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DEVELOPING A NEW MODEL FOR ASSESSMENT OF HEAVY VEHICLE-PEDESTRIAN COLLISIONS

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Abstract. The treatment and analysis of accidents involving heavy transport vehicles and pedestrians include the identification and treatment of a certain number of factors that may differ from the cases of passenger vehicle-pedestrian accidents. The aim of this paper is to develop a new model with better performance for speed estimation and reconstruction of accidents involving heavy vehicles and pedestrians. In a large number of cases during the research, it was observed that the experts used the same models for passenger vehicles as for transport vehicles. Likewise, a number of factors that have an impact on heavy vehicle accidents with pedestrians are not included as factors that have an impact on other accidents. The newly developed model, which has better performance than other models, can help experts in the case of analysis, speed determination, and reconstruction of accidents involving heavy vehicles and pedestrians. The model describes more than 94% of the most influential factors in the model (R^2 = 0.945). This model will provide a novel way to examine crashes involving heavy vehicles and pedestrians, generating highly precise results for speed calculation which can be used to recreate the technical aspects of the accident. Additionally, it will help specialists in the field when preparing

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their expert opinion, specifically when heavy vehicles and pedestrians are involved, by providing a model which is different from the standard approach and yields more reliable outcomes.

Keywords: heavy vehicles, length of throw, length of pedestrian, neural network, road friction.

Introduction

The unacceptable level of road safety in Kosovo has currently increased the number of accident cases in all courts of Kosovo. Since judges' final verdicts regarding accidents rely on the expertise of traffic experts, it is very important that this expertise is qualitative and based on scientific models that provide the most accurate results. Reconstructing the technical process of accidents as accurately as possible in these cases is the main issue for further analysis within the framework of traffic expertise and finding the causes of the accident (Hoxha et al., 2018).

The World Health Organization's Global Status Report on Road Safety indicates that traffic collisions are a major source of fatalities, with an estimated 1.35 million people being killed in road accidents worldwide annually (Nogayeva et al., 2021).

One of the main factors in the correct reconstruction of the technical process of the accident is the determination of the speeds of those involved in the accident (Hoxha et al., 2018; Islam, 2023).

Since traffic experts are often confused about the use of adequate models for certain situations, the main aim of this research is a new approach through the formulation of a new mathematical model for determining the speeds of heavy vehicles in the case of pedestrian collisions. This model will then help the expert in the correct technical reconstruction of accidents and the highest-quality expertise.

We will address three questions in response to the topic:

1. What is the effect of the main factors on crashes involving pedestrians and heavy vehicles?
2. How reliable is the recently developed model?
3. What are the differences between the new model and existing models?

Previous studies have mainly focused on pedestrian accidents, using various methods and examining the specific characteristics of each accident. There are many different studies about how to analyse pedestrian accidents, but there is a lack of research into models of accidents involving pedestrians and heavy vehicles (Hoxha et al., 2018; Martinez et al., 2016). Pedestrian-heavy vehicle accidents, which often involve multiple vehicles and pedestrians, present a unique set of challenges that require further research. Pedestrian-heavy vehicle accidents are becoming increasingly common due to rising populations in urban zones and changes of transportation modes. Based on research (Martinez et al., 2016), in the case of a vehicle-pedestrian crash, pedestrian height and weight are anthropometric data from population studies, which vary between men and women.

Forensic scientists twenty years ago employed methods for reconstructing vehicle-pedestrian collisions that are no longer applicable to modern vehicles (Nogayeva et al., 2021).

Some other authors, in their research conclusions recommend for future, advanced artificial intelligence software to be utilized to help reduce and manage the number of traffic accidents due to its effectiveness in managing traffic (Mohammed et al., 2019).

In their paper, Rahul Goel has devised a novel model that approximates the changes in pedestrian fatalities due to changes in the rate of speed. This study takes into account the two forms of speed explicitly and bases its findings on empirical evidence (Goel, 2021).

Zhu employed an Artificial Neural Network model to identify the most influential factors in fatal and serious automobile-pedestrian collisions at intersections. According to the outcomes of the study, the chance of fatal or severe collisions is greater when there is light rain and when the junction control type is either a traffic signal or no control (Zhu, 2022).

The pedestrian angle is usually set to 90°, which corresponds to a pedestrian crossing perpendicularly to the vehicle. The pedestrian position to the vehicle's longitudinal axis is typically 0 m, which corresponds to a centred collision (Martinez et al., 2016).

Shen and Jin developed an optimized model for reconstructing pedestrian-vehicle accidents and tested its performance. This method enables the optimizer to automatically adjust the boundary conditions of multi-body dynamic simulations in order to generate the best fit between the simulation and real accident data (Shen & Jin, 2007).

The authors propose a method that can effectively and easily reconstruct pedestrian accidents; however, due to computational cost constraints, the pre-impact parameters must be estimated through engineering experience (Shen & Jin, 2007).

Talaia et al. used a hybrid approach to model accident simulation from the crash until full stop, performing the computer simulations with multi-body simulation (MBS) and finite element analysis (FEA). In this model, the initial stage of this approach was to use a pedestrian as a test subject. To further validate the efficacy of this approach, more complex scenarios such as multiple impacts with one or more vehicles should be tested and compared with actual accidents (Talaja et al., 2009).

The throw distance of a pedestrian following a vehicle collision can be used to assess the impact speed of the vehicle. Several studies have proven the link between the vehicl impact speed and the pedestrian's throw distance (Hoxha et al., 2018; Happer et al., 2000; Hoxha et al., 2017; Geca, 2011; Sheykhfard et al., 2021; Richardson et al., 2015).

In vehicle-pedestrian interactions, the behaviour of both the vehicle driver and the pedestrian as well as their relationship are complex. Pedestrians can detect the vehicle intention by using two distinct types of gazes: tentative gaze and confirmative. The authors presented a damage record for a vehicle in an ordinal scale and developed a model for predicting the distance a pedestrian would be thrown from the vehicle based on the established damage (Zang et al., 2021).

