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A PLS/SEM Approach Risk Factor Analysis in Road Accidents Caused by Carelessness

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Abstract*— Many developed countries in line with the increase in road transport, and consequently an increase in the rate of accidents, are searching for effective ways to reduce road accidents. In the area of traffic safety, in order to identify factors contributing to accidents, conventional methods which generally based on regression analysis are used. However, these methods only detect accidents in different roads, but cannot clearly identify the cause of accidents and define the relationship between them. In addition, the methods used have two major limitations: 1- Postulate the structure of the model, and, 2- Observability of all variables. Due to the limitations discussed and also due to the complex nature of human factors, and the impact of road conditions, vehicle and environment on human factors, the aim of this study is to provide a useful tool for defining and measuring road, traffic and human factors, to evaluate the effect of each of them in accidents which caused by carelessness, directly and indirectly by using structural equation modeling with the partial least squares approach. Compared with the regression-based techniques or methods of pattern recognition that only a layer of relationships between independent and dependent variables is determined, the SEM approach provides the possibility of modeling the relationships between multiple independent and dependent structures. Moreover, the ability to use unobservable hidden variables, by using observable variables would be possible.

Index Terms*— Human factors, Road safety, Road factors; accident analysis; Partial Least Square (PLS); Structural Equation Modeling (SEM).

I. INTRODUCTION

With ever increasing speed in the movement of goods and passengers and the economic benefits, accidents and their severity is also expanding [1]. Also road accidents annually cause irreparable damage to life and property imposed on communities. Therefore, safety management is a key issue in reducing injury accidents. Road accidents by applying proper scientific research can be prevented and many factors which affect the accident can be identified by using analytic methods [2]. In the area of traffic safety, in order to identify factors contributing to accidents, conventional methods that are generally based on regression analysis were used. However, these methods only detect accidents in different roads, but cannot clearly identify the causes of accidents and define the relationship between them. Several statistical methods with different parameters were used to predict the number of accidents. From a general point of view, these methods can be classified in four categories: 1- Multiple Regression Models (MRM), 2-Pattern Recognition Models (PRM), 3-Multi-Criteria Decision Making (MCDM) models, and 4- Structural Equation Modeling (SEM). MRM models [3], [12] have a high ability to predict accident frequencies, however their results are affected by unreliable measurements. Moreover, MRMs are only able to model the direct effect of the examined factors in the occurrence of traffic accidents, and provide no information about the indirect effect of factors. Therefore, these models are not proper to descriptive analysis of the effective factors on traffic accidents [4], [13]. PRM models [14], [23] have a higher ability to model specific types of crash counts [13], [16], to examine heterogeneous populations [17], [20], analyzing data that are characterized by correlated responses [6], and to exhibit better linear/non-linear approximation properties [21]. However, these models often cannot be expended to other data sets [21] and are not proper to descriptive analysis of the effective factors in traffic accidents.

In the SEM based studies [24],[30], the influence of different factors such as traffic volume, roadway geometry, driver behavior, weather condition, and other environmental parameters were examined on the incidence of traffic accidents. In addition to accidents predictability, these models can be used, for quantitative description of risk factors as well [27]. This is because of considering the correlation between observations, adjustment error of observed variables, taking into account the causal relationship between latent variables, and ability to estimate direct and indirect effects of each of the parameters [13], [25], [29]. In the present study, the cause effect relationships of human, traffic and roadway factors were studied on accident information of the main roadway network of Hamadan province, using a variance-based SEM model. In contrast with the covariance-based SEM used in the previous studies, variance-based SEM model considers no statistical distribution for the data used, provides more reliable results using small data sets, and latent variables can be defined using only one observable indicator. In most studies, the role of humans in accident modeling due to its complex nature has not been considered. Thus the vacuum of a comprehensive study on the impact of human factors and its interaction with other factors in the accident analysis is feeling. For example, carelessness is one of the human factors in accidents which changes in different environments.

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Therefore, in this study, SEM has been used to create networks between the different variables involved in accidents to investigate the direct and indirect effects of them. The interaction between road characteristics and human factors in accidents investigated. Factors affecting accidents are broken in different ways in which with respect to different references, three factors, human, traffic and roads are the main cause of accidents [30].

