics” variable has a negative effect on “Road accident severity” variable and this means that accidents are more severe in a straight stretch than in a crossing, probably because in a crossing drivers are more prudent; however, a more exhaustive analysis should be made by taking into account the kilometres of straight roads in comparison with the number of crossings. “Road classification” variable has a negative effect on “Road accident severity” variable, and this fact suggests that accidents are more severe in narrow and tortuous streets, like local and provincial way, than in motorways and in built-up area; these results agree with the analyses of the experimental data reported in Esposito and Mauro (2003).“Road signposting” variable has a negative effect on “Road accident severity” variable and this means that accidents are more severe where there are road markings and signs, probably because in road without signposting drivers are more alert; finally, as expected, accidents are less severe in one-way street. By considering the observed variables linked to the “Environmental context”, we can observe that “Atmospheric condition” variable has a negative effect on “Road accident severity” variable and this means that accidents are less severe when the atmosphere is serene and the severity is greater when the atmospheric conditions get worse; analogously, accidents are less severe when the road bed condition is dry and the severity is greater when the road bed condition get worse; finally, as expected, accidents are less severe if the safety belt is used. In addition, “Road classification” and “One-way street” variables have a greater effect through the “Road characteristics” latent variable, on accident severity; while, through the “Environmental context” latent variable, “Atmospheric condition” and “Road bed condition” variables have the greater effect.

6. CONCLUSIONS

In this paper a structural equation model has been proposed in order to show the relationship between the severity of road accidents and accident characteristics. Although SEM methodology is well-known and widely applied in several fields of research, nowadays there are not many practical applications in the field of road safety. Compared with the regression modelling techniques, the applied SEM methodology shows its advantages because allows the severity accident to be described by more than one indicator simultaneously. This study is useful because allows the correlation between accident causes to be analysed by taking directly into account the unobserved "latent" factors influencing the road accident severity. Therefore, the proposed model represents for researchers a tool more advanced than the traditional methods used for analysing crash phenomena. The research is also helpful for practitioners because permits to measure the weight of the different crash causes on the severity of road accidents.

A more accurate analysis should be based on a greater database in order to investigate on other aspects of an accident. In spite of its limitation, this study could be a starting point for a more exhaustive research.

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