The study (Saulić et al., 2020) found that the parameters for calculating the throw distance of a pedestrian who was hit by a vehicle could be determined using the damage to the vehicle and by applying some of the models for determining the vehicle speed. This approach was found to be successful. According to these authors, all models used to calculate vehicle speed in cases of vehicle-pedestrian collisions are based on the pedestrian throw distance, which is not always known due to an unidentified collision point or the final resting position of the pedestrian after the collision (Saulić et al., 2020).

In their work Wang et al. proposed an improved method for traffic accident reconstruction which combined geomatics techniques and numerical simulations, specifically finite element (FE) simulations through the THUMS model, to accurately forecast injuries (Wang et al., 2022).

In many studies, it was observed that greater attention was given to pedestrian–car collisions, and the same models that were used for passenger vehicles were utilized for heavy vehicles. Furthermore, the factors that influence heavy vehicle accidents involving pedestrians were not included in the other accident models.

The development of a new model to calculate velocity in cases involving collisions between heavy vehicles and pedestrians is of great importance, as it will provide evaluators with the necessary data to accurately assess such accidents. This model would give a more accurate representation of these accidents than has been previously possible.

In order to accurately and precisely estimate the speed of vehicles involved in pedestrian-vehicle accidents, a new model has been developed based on data collected from accidents that occurred in Kosovo between 2010 and 2020.

The paper is structured into five sections. The first section outlines the data collection and methodological approach used to gather information on accidents that occurred in Kosovo. The second section focuses on data analysis and evaluation of the most influential factors. This is done by performing a multiple linear regression analysis using SPSS software. The third section applies a multi-regression model to create a new model formulation. The fourth section compares the results obtained from the new model to those of other existing models. Finally, the fifth section provides the conclusions drawn from the study.

1. Data collection and methodological approach

For research purposes, the collected data include different locations of accidents that occurred in Kosovo, in the framework of which different data are included regarding the height and weight of pedestrians, the end position of pedestrians (throw distance) who were hit by different types of heavy vehicles, and different conditions of the road surface.

The accurate and dependable collection of information on the type and occurrence of traffic accidents is necessary for successful research, analysis, and modeling of traffic systems (Hoxha et al., 2023).

The data were collected over a long period, from 2010 until 2020, and were mainly based on the professional expertise of road accidents caused during this period. In addition to individual analysis by the authors, a joint group was formed to examine accidents involving heavy vehicles and pedestrians, from which important recommendations and conclusions were derived.

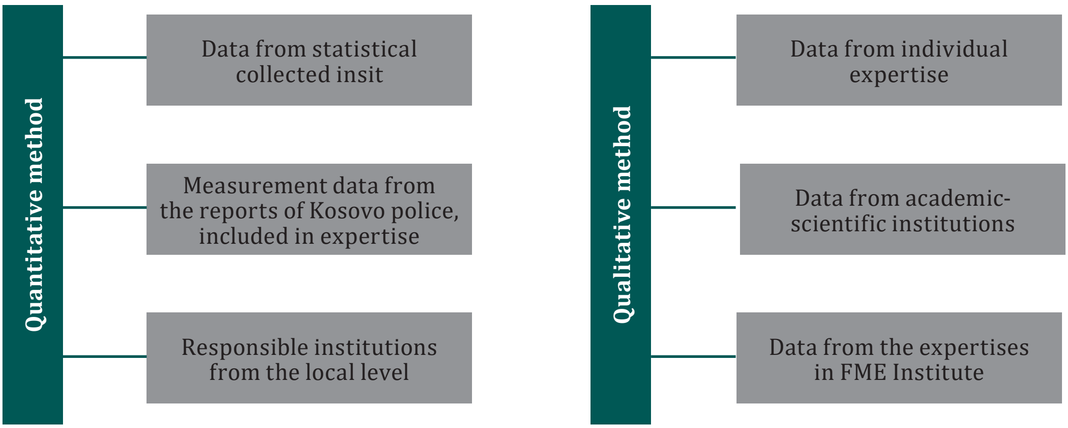

Figure 1. Grouping the collected and classified data for research goals

The data groups collected are classified according to two methods (Figure 1).

The selection of locations for accidents in Kosovo is comprehensive, covering the entire territory of Kosovo. Special attention was given to the urban areas of the main cities, such as Prishtina, Gjakova, Prizren, Mitrovica, Gjilan and Peja (Figure 1). This is important for understanding the prevalence of traffic accidents in Kosovo, as these areas are typically more densely populated and have higher levels of traffic.

The following algorithm outlines the procedure for data collection and formulation of a model:

Phase 1: Collection of relevant data needed to reach the aims.
Phase 2: Identification of the main factors related to aims of the model.
Phase 3: Analysis of the collected data to identify patterns and trends.
Phase 4: Formulating a model based on the analysis of the data.
Phase 5: Comparison of results with other models.
Phase 6: Validation of the model.