- Human includes: age, sex, skill, fatigue, attention, experience [31-33]
- Traffic includes: hourly speed and heavy vehicle traffic [34-36]
- Roads- environment includes: geometric characteristic of the road, traffic control devices, signs, road friction, weather and visibility [37-41]

Therefore the system which consists of human, vehicle and traffic is our conceptual framework for analyzing road accidents. So, in section 2, partial least squares structural equation modeling is introduced and in section 3 methodology is explained. In section 4 modeling and evaluation of the model and also in section 5 the data used is provided. Finally, in section 6 the discussion and conclusion of the research are presented.

II. PARTIAL LEAST SQUARES STRUCTURAL EQUATION MODELING

A. Structural Equation Modelling

Structural Equation Modeling (SEM) is a second-generation multivariate data analysis. SEM can test theoretically supported linear and additive casual models. By SEM we can visually examine the relationships that exist among variables of interest. Actually unobservable latent variables can be used in SEM [42]. There are two sub-models in a structural equation model; the inner model (structural model) and the outer model (measurement model). In the inner model latent variables cannot be observed directly and in the outer model the observed indicators can be measured directly. In SEM, a variable is either exogenous or endogenous. An exogenous variable has path arrows pointing outward and non-leading to it. Meanwhile, an endogenous variable has at least one path leading to it and represents the effects of other variables.

B. Partial Least Squares Approach in SEM

PLS is a soft modeling approach to SEM with no assumption about data distribution. The PLS (Partial Least Squares) approach to Structural Equation Models, also known as PLS Path Modeling (PLS-PM) has been proposed as a component-based estimation procedure different from the classical covariance-based LISREL-type approach. There are some situations that we can use the PLS approach instead of the CB approach as listed below [42-43]:

1- Sample size is small
2- Application have little available theory
3- Predictive accuracy is paramount
4- Correct model specification cannot be ensured

PLS Path Modeling is a component-based estimation method. It is an iterative algorithm that separately solves out the blocks of the measurement model and then, in a second step, estimates the path coefficients in the structural model [44]. It also leads to less ambitious statistical properties for the estimates, e.g. coefficients are known to be biased but consistent at large. In PLS Path Modeling framework, different types of measurement model are available: the reflective model (or outwards directed model), the formative model (or inwards directed model) and the MIMIC model (a mixture of the two previous models). So, we can summarize the main block contents of SEM as Fig. 1:

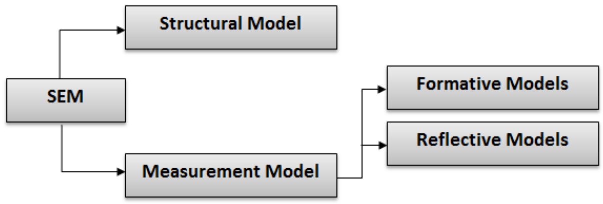

Figure 1: SEM block diagram

In the present study for creating and evaluating our model, we used SmartPLS software

III. METHODOLOGY

The Accident is a stochastic phenomenon with multiple causes. SEM is one of the strongest methods of multivariate statistical analysis. Variance and covariance based modeling are the main methods for analysis of complicated and multi-criteria structures [45]. In this study, we will use SEM to assess the rate of high intensity accidents (leads to injury or death) caused by carelessness and identification of key factors associated with the occurrence of accidents on the main road network of Hamedan province. Therefore, in this research, drivers, road traffic, light and heavy vehicle’s parameters and effects related to the probability of accidents will be discussed and modeled. The process of conducting this study is shown in Fig. 2. Gathering information is the first step in this research which should earn from different sources. We can say that gathering information is one of the basic and important sections of this study. Police, Legal Medicine Organization and Ministry of Road Transport are organizations which gather accident information. Then, after preprocessing, matching the data and determination of dependent and independent variables, the roadway network is segmented and high collision concentration locations (HCCLs) were identified. In the next step, in order to detect effective factors and the mutual effect of them on each other, the model is created and evaluated. Therefore, rests of the research is included: modeling and the evaluation process, study area and data used, results and conclusion sections, respectively.

IV. MODELING AND EVALUATION OF THE MODEL

A. Modeling

At the first step we have to define our latent and observable variables. As mentioned in the introduction, we consider three main factors, human, traffic and road as first order latent variables. The other second and third latent variables and their observable variables are listed in Table. 1.

