A Brief Overview of Pedestrian Accident Modelling

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Abstract. Thanks to the advancement of models and methodologies to handle large amounts of data in conjunction with the increased attention of national and international governments toward safety issues, this paper aims to provide a brief overview of the main models that are used to study pedestrian crashes. The reason why this type of analysis is conducted starts from three main research questions: What are the main datasets needed to study pedestrian accidents, what are the main models utilized, and what are the main gaps that emerge in the pedestrian safety field? This proposed state-of-the-art overview starts from the analysis of statistical approaches in the context of risk factor analysis to the most recent machine learning methods to evaluate pedestrian crash severity by emphasizing the purposes for which the models are used, why they are used, and the data needed to achieve the task. The results of the analysis show how the models could be classified and the main research gaps in this field that could be useful for researchers as starting points in their studies.

Keywords: Pedestrian crashes · Pedestrian accident modeling · Empirical Bayes Approach · Statistical Frequency Models · Econometric Models · Machine Learning

1 Introduction

As a leading plan for improving safety conditions for all road users, Agenda 30, promoted by the United Nations (UN) [1], is one of the first plans to address environmental and safety issues. The shared models, approved back in 2015, define 17 goals (Sustainable Development Goals, SDGs); the problem of road users' safety falls under objective 3.6 (under the SDG "Good Health and Well-being") and objective 11.2 (under the SDG "Sustainable Cities and Communities"). With objective 3.6, the UN plan aims to halve, by 2020, the number of injuries and deaths in road accidents, and, with objective 11.2, by 2030, ensure access to a safe, sustainable, and affordable road transportation system.

In 2010, the UN General Assembly proclaimed the 2011–2020 Decade of Action for Road Safety to reduce road accidents with the resolution A/RES/64/255 [2, 3]. A

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year later, there was the launch of "The Decade of Actions for Road Safety 2011–2020", to "help all countries drive along the path to a more secure future" and "save millions of lives", according to the UN Secretary-General Ban Ki-moon [2]. Some years later, in 2017, the WHO, in collaboration with the UN, the Global Road Safety Partnership (GRSP), and the VIAS Institute, known until recently as BRSI (Belgian Road Safety Institute), provided a document on safety issues and measures to reduce the number of accidents, all resumed in 12 voluntary global targets for road safety [4].

In August 2020, the resolution A/RES/74/299 "Improving Global Road Safety" was approved by the United Nations General Assembly, and the second "Decade of Action for Road Safety 2021–2030" was launched [2, 5]. This second decade of actions aims to reduce at least 50% of road traffic deaths by 2030. The UN General Assembly, with the WHO (World Health Organization), and the UN Regional Commission, prepared the plan for this second decade [6].

In February 2020, "The Ten Step Plan for Safer Road Infrastructure", produced by the Project Group "Safer Roads and Mobility" of the United Nations Road Safety Collaboration Group (UNRSC), was published [7]. As the name of the plan suggests, the action to promote was resumed in ten steps. Still, they could be resumed in three main priority actions: the first is to make a gap analysis, the second regards the development of National standards and training, and the third is the Infrastructure Safety Management, to enhance a National Road Assessment Programme and make Road Safety Audits.

In the European context, the European Commission launched the EU Road Safety Policy Framework 2021–2030, a comprehensive document outlining the EU's objectives and actions to reduce road deaths and serious injuries by 50% by 2030 and ultimately achieve "Vision Zero" by 2050 [8]. Adopted by the European Parliament on October 6, 2021, this framework builds upon a resolution from April 27, 2021, welcoming the implementation report on the road safety aspects of the Roadworthiness Package [9].

The framework is rooted in a staff working document published in June 2019, introducing a new EU road safety policy approach and a medium-term strategic action plan [8]. The novel approach emphasizes fostering a culture of zero fatalities and serious injuries by addressing the root causes of road crashes, enhancing enforcement and compliance, improving data collection and analysis, promoting innovation and research, and strengthening international cooperation. This framework is part of the "Europe on the Move" package [10], which also encompasses documents related to sustainable and smart mobility, such as the Sustainable and Smart Mobility Strategy [11].

The objectives of the plan are organized in a three-time period. Between intermediate outcome targets (based on Key Performance Indicators) and long-term goals (zero deaths by 2050), there is an interim target of reducing half-serious injuries and deaths by 2030. An interesting point is the definition of action areas and their relative Key Performance Indicators (KPIs), highlighting which variables are related to road accidents. As action areas is it possible to find safe infrastructure, vehicles, speed, driving, use of the road, use of seat belts and helmets, post-care services. The KPIs are so related to evaluating the percentage of users that have safe behaviours, according to the areas described.