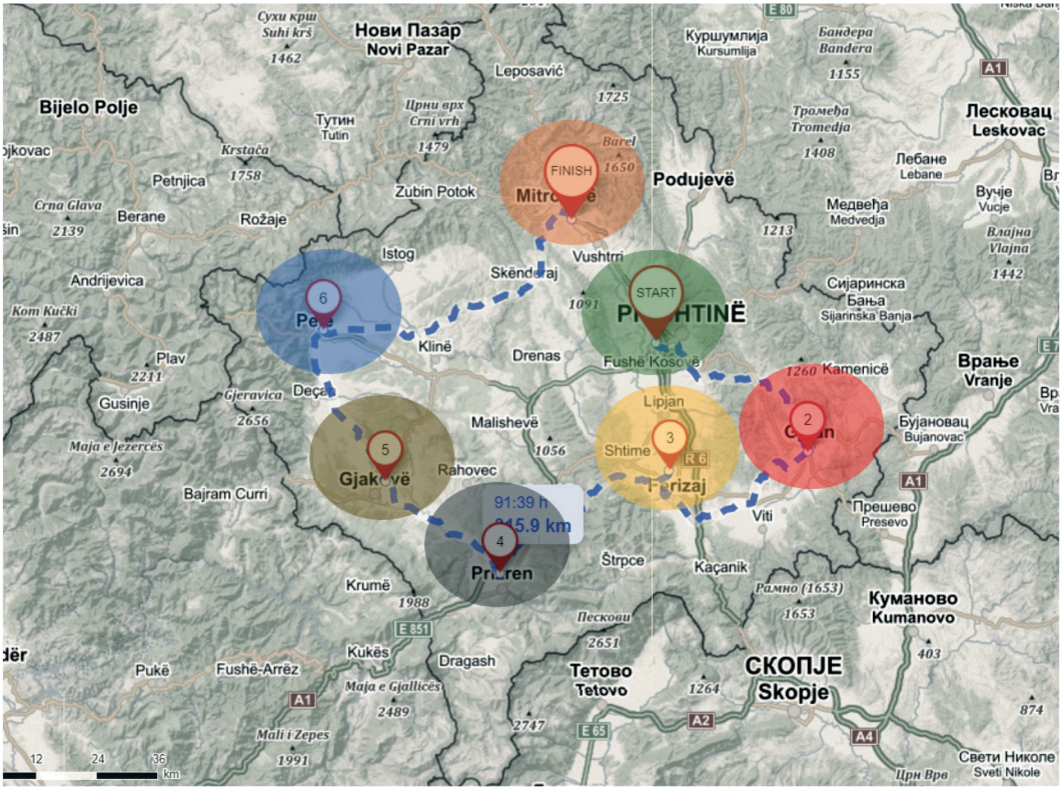

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Figure 2. Data collections locations

The methodological steps for data collection and model formulation are shown in the algorithm below.

According to the research conducted by the experts at the Vehicle Institute of the University of Berlin, the impact speed of the vehicle in a pedestrian collision can be calculated using Equation (1) (Geca, 2011).

$$v_g = 12\sqrt{S_{\text{hudh}}} \tag{1}$$

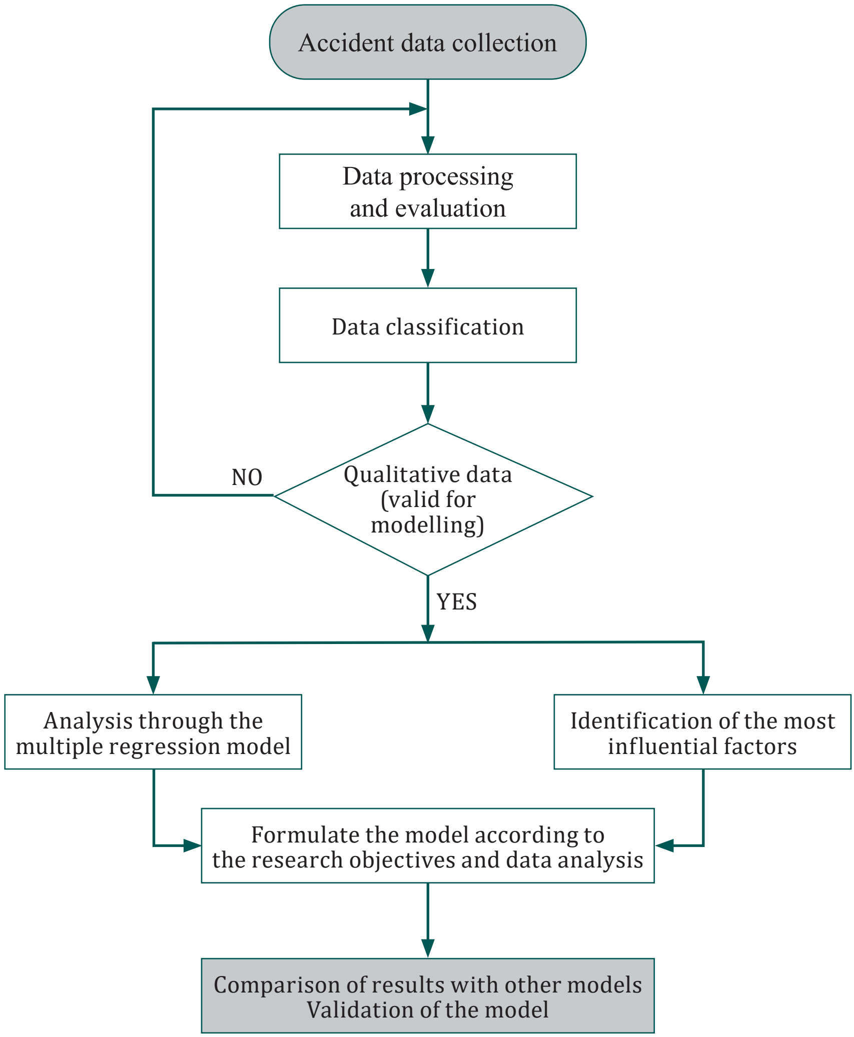

Figure 3. Methodological approach

Kramer has demonstrated that the relationship between the average throwing distance of an adult and the impact speed of a personal vehicle can be expressed using a quadratic Equation (2) (Geca, 2011):

$$L_{\text{throw}} = -0.348 + 0.28v_g + 0.062v_g^2. \tag{2}$$

Equations (1) and (2) are used for all types of vehicles, including passenger vehicles and transport vehicles (trucks, minibuses, buses, etc.), considering the different kinematics of collisions with pedestrians by these types of vehicles in relation to small vehicles (Geca, 2011). The validity of the results obtained by these models can be discussed when they are used on a heavy vehicle-pedestrian crash.

Based on the model of Happer and other authors, the relations between vehicle speed and pedestrian throw distance are combined as in Equation (3) (Happer et al., 2000):

$$V = 9.19d_{throw}^{0.59}. \tag{3}$$

All these models provide different estimates regarding the speed of heavy vehicles when they strike pedestrians.

2. Data analysis and evaluation of the most influential factors

The analysis of the data distribution was realized through multiple linear regression using SPSS software. Based on the obtained results (Figures 4–6), the data show a linear dependency and distribution.