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After identifying the latent and observable variables in the modeling of the factors which affecting road traffic accidents, it is time to create the model. At this stage causal relationship between variables in the structural model is determined by drawing directed arrows.

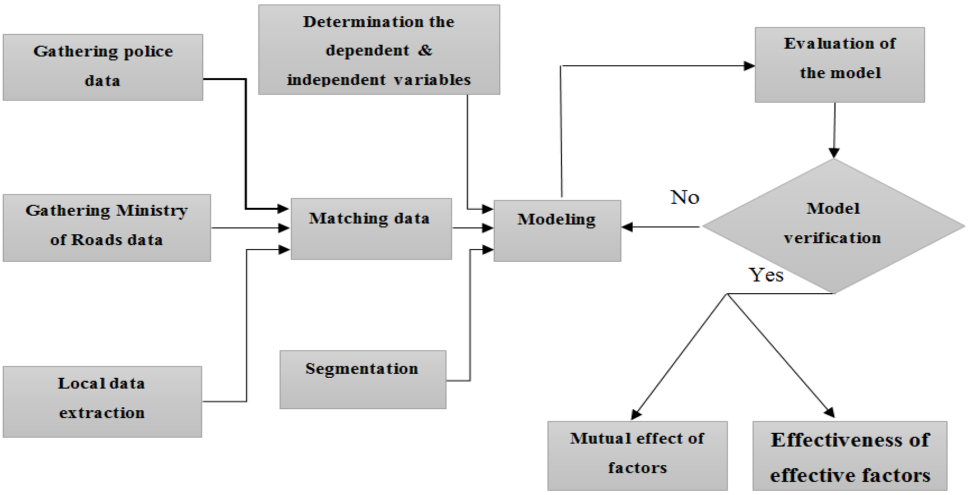

Figure 2: Overview of the research

After creating the structural equation model, it is time to solve the model. PLS-SEM approach is performed in a two-stage process

In the first step, the outer weights and the values of latent variables is calculated in an iterative process and secondly, ordinary least squares regression coefficients path between exogenous and endogenous latent variables are estimated. So we can summarize the solving process in the four following stages:

First step: outer weights calculation

At this stage, the outer weights for each latent variable and its observed relevant variables is calculated. The calculation of the outer weights for two combinational and reflective models are as follows:

Reflective measurement model: in the reflective measurement model, the correlation among inner latent variable estimation (step4) and each one of the observed relevant variables is calculated as the outer weight.

$$w_{pq} = corr\left(x_{pq}, V_q\right) \qquad (1)$$

Where:

= inner estimation of the latent variable q

x_{pq} =observed variable related to the latent variable q

w_{pq} = outer weight of the observed variable p and the latent variable q

Formative measurement model: in the formative measurement model, the coefficient of the multiple linear regression among observed variable as the independent parameter and the inner estimation of the latent variable (step 4) as the dependent parameter, are calculated as the outer weight.

$$w_q = \left(X_q^t X_q\right)^{-1} X_q^t V_q \qquad (2)$$

Where:

Xq =The matrix consists of all observed variables related to latent variable q

t : transpose operator

w_q = The vector consists observed variables related to the latent variable q

It should be noted that in the first iteration, the outer weights of all observed variables are considered equal to 1, and the second iteration to the next, after the inner estimation of the latent variables in the fourth step of the first iteration, the outer weights of the observed variables are calculated from the above equations.

Second step: outer estimation of the latent variables

In the second steps, The value of each latent variable is calculated as the total weighted observed variables related to it.

$$\upsilon_q = \pm \sum_{p=1}^{P_q} w_{pq} x_{pq} = \pm X_q w_q \qquad (3)$$

Where:

= outer estimation of the latent variable q

Third step: the inner weight estimation of the latent variables

In the third step, inner weights among the latent variables are calculated. The path method which is used in the calculation of inner weights due to the theoretical support [46], will be described below:

In this method, depending on how latent variables are connected to each other, regression coefficients or correlation between two variables is used as an internal weight. If latent variable is exogenous (independent), the correlation between two variables, and if latent variable is endogenous (dependent), the regression coefficient use as the inner weight of the two latent variable.

$$e_{qq'} = \begin{cases} corr\left(\upsilon_q, \upsilon_{q'}\right) & independent \\ \left(\upsilon_q^t \upsilon_q\right)^{-1} \upsilon_q^t \upsilon_{q'} & dependent \end{cases} \qquad (4)$$

Fourth step: the inner estimation of the latent variables

In the fourth step, the estimation of the each one of the latent variables, based on the total weighted (internal weights from step 3) of all latent variables (external estimate the latent variables in the second step) related to them, is calculated.