Regarding the Management of Road Infrastructures in the field of Safety Issues, the European Parliament, in 2008, enacted the "Directive 2008/96/EC of the European

Parliament and of the Council of 19 November 2008 on road infrastructure safety management" [12], aimed to create and promote "the establishment and implementation of procedures relating to road safety impact assessments, road safety audits, the management of road network safety and safety inspections by the Member States". As it is possible to read in this Directive, it is crucial to assess safety in the initial planning stages and after the project's approval. All safety design solutions need to be justified with proper analysis to assess the impact in terms of safety advantages. The Directive also stresses the importance of Safety Audits (Article 4) as an important step in the design phase, as well as controls on existing infrastructure that have a high ranking in terms of accident concentration, at least every three years, and safety inspections during operational phases.

On 16 January 2023, the European Commission released guidelines containing also methodologies for conducting network-wide road safety assessments [13]. These guidelines are designed to assist public authorities in EU Member States in fulfilling the requirements of the Road Infrastructure Safety Management Directive [14].

The guidance encompasses a comprehensive framework that addresses both reactive (accident-based) and proactive (feature-based) safety assessments. It covers various factors such as lane width, road curvature, junction design, roadside layout, and potential conflicts between motorized vehicles and vulnerable road users. Additionally, it proposes a methodology for establishing a common safety rating system to classify the existing road network, allowing each road section to be rated on a 5-level scale. This approach aims to help authorities identify priorities for future actions and investments to improve road safety.

At the bottom of this methodology, there are two approaches: the Reactive and the Proactive Approach. The main difference is that in the reactive approach, safety problems are studied after a crash happens, while in the Proactive Approach, the aim is to improve the safety of the road before an accident happens. In other terms, with the Reactive Approach, it is possible to evaluate the frequency of accidents, while with the Proactive Approach, how the risk could be reduced.

The proposed paper aims to give researchers a brief guide and comprehensive framework of the most used models in the pedestrian accident field. To conduct this brief analysis of the state-of-the-art, seventy-seven (77) studies are analysed. In Sect. 2, the main research questions and the selection criteria are shown, while in Sect. 3, a classification of the main models used is proposed, to answer the research questions. Lastly, a brief discussion of the results obtained is proposed in Sect. 4, alongside the conclusions.

2 Research Questions and Selection Criteria

National and International Safety Plans emphasize the need to guarantee safety for vulnerable road users and achieve sustainable development goals at the same time. Several researches' studies have been conducted in the past and nowadays on this topic. This proposed overview of the current state of the art aims to give a clear framework of the data required and the models needed to model pedestrian accidents, as well as the new challenges in this field for the future. For these reasons, the research questions that have emerged and led to the writing of this paper are:

1. What are the main datasets needed to study pedestrian accidents?
2. What models are used to study pedestrian accidents?
3. What are the main gaps that emerge in this field?

To try to answer these research questions, a collection of papers is made to create an exhaustive database. Seventy-seven (77) studies are selected according to several inclusion and exclusion criteria. For the inclusion criteria, the papers that respond to the following requirements are selected:

1. Papers that dealt with pedestrian crashes without any time-period restriction;
2. Studies that use national or available datasets collected by agents or agencies;
3. Studies that implement models or descriptive analysis.

The exclusion criteria adopted are listed below:

1. Vulnerability-based studies are not included because they focus on what happens in particular crash scenarios after the crash happens.
2. Studies that rely on the use of Floating Car Data (FCD) and video cameras or that focus on pedestrian behaviours.
3. Studies in which pedestrian crashes are combined with other vulnerable user accidents to make a common class of analysis.

The reasons related to these selection and exclusion criteria are that the main idea behind them is not to exclude too many papers, but at the same time, to focus on the papers that present studies that could be replicated by other researchers.

3 Classification of Pedestrian Crash Models

Starting from the analysis of the selected papers, it emerges that mainly three subsets could be drawn according to the outcomes and purposes to achieve (see Fig. 1). A first class includes Risk Factor Analysis, which could be seen as a preliminary and explanatory type of analysis of pedestrian crash data, that aim to identify contributory factors and crash scenarios.

The second subset includes pedestrian crash frequency models that aim to evaluate and estimate the number of pedestrian crashes at road segments, intersections, traffic analysis zones (TAZ), and census tracts. The two main classes of methods that emerge from the analysis of the literature are Statistical Frequency Models and the Empirical Bayes Approach.

Lastly, Pedestrian Crash severity Models are identified as a third subset of methods for analysing pedestrian accidents. This category of methods (from the Econometric and Machine Learning fields) is implemented to evaluate the probability of the severity of accidents, which are the features that lead to a fatal outcome, for instance.

The following three subsections are proposed with the aim to give a deeper dive into these three classes of approaches, while, in Fig. 1, a graphic and conceptual framework is shown to guide readers and have a clear vision of the classification performed.