Skewness and kurtosis statistics have results of −2.31 and −1.47, respectively. Referring to the values of skewness and kurtosis, over 95% of the data are normally distributed because they fall in the middle of the standard deviation between +2.5 and −2.5 from the mean, which is normal for this type of study.

For the analysis of the normality of the data, a probability chart is also used, which compares the observed values of the data with the expected values on a chart (Figure 6).

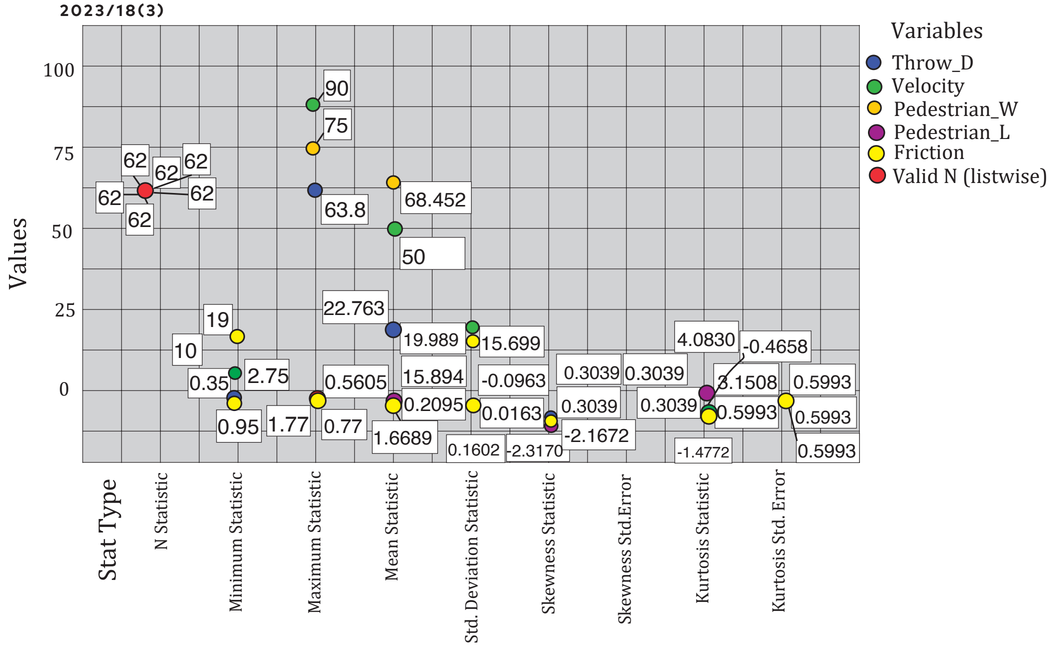

Figure 4. Descriptive statistics

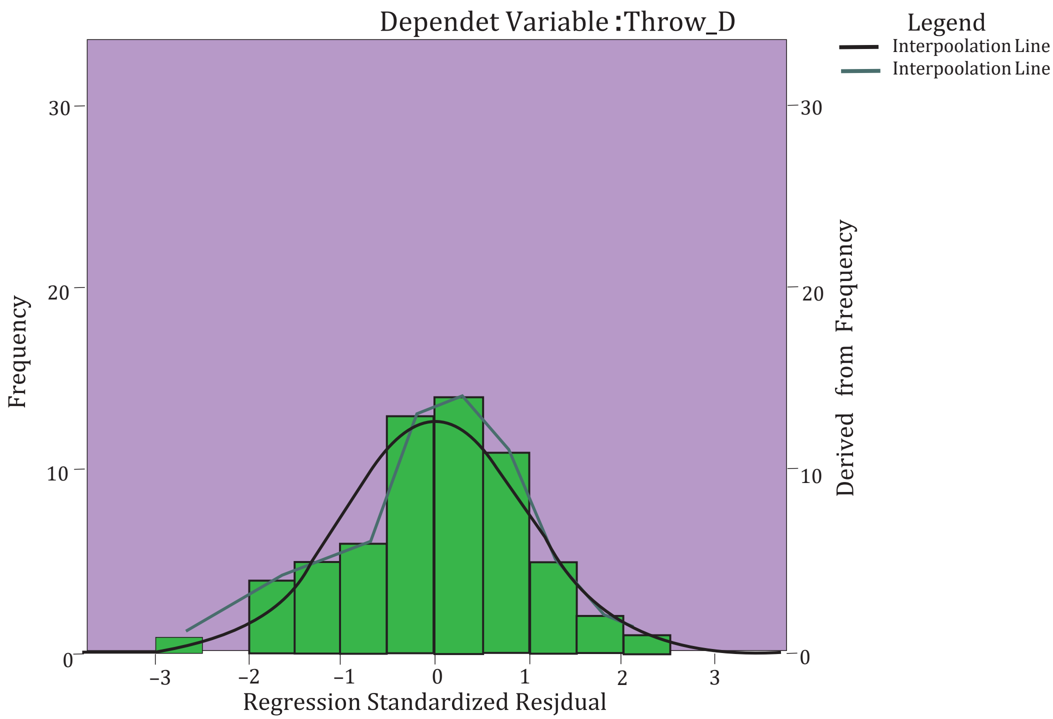

Figure 5. Dependent variable and description of the data

A P-P plot, also known as a probability plot, is a graphical technique used to compare two probability distributions and assess whether a dataset follows a particular distribution, such as a normal distribution. For a normal P-P plot, the points should be close to a straight line, indicating that the data follow a normal distribution (Albayrak, 2008).