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$$V_q = \pm \sum_{q'=1}^{Q'} e_{qq'} \upsilon_{q'} \qquad (5)$$

Table 1: Latent variables

Measurement model	Observable variables	symbol	Third order	symbol	Second order	symbol	Latent variable
reflective	Under 18 years 18-35 years	ζ_1	18-35 years	ζ_9	Age	ζ_{13}	Human
reflective	35-60 years More than 60 years	ζ_2	35-60 years				
reflective	Male	ζ_3	Male	ζ_{10}	Sex		
	Female	ζ_4	Female				
reflective	Lower than diploma diploma	ζ_5	Lower than diploma	ζ_{11}	Education		
reflective	BSc MSc and higher	ζ_6	Higher than diploma				
reflective	Local	ζ_7	Local	ζ_{12}	Local/non-Local		
	Non-Local	ζ_8	Non-local				
formative	slop Segment length curvature Distance from population center The product of the slope and curvature		-			ζ_{14}	Road
reflective	Average vehicle speed at the time of the accident	-		ζ_{15}	Average vehicle speed at the time of the accident	ζ_{17}	Traffic
	Average vehicle speed at the time of the accident	-		ζ_{16}	Percentage of heavy vehicle at the time of the accident		
reflective	Accident frequency at the time of the accident Accident frequency at the day of the accident		-			ζ_{18}	Accident

* ζ (zeta) stand for latent variables

The above steps are repeated until the changes in the outer weights (ie, the difference between outer weights which calculated in two consecutive repetitions) become less than a threshold (usually 10-5) or the number of iterations reaches a specified maximum (usually 300 repeats).

Structural equations of the model that depicted in Fig. 5 are:

$$\begin{aligned}
\xi_9 &= \beta_{19}\xi_1 + \beta_{29}\xi_2 + \zeta_9 \\
\xi_{10} &= \beta_{310}\xi_3 + \beta_{410}\xi_4 + \zeta_{10} \\
\xi_{11} &= \beta_{511}\xi_5 + \beta_{611}\xi_6 + \zeta_{11} \\
\xi_{12} &= \beta_{712}\xi_7 + \beta_{812}\xi_8 + \zeta_{12} \\
\xi_{13} &= \beta_{913}\xi_9 + \beta_{1013}\xi_{10} + \beta_{1113}\xi_{11} + \beta_{1213}\xi_{12} + \beta_{1713}\xi_{17} + \zeta_{13} \\
\xi_{14} &= \beta_{1314}\xi_{13} + \beta_{1714}\xi_{17} + \zeta_{14} \\
\xi_{17} &= \beta_{1517}\xi_{15} + \beta_{1617}\xi_{16} + \zeta_{17} \\
\xi_{18} &= \beta_{1318}\xi_{13} + \beta_{1418}\xi_{18} + \beta_{1718}\xi_{17} + \zeta_{18}
\end{aligned} \qquad (6)$$

Where:

ζi = The value of the latent variable i

βij = The Path coefficient of the latent variable i and the latent variable j.

The matrix form of these equations is shown in (7):

$$\begin{bmatrix} \xi_9 \\ \xi_{10} \\ \xi_{11} \\ \xi_{12} \\ \xi_{13} \\ \xi_{14} \\ \xi_{17} \\ \xi_{18} \end{bmatrix} = \begin{bmatrix}
\beta_{19} & \beta_{29} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \beta_{310} & \beta_{410} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \beta_{511} & \beta_{611} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \beta_{712} & \beta_{812} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{913} & \beta_{1013} & \beta_{1113} & \beta_{1213} & 0 & 0 & 0 & 0 & \beta_{1713} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{1314} & 0 & 0 & 0 & \beta_{1714} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{1517} & \beta_{1617} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{1318} & \beta_{1418} & 0 & 0 & \beta_{1718}
\end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \\ \xi_6 \\ \xi_7 \\ \xi_8 \\ \xi_9 \\ \xi_{10} \\ \xi_{11} \\ \xi_{12} \\ \xi_{13} \\ \xi_{14} \\ \xi_{15} \\ \xi_{16} \\ \xi_{17} \end{bmatrix} + \begin{bmatrix} \zeta_9 \\ \zeta_{10} \\ \zeta_{11} \\ \zeta_{12} \\ \zeta_{13} \\ \zeta_{14} \\ \zeta_{17} \\ \zeta_{18} \end{bmatrix} \qquad (7)$$