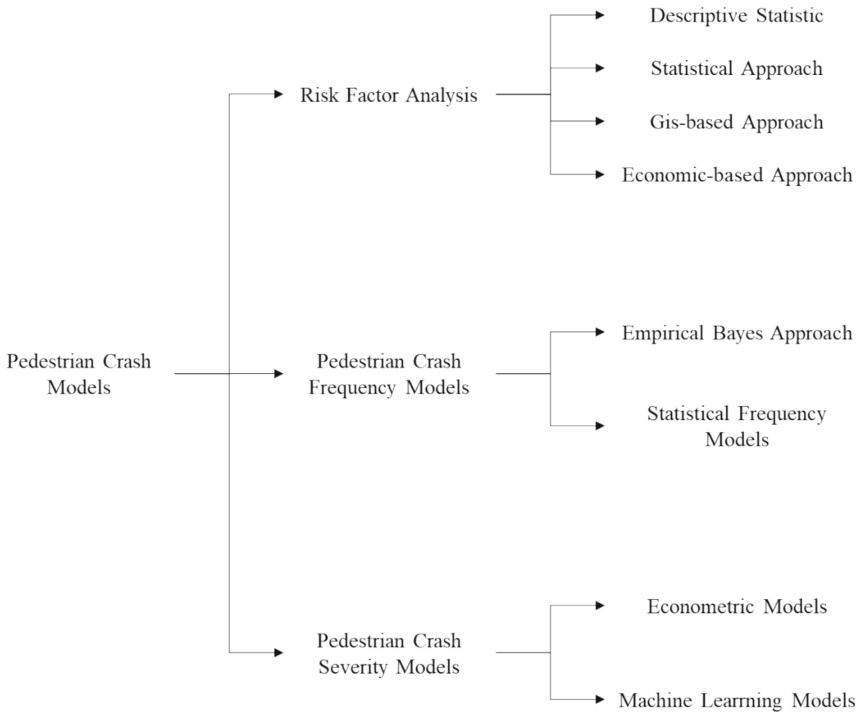

Fig. 1. Proposed classification of implemented models and approaches in the pedestrian safety field.

3.1 Risk Factor Analysis

This model category aims to identify contributory risk factors when pedestrian crashes occur. As it emerges in Table 1 below, four different categories to study the contributory risk factor in pedestrian accidents are reported. Descriptive statistics [15] are often used to measure the frequency and how often that particular scenario or that particular variable occurs. The higher the frequency, the higher the contribution of the variable [16–29].

The other class, defined as Statistical Approach, contains mainly three methods, as it emerges from this review of the state of the art. Double Pair comparisons Approach focuses [28, 30–45] on the comparisons of different scenarios or conditions. Usually, as the name suggests, only two pair conditions are compared to identify some effects and some factors that play a key role. Two pairs of comparisons need to be illustrated to clarify the method. For instance, it is possible to imagine a city manager installing a pedestrian crossing table (CPT) to decrease speeds and reduce pedestrian accidents. The big question is whether this measure can effectively decrease crashes. For this reason, two pairs are created: the first pair include roads where CPT are installed (threaded locations); the second pair include roads (control locations) on which no CPT are installed. For both pairs, accident data before and after the installation are collected. By evaluating the predicted reduction, compared with the actual reduction, the method is able to evaluate the reduction in terms of accidents and also to quantify the contribution of a factor.

Quasi-induce Exposure Models (QIE) are one of the most common responsibility-based methods [37–39]. As suggested, the model selects only crashes in which it is possible to attribute two different roles: one user is responsible, the other one not. The non-responsible user is passively involved in the crash. The ratio between responsible and non-responsible users defines the relative accident involvement ratio, which is similar to the odd ratio. This coefficient substitutes the crash rate.

The third method is called the Two-step clustering algorithm [40–42]. The technique aims to group observations in some clusters based on similarities or differences. The method involves two steps during the clustering task to reduce the total amount of computational requirements.

A third category is represented by the Gis-based Approach [28, 43]. These methods are often used in the context of supporting plans, making comparisons among municipalities, or ranking high pedestrian crash zones on several territory or city levels. For example, Lam et al. [45] explore the spatiotemporal relationships of individual travel patterns and crash locations. In addition, this study demonstrates that the travel diary data can generate a uniquely useful exposure measure because of its highly disaggregated nature. From the analysis, one can see that both crash frequency and risk varied by space and time. The results show that the district's town centre during the afternoon rush hours was the most hazardous location and time for elderly pedestrians.