Table 1. Independent variable importance

	Importance	Normalized Importance
Friction	0.253	65.1%
Pedestrian_L	0.234	60.4%
Pedestrian_W	0.125	32.2%
Velocity	0.388	100.0%

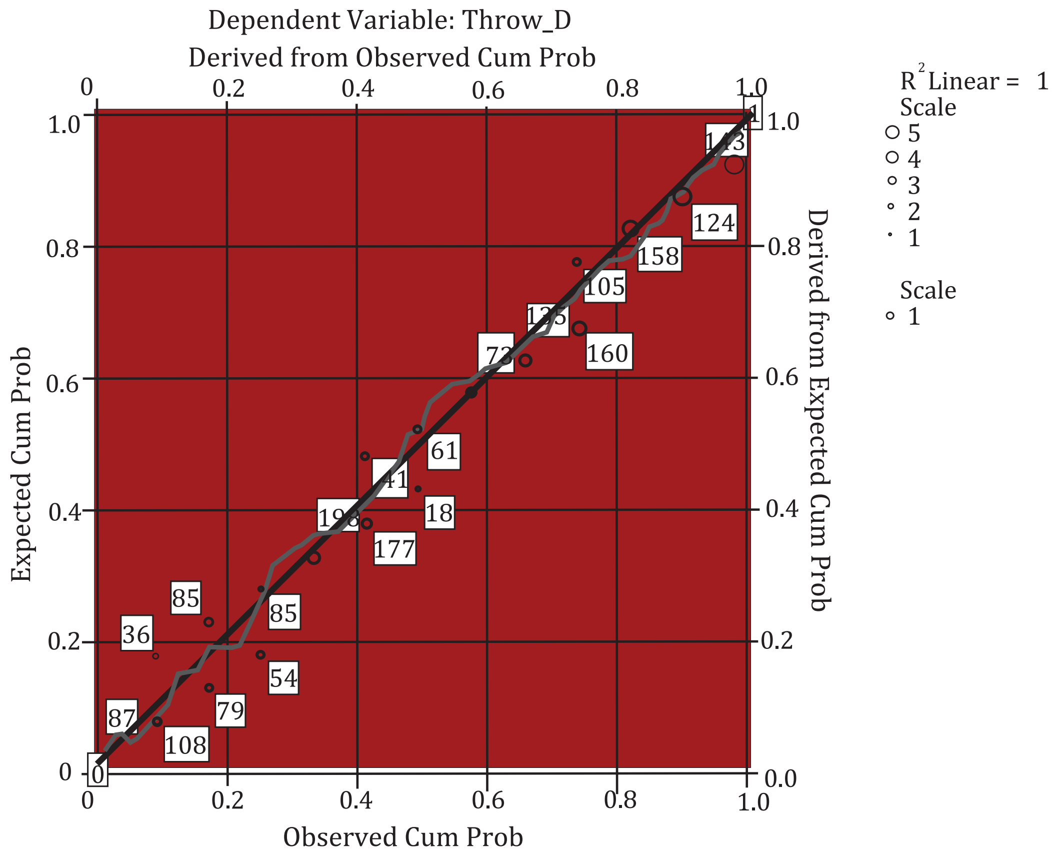

Figure 6. Normal P-P plot of regression

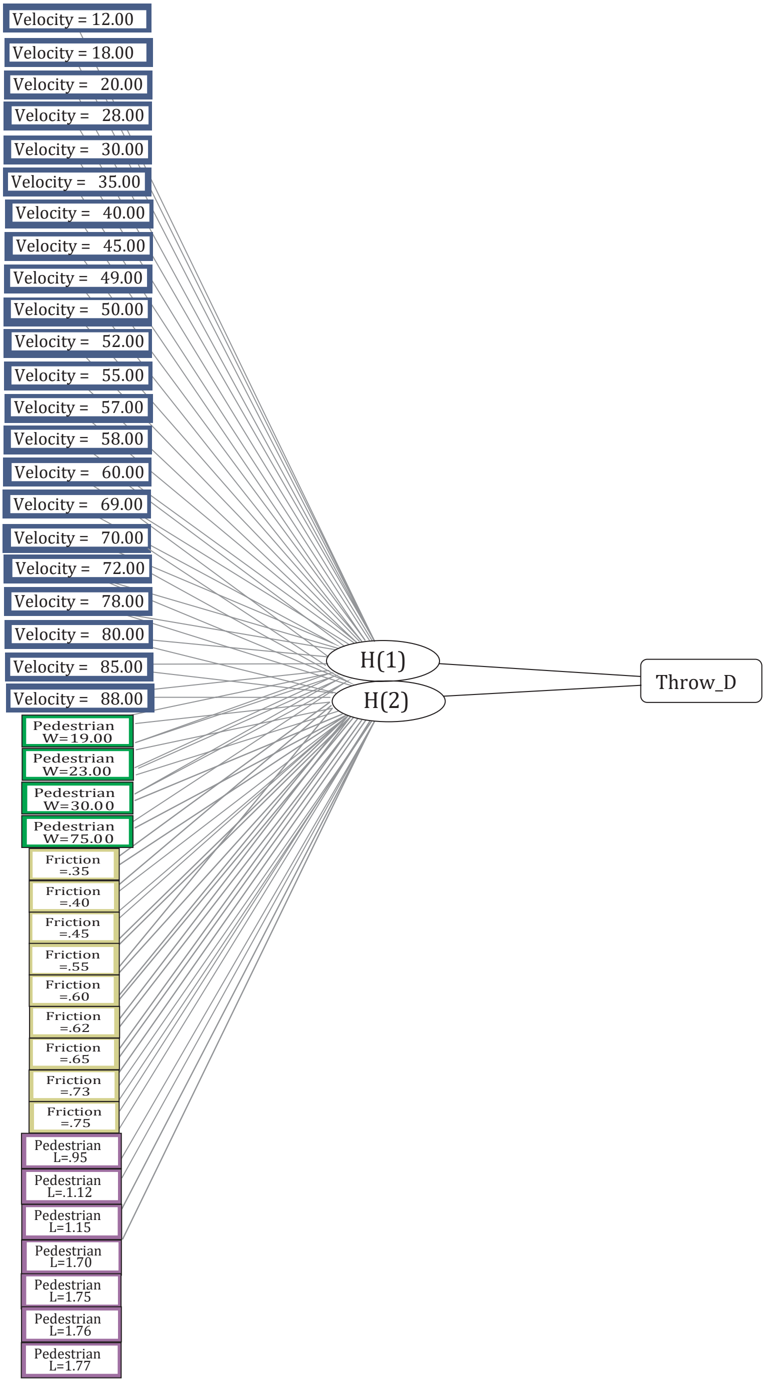

Figure 7. ANN – Importance of independent variables

An artificial neural network (ANN) model is used to assess the impact of various factors on heavy vehicle-pedestrian crashes. This model is a type of artificial intelligence that uses interconnected neurons to process data and make assessments (Table 2, Figures 7 and 8).