The above steps are repeated until the changes in the outer weights (ie, the difference between outer weights which calculated in two consecutive repetitions) become less than a threshold value (usually 10-5), or the number of iterations reaches a specified maximum value (usually 300 repeats). The details of the calculations and equations can be found in [42], [43], [45], [46].

B. Evaluation of the model

To assess the structural equation model and to investigate the direct, indirect and effective interaction on the accidents which caused by carelessness, the measurement model, the structural model and the overall model was evaluated to ensure the constructed model. The evaluation process can be summarized in Table. 2.

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Table 2: Evaluation of the PLS Path modeling

PLS Path modeling	Reflective measurement model	Indicator reliability	[43, 46]
		Composite reliability	[47-48]
		Convergent validity (AVE[1])	[49]
		Discriminant validity	[43, 46]
	Formative Measurement Models	Collinearity among indicators	[48]
		Significance and relevance of outer weights	[43, 46]
		Convergent validity	[48]
	Structural models	Coefficients of determination (R^2)	[48]
		Size and significance of path coefficients	[47]
		Effect sizes (f^2)	[50]
		Predictive relevance (Q^2)	[48]
	Global model	Goodness of fit (GoF)	[44]
	Mediating variables	Mediating variable Significantly	[51]
		Mediator variable impact strength (VAF)	[52]

V. Study Area and Data Used

In this study, collision data, traffic volume, and geometric characteristics of the main roadway network in Hamedan province with the total length of 900 kilometers in four axes including road 37 (Hamedan-Malayer segment) and road 48 (Hamedan-Asad Abad segment, Hamedan-Saveh segment, and Hamedan-Kabodrahang segment) in a three-year period from year 2011 were used (Fig. 3)

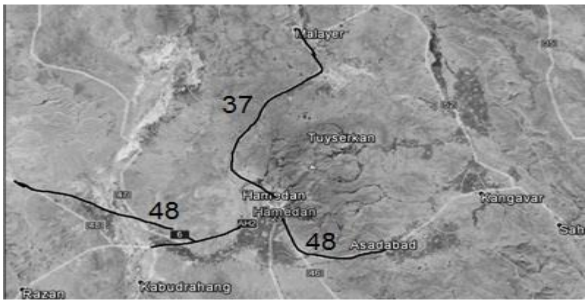

Figure 3: The study area

During this period a total number of 1145 traffic collisions were recorded by Police, which unfortunately led to death and injury of 1265 and 357 persons, respectively. 611 of these collisions are the cause of carelessness. Therefore, we use these collisions as reference data. In addition to the location and the time of collisions, some information such as sex, age, education, and locality of the drivers were extracted from the recorded data sheet by police staff called COM114. Traffic data were received from Islamic Republic of Iran's Road Maintenance and Transportation Organization (I.R. RMTO). The Roadway network was segmented using dynamic model [35] to produce the reference population. Segments with a total number of crashes greater than or equal to the average crashes of the reference population multiplied by two were identified as (HCCL) [3]. The geometric characteristics of the identified HCCLs were collected in situ using a dual-frequency GPS receiver.

Collision data, traffic data, and geometric information of HCCLs of the roadway network were used in the modeling procedure.

[1] Average Variance Extracted

VI. Results

In this model, three latent dependent variable is used to interpret the accidents which caused by carelessness. The model variables used in this model are human, road and traffic. The paths between the variables approved at the 95% level of significance by using T-test.

VII. Results in Details

A. Reflective measurement model Results

According to Table. 3 composite reliability values are more than 0.7, therefore reflective measurement models, have enough reliability to explain the latent variable. The convergent validity results calculated and based on that, the Average Variance Extracted (AVE) parameter of the latent variables of the reflective model were more than 0.4, except Age and Human. So, observable variable (Age >60 years) which had minimum value, removed from the model. Based on Table 5, the square root of AVE of each latent variable is more than its maximum correlation to other latent variables. Therefore the discriminant validity of the reflective measurement approved at the level of latent variable.