In the case of heavy vehicle-pedestrian collisions, the most influential factors (Figure 8) in the length of the pedestrian's throw, have result: vehicle speed (0.388), pedestrian slip coefficient on the road surface (0.253), pedestrian length (0.234) and pedestrian weight (0.125).

The impact of the road friction coefficient has been argued as a very important factor even through the software model, because after the crash, the most of the throw path of pedestrian until end position is sliding with the road. This happened because of the front shape of heavy vehicles and the impulse that this vehicle exerts on the entire length of the pedestrian when they are hit.

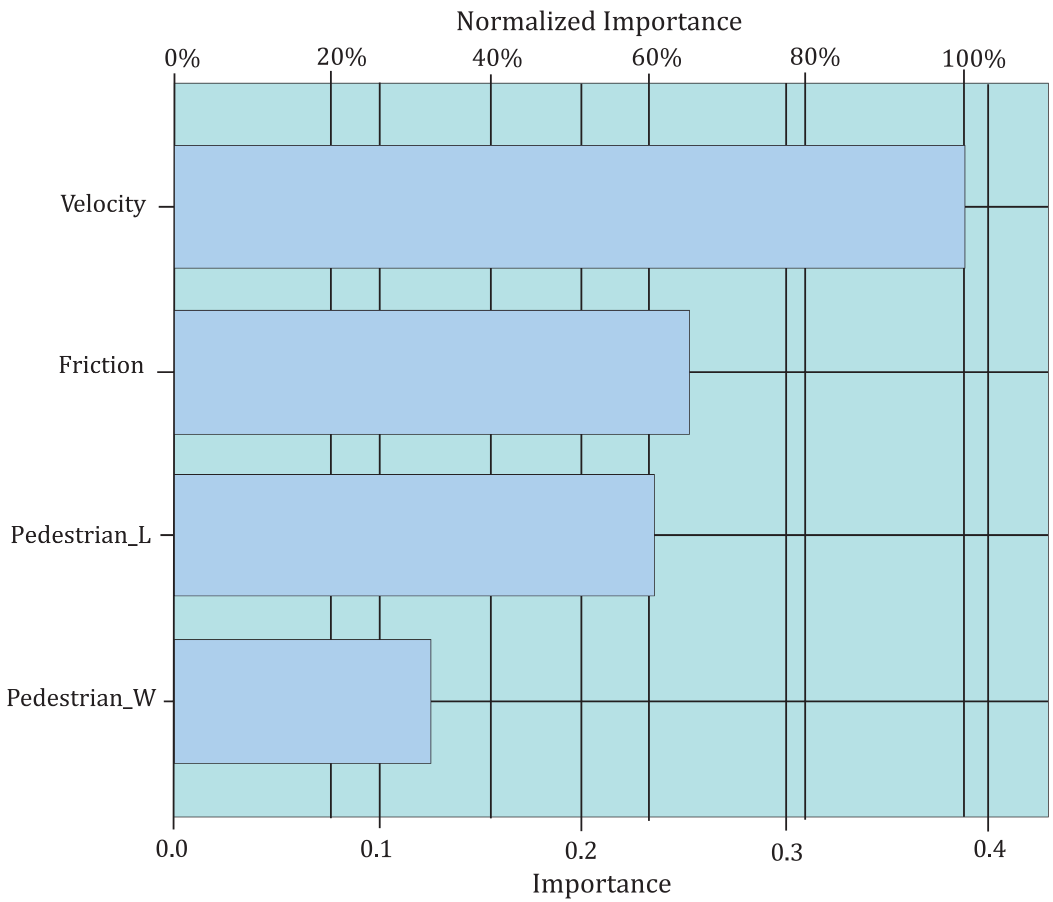

Figure 8. Normalized importance of identified factors

3. Multi-regression model applied for new model formulation

For the purposes of model formulation and analysis through the multiple linear regression model, the variable length of the throw of the pedestrian is treated as a dependent variable, while the other variables – heavy vehicle speed, friction coefficient, pedestrian height, and pedestrian weight – are treated as independent variables.

From the correlation table of independent variables, it can be inferred that there is a strong correlation between the pedestrian height and weight variables, as indicated by a Pearson correlation of 0.989. As such, to prevent the impact of one variable from outweighing the other, it is recommended that these two variables should be treated as a single variable.

The summary table reveals a strong correlation between the dependent variable (throwing after the pedestrian is hit) and the independent variables, as indicated by the R^2 value of 0.945, which suggests that approximately 95% of the variation in the dependent variable is explained by the influence of the independent variables (Table 3).

Table 2. Correlations

		Throw_D	Friction	Pedestrian_L	Pedestrian_W	Velocity
Pearson Correlation	Throw_D	1.000	−0.244	0.210	0.256	0.932
	Friction	−0.244	1.000	−0.452	−0.502	−0.013
	Pedestrian_L	0.210	−0.452	1.000	0.989	−0.022
	Pedestrian_W	0.256	−0.502	0.989	1.000	0.013
	Velocity	0.932	−0.013	−0.022	0.013	1.000
Sig. (1-tailed)	Throw_D		0.028	0.051	0.022	0.000
	Friction	0.028		0.000	0.000	0.460
	Pedestrian_L	0.051	0.000		0.000	0.431
	Pedestrian_W	0.022	0.000	0.000		0.460
	Velocity	0.000	0.460	0.431	0.460	
N	Throw_D	62	62	62	62	62
	Friction	62	62	62	62	62
	Pedestrian_L	62	62	62	62	62
	Pedestrian_W	62	62	62	62	62
	Velocity	62	62	62	62	62

The Durbin-Watson indicator is an important tool for assessing multicollinearity in a multiple linear regression analysis. This is an indicator of the presence of autocorrelations and of eventual errors in the model, and in this particular case, it resulted in a value of 1.082. The built model has a low probability of introducing errors due to autocorrelation, as values from 1.5 to 2.5 generally do not show autocorrelations. However, values above 2.5 have an increased chance of introducing errors (Glass et al., 1972; Zhang et al., 2020).

The Variance Inflation Factors (VIF) from the collinearity diagnostics section is an important statistic that can help determine if there are multiple relationships between the independent variables. Low tolerance values and high VIF values indicate that multiple relationships exist between the variables (Albayrak, 2008; Glass et al., 1972; Zhang et al., 2020). In our case, the tolerance values were low (0.651, 0.017, 0.016, 0.933) and the VIF values were high in the case of the length of legs and

Table 3. Model summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	0.972[a]	0.945	0.941	3.85732	0.945	244.655	4	57	0.000	1.082

Note: a. Predictors: (Constant), Velocity, Friction, Pedestrian_L, Pedestrian_W
b. Dependent Variable: Throw_D

Table 4. Coefficients[a]

	Unstandardized Coefficients					Correlations			Collinearity Statistics	
	B	td. Error	Stand. Coef. Beta	*t*	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	−6.068	13.452		−0.451	0.654					
Friction	−13.264	3.820	−0.134	−3.472	0.001	−0.244	−0.418	−0.108	0.651	1.535
Pedestrian_L	−16.607	17.955	−0.219	−0.925	0.359	0.210	−0.122	−0.029	0.017	58.009
Pedestrian_W	0.398	0.247	0.393	1.613	0.112	0.256	0.209	0.050	0.016	61.600
Velocity	0.732	0.026	0.920	28.608	0.000	0.932	0.967	0.889	0.933	1.072

Note: a. Dependent variable: Throw_D

Table 5. Collinearity diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	Friction	Pedestrian_L	Pedestrian_W	Velocity
1	1	4.771	1.000	0.00	0.00	0.00	0.00	0.01
	2	0.116	6.425	0.00	0.01	0.00	0.00	0.87
	3	0.103	6.801	0.00	0.31	0.00	0.00	0.01
	4	0.010	22.091	0.09	0.55	0.00	0.02	0.04
	5	0.000	165.101	0.91	0.12	1.00	0.98	0.07

Note: a. Dependent Variable: Throw_D

feet factors. Applying the "Stepwise" method, one of these factors was removed from the final model due to its negligible influence.

Referring to the initial analysis, the newly formulated model is as in Equations (4) and (5).

$$\text{Throw} = -6.068 - 13.264 \times \mu - 16.607 \times l + 0.398 \times w + 0.732 \times v_g \quad (4)$$

$$v_g = \frac{1}{0.732}\left[\text{Throw} + 6.068 + 13.264 \times \mu + 16.607 \times l - 0.398 \times w\right] \quad (5)$$

The indicators of significance in the case of the two variables were found to be unacceptable because they had a value greater than 0.05. This is also due to the relationship between two independent variables (the pedestrian's height and weight). In this case, the length of the pedestrian, which is the independent variable, has been removed as it is strongly correlated with the weight of the pedestrian and therefore does not provide an independent influence on the dependent variable.

Therefore, in continuation of the analysis and formulation of the model as closely as possible to the description of the current phenomenon, in the final model, one variable was removed, and only pedestrian weight was included. During the analysis through multiple linear regression, the use of the Stepwise method also automatically removed one independent variable (pedestrian height).

With the removal of one independent variable from the model, the correlations between the other independent variables became weaker, making the impact of each one individually more significant (Table 8 and Table 9).

Table 6. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–14.422	2.007		–7.185	0.000
	Velocity	0.741	0.037	0.932	19.919	0.000
2	(Constant)	–31.190	2.831		–11.019	0.000
	Velocity	0.739	0.028	0.929	26.599	0.000
	Pedestrian_W	0.247	0.035	0.244	6.982	0.000
3	(Constant)	–17.914	4.111		–4.358	0.000
	Velocity	0.738	0.025	0.928	29.895	0.000
	Pedestrian_W	0.172	0.036	0.170	4.748	0.000
	Friction	–14.536	3.559	–0.147	–4.084	0.000

Note: a. Dependent variable: Throw_D

Table 7. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13384.896	1	13384.896	396.773	0.000[b]
	Residual	2024.064	60	33.734		
	Total	15408.960	61			
2	Regression	14300.574	2	7150.287	380.614	0.000[c]
	Residual	1108.386	59	18.786		
	Total	15408.960	61			
3	Regression	14548.130	3	4849.377	326.736	0.000[d]
	Residual	860.830	58	14.842		
	Total	15408.960	61			

Note: a. Dependent variable: Throw_D
b. Predictors: (Constant), Velocity
c. Predictors: (Constant), Velocity, Pedestrian_W
d. Predictors: (Constant), Velocity, Pedestrian_W, Friction

Table 8. Coefficient correlations[a] (stepwise method)

Model			Velocity	Pedestrian_W	Friction
1	Correlations	Velocity	1.000		
	Covariances	Velocity	0.001		
2	Correlations	Velocity	1.000	–0.013	
		Pedestrian_W	–0.013	1.000	
	Covariances	Velocity	0.001	–1.282E–5	
		Pedestrian_W	1.282E–5	0.001	
3	Correlations	Velocity	1.000	–0.008	0.007
		Pedestrian_W	–0.008	1.000	0.501
		Friction	0.007	0.501	1.000
	Covariances	Velocity	0.001	–6.843E–6	0.001
		Pedestrian_W	6.843E–6	0.001	0.065
		Friction	0.001	0.065	12.668

Note: a. Dependent Variable: Throw_D

Table 9. Collinearity diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Velocity	Pedestrian_W	Friction
1	1	1.930	1.000	0.03	0.03		
	2	0.070	5.252	0.97	0.97		
2	1	2.876	1.000	0.00	0.02	0.01	
	2	0.102	5.319	0.03	0.87	0.13	
	3	0.023	11.247	0.97	0.11	0.87	
3	1	3.789	1.000	0.00	0.01	0.00	0.00
	2	0.111	5.840	0.00	0.80	0.00	0.15
	3	0.090	6.477	0.00	0.14	0.22	0.21
	4	0.010	19.733	0.99	0.05	0.78	0.63

Note: a. Dependent Variable: Throw_D

In the final model, when subjected to an ANOVA test, all the significant indicators have a result of 0.000. Also, other indicators from T and F tests have acceptable results.