Table 3: Composite reliability of the reflective variables

Latent variable	Composite reliability	AVE
Accident	0.98	0.96
Age	0.718	0.479
Age 1	0.792	0.656
Age 2	0.808	1
Edu 1	0.746	0.6
Edu 2	1	1
Education	0.757	0.519
Hourly Speed	1	1
Human	0.883	0.509
Hv traffic	1	1
Local	1	1

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Locality	0.727	0.572
NO Local	1	1
Traffic	0.84	0.736

B. Formative measurement model Results

According to Table 4, the VIF values are less than 5, therefore the constructive indicators of road are independent.

Table 4: The formative measurement model test values

	VIF	T Statistics	P Values
DCI - Road	1.083	2.712	0.007
Segment - Road	1.008	4.592	0
Slope (+) - Road	3.764	2.491	0.013
Slope*Curvature - Road	3.854	2.53	0.012

C. Structural model Results

According to Table 5 and 6, the determination coefficient of the latent variables human and traffic are high and the determination coefficient of the road is medium which shows a good fit in the model. Q2 values are greater than zero, which means observed values reconstructed good and the model has the ability to predict. Also, f_2 values show the effectiveness of the exogenous variables which approved in the previous steps. Based on f_2 values human factor has maximum effect and also traffic and road are in the second and third level of effectiveness, respectively. The mutual effect of human and road on each other is weak.

Table 5: The determination coefficient of the latent variables

Latent variable	R^2	Redundancy index (Q^2)
Accident	0.675	0.637
Human	0.998	0.476
Road	0.244	-
Traffic	1	0.726
Locality	1	0.486
Education	1	0.498
Age	1	0.442

Table 6: Mutual effect of the exogenous variables (f^2)

	Accident	Human	Road	Traffic
Accident	1	-------	-----	-----
Human	0.821	1	0.24	-----
Road	0.131	-----	1	-----
Traffic	0.318	0.04	0.071	1

D. Mediating variables Results

Based on Table 9, human has 13% in direct effect on the accident and also through the road traffic has 12% effect, indirectly. However, the indirect effect of the traffic through the human approved, but it can be ignored because of its low intense.

E. Overall Model evaluation

The calculated GoF (Table 7) for the overall model is more than 0.36 and therefore, we can conclude that the structure of the model is acceptable and has a strong fitness. Given that the traffic has a little impact on the human and consequently the human factor removal from the overall model, the shape of the final model along with direct and indirect effects (Table 8) would be as Fig.5a and Fitness of the model as Fig.5b.

Table 7: Goodness of fit of the overal1 model

Latent variable	Determination coefficient	Common values	(GoF)
Accident	0.675	0.636	0.631
Human	0.998	0.477	
Road	0.244	0.037	
Traffic	1	0.726	
Locality	1	0.486	
Age	1	0.442	
Education	1	0.495	
	R^2_{mean} = 0.845	Com_{mean} = 0.471	

Table 8: Direct, indirect, and all effective factors accidents

Latent variable	Direct	Indirect	Overall
Accident			
Third order			
Age 1	-	0.23	0.23
Age 2	-	1	0.1
Edu 1	-	0.14	0.14
Edu 2	-	0.09	0.09
No local	-	0.17	0.17
Local	-	0.13	0.13
Second order			
Hourly Speed	-	-0.2	-0.2
Locality	-	0.23	0.23
HV traffic	-	0.26	0.26
Age	-	0.26	0.26
Education	-	0.19	0.19
First order			

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Human	0.58	0.1	0.68
Road	0.24	-	0.24
Traffic	0.33	-	0.39

VIII. Discussion and Conclusion

One of major prerequisites to reducing accidents is the investigation of traffic collisions' risk factors.

So far, many studies have been conducted to gain a better understanding of the factors that affect the likelihood of a vehicle crash, which almost can be categorized in four main groups, including studies based on: 1- Multiple Regression Models, 2- Pattern Recognition Models, 3- Multi-Criteria Decision Making models, and 4- Structural Equation Modeling (SEM). The first three categories have a high predictability and frequently were used for predictive purposes. But, these models are only able to model the direct effect of the examined factors in the occurrence of traffic collisions, and provide no information about the indirect effect of factors. Therefore, these models are not proper to descriptive analysis of the effective factors on traffic accidents.