Referring to the final analysis, the newly formulated model is as in Equations (6) and (7).

$$\text{Throw} = -17.91 - 14.53 \times \mu + 0.172 \times w + 0.738 \times v_g \tag{6}$$

$$v_g = 24.26 + 19.68 \times \mu + \frac{\text{Throw} - 0.172 \times w}{0.738} \tag{7}$$

This model Equation (7) will serve to create a new approach in the analysis of accidents involving heavy vehicles and pedestrians, and the obtained results will help in the reconstruction of the technical process of the accident as closely as possible. It will also help the experts in the field during the drafting of their expertise, when heavy vehicles and pedestrians are involved, to use a special model that differs from other models and offers them more accurate results.

4. Comparison of results between models

The results of the analysed models and the reformulated model that takes friction between the pedestrian and the road, as well as the pedestrian's weight, into account are presented in Figure 9 and Table 10 for comparison. The results of this research showed that the proposed model was approximately 10% more accurate than the other two models taken for comparison. It is advised that the recently developed model is only utilized when there are heavy vehicles and pedestrians involved in collisions.

The new model is recommended for use in cases of frontal collision involving heavy vehicles and pedestrians.

Table 10. Comparison of results between models

The data			Velocity by used models		
Pedestrians weight, kg	Road Friction	Throw distance by heavy vehicle, m	Model 1: $v_g = 12\sqrt{S_{hudh}}$ km/h	Mode 2- Happer model $V = 9.19\, d_{throw}^{0.59}$, km/h	Model 3 New formulated model $v_g = 24.26 + 19.68 \times \mu + \dfrac{Throw - 0.172 \times w}{0.738}$, km/h
75	0.75	20	53.6	53.81	48.64
75	0.75	29.7	65.39	67.9	61.78
35	0.75	14.3	45.37	44.15	50.23
75	0.65	4.97	26.7	23.66	26.30
19	0.75	11	39.79	37.82	49.49
75	0.55	13.2	43.5	42.11	35.49
75	0.55	7.7	33.2	30.64	28.03
75	*0.35*	3.85	23.5	20.35	18.88
45	*0.75*	16.5	49.11	48	47.78
75	*0.4*	26.4	61.65	63.3	50.42

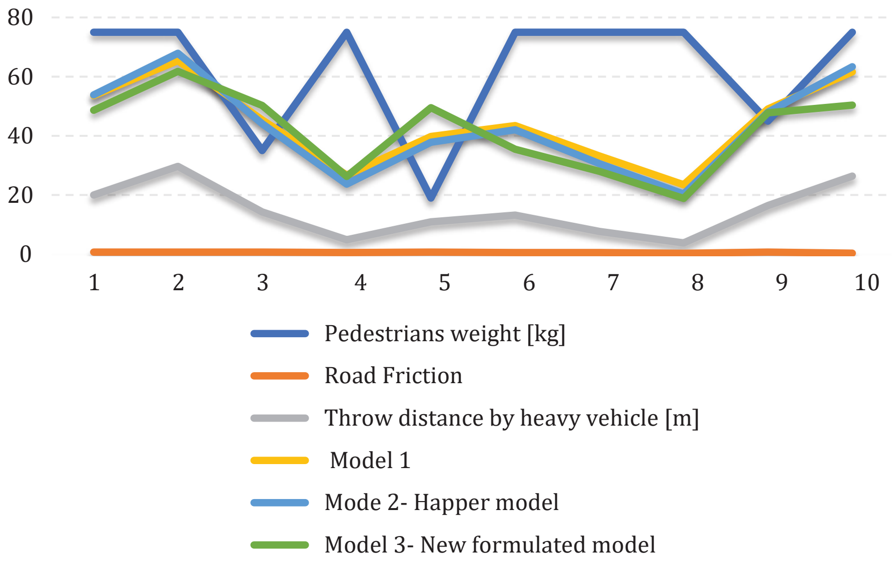

Figure 9. Comparison of results

Conclusions

The research yielded a new model which could be used to analyse accidents involving heavy vehicles and pedestrians. The model is represented by Equations (6) and (7).

The ANOVA test results for all the significant indicators in the final model were 0.000, indicating that the model was valid. Additionally, the results from the T and F tests were also acceptable. The Durbin-Watson test, which is used to assess multicollinearity and identify autocorrelations, had a result of 1.082, indicating that the model was unlikely to introduce errors due to autocorrelation.

The new reformulated model is valid for heavy vehicle-pedestrian crashes, and it offers approximately 10% more accurate results in relation to the other two models taken for comparison in the framework of this research. It is highly recommended to be used in cases where the road friction coefficient is between 0.3 and 0.6 because in these cases, the pedestrian's slide path (after being hit by a heavy vehicle) along the road has an extremely large impact on the accurate calculation of the vehicle hit speed. This impact in heavy vehicle-pedestrian crashes has not been taken into account at the appropriate level in other models. This model will serve to create a new approach in the analysis of accidents involving heavy vehicles and pedestrians, and the obtained results will help in the reconstruction of the technical process of the accident as closely as possible. It will also help the experts in the field during the drafting of their expertise, when heavy vehicles and pedestrians are involved, to use a special model that differs from other models and offers them more accurate results.

The authors' next study will focus on developing an AI-based approach for predicting and assessing the risks associated with vehicle-pedestrian collisions in an urban zone.

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