In contrast, SEM is designed to test a conceptual or theoretical model and can properly evaluate direct and indirect effects. Due to considering the correlation between observations, adjustment error of observed variables, the causal relationship between latent variables and ability to estimate the direct and indirect effects of each of the parameters, this model can be used to quantitative description of risk factors as well as predictive purposes. In the present study, the cause effect relationships of human, traffic and roadway factors were studied on accident which caused by carelessness information of the main roadway network of Hamedan province which caused by carelessness, using PLS path modeling.

Direct effects of the model of the accidents caused by carelessness (Table 8), show that the hidden variable human has the greatest impact on accidents, and among the factors explaining human variable, age groups 18 to 30 and 30 to 45 years have the most important roles. Also non-local drivers and people with lower education are more active role in this type of accident. The overall effects of human factors on accidents show that 13% of road and 1.5% of traffic indirectly involved in these accidents.

The road factors also have a direct effect on accidents caused by carelessness and increases the effect of the human factor in accidents. By increasing the length of the segment and closing to population centers, the possibility of the accident increases. Although the amount of longitudinal slope, reduce accidents caused by carelessness, but the simultaneous high longitudinal slope and curvature of the path will lead to increased rates of this type of accident. The ratio of heavy vehicles in total vehicles passing at the time of the accident has a positive role, while observation of the minimum and maximum speed limits on traffic hours will reduce the possibility of accidents.

Table 9: The significance of the mediating variables

path	Path coefficient		Standard deviation		Z-value	VAF
	Independent to Mediating	Mediating to dependent	Independent to Mediating	Mediating to dependent		
Human-Road-Accident	0.427	0.238	0.12	0.062	3.466544	0.130352
Traffic-Human-Accident	0.009	0.576	0.005	0.073	1.799647	0.015251

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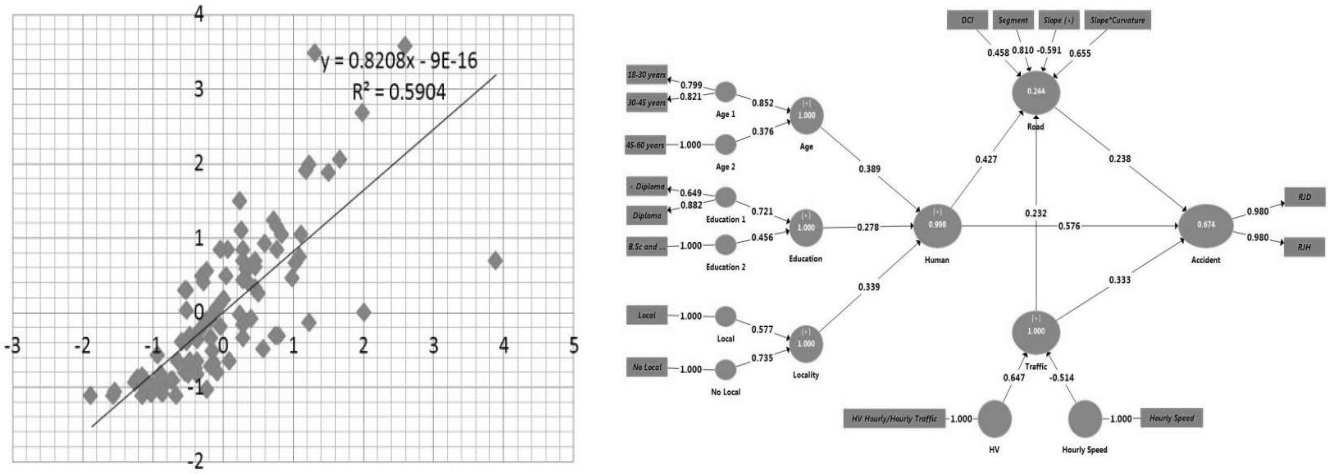

(B) **(A)**

Figure 4: (A) The final model of the accidents which caused by carelessness, (B) Fitness of the model by using observed values in PLS method

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