Lastly, economic-based studies implemented to highlight contributory factors in pedestrian crashes are classified. The study of this category [44] applies two methods to make an analysis: Willingness to pay and Contingent Evaluation Method alongside Descriptive Statistic Analysis. The study finds that the estimated value of statistical life (VOSL) for Sudanese people is between US$0.019 to US$0.101 million. The willingness to pay to reduce fatalities increases with age, income, education level, safety perception, and time spent on social activities. The willingness to pay method is widely applied in road accidents, but as it emerges from this review, exclusively for road crashes in general [45–50], to evaluate the maximum amount of money to avoid a risk. As far as the contingent valuation (CV) method [51], it is a widely applied approach for non-market valuation, particularly in environmental cost-benefit analysis and environmental impact assessments. In environmental economics, it is used to estimate non-use values, nonmarket use values, or a combination of both for environmental resources.

3.2 Pedestrian Crash Frequency Models

Crash-frequency models represent the second modelling category. Common applications of these models regard the understanding of relationships between dependent and independent variables, screening variables to understand if a variable has a significant effect on the outcome (by using technique to rank the importance of variables) and sensitivity of variables, which is an in-depth analysis of the coefficients of the model in greater detail than the screening variable (by evaluating the marginal effects of a variable and so how dependent variable changes when an independent variable changes), and finally to make prediction, and in this case, to forecast the number of the accident on a road or at intersections [52].

Following this classification according to the application of the models, the collected and analysed papers fall into two classes: understanding relationships, and modelling.

Table 1. Risk Factor Analysis Categories.

Categories	Methods	Datasets	Results	References
Descriptive Statistics	Frequency Distribution	Accident data	Recurrent patterns and scenarios Risk reduction assessment	[16–29]
Statistical Approach	Double Pair Comparisons Approach, Quasi-induce Exposure Models, Two-step cluster analysis,	Accident data Census data	Risk reduction assessment Crash rate	[36, 39, 42]
GIS-based Approach	Spatial Statistical Analysis, Kernel-based Methods	Accident data Census data	Ranking High pedestrian crash zone	[28, 43]
Economic-based Approach	Willingness to pat methods Contingent evaluation methods	Survey	Willingness to pay	[44]

In all cases analysed, relationships among variables and the need to forecast accident frequency were bounded, which were also the main objectives of the collected papers. For this reason, it was not possible to follow this classification.

From the analysed literature, it emerges that the distinctive feature regards the spatial unit, namely the unit on which the analysis is carried out. In the context of determining the pedestrian crash frequency, the forecasting number of accidents could be evaluated on pedestrian crossings [53], road segments [54–59], intersections [60–64], Traffic Analysis Zone (TAZ) [65–70], or Census Tracts level [56, 57]. As it is possible to observe in Table 2, in comparison also with Table 1 in the previous section, the need to create accident prediction models requires a larger amount of data than the data required for risk factor studies: the higher the complexity of the spatial unit, the higher the number of datasets required to describe in an adequate way the unit. A common characteristic regards the employment of traffic data and, in particular cases, also pedestrian exposures [53, 55–57, 70, 72].

It emerges also that by increasing the complexity of the spatial unit, different models could be employed. For pedestrian crossings, road segments, and intersections, both the Empirical Bayes Approach and Statistical models are often used [53–64]; while the complexity of the spatial unit increases (TAZ and Census Tracts), Statistical Distributions are exclusively implemented [65–72].

Statistical Frequency Models can predict a crash that happens at a constant average rate (such as Poisson Models) or with a higher variability (i.e., Negative Binomial Models, which are more able than Poisson Models to describe this phenomenon when the

Table 2. Classification of the pedestrian crash frequency studies according to the spatial unit.

Spatial Unit	Datasets	Models	References
Pedestrian Crossings	Pedestrian crashes, Geometric Characteristics, Pedestrian and Traffic data	Empirical Bayes Approach	[53]
Road Segment	Pedestrian crashes, built environment, Pedestrian and traffic data, survey	Empirical Bayes Approach, Statistical Frequency Models	[54–59]
Intersection	Pedestrian crashes, built environment, Pedestrian and traffic data, socio-demographic data	Empirical Bayes Approach, Statistical Frequency Models	[60–64]
Traffic Analysis Zone (TAZ)	Pedestrian crashes, built environment, Pedestrian and traffic data, socio-demographic data	Statistical Frequency Models	[65–70]
Census Tracts	Pedestrian crashes, built environment, Pedestrian and traffic data, socio-demographic data	Statistical Frequency Models	[71, 72]

variance is greater than the mean) [52, 73, 74]. The vast majority of analysed papers heavily rely on Negative Binomial Models. As highlighted by some authors [75, 76], it is common that such type of models are characterized by the regression to the mean frequency, a statistical phenomenon that occurs in forecasting future crashes in locations in which the number of accidents is very high or very low. Future values are more likely to assume the average value. The Empirical Bayes Approach can mitigate this issue.

The Empirical Bayes Approach is often implemented to evaluate Safety Performance Functions (SPFs), which are regression models that can predict the number of road accidents, based on several factors such as traffic volumes, geometry, and so on [77, 78]. The Empirical Bayes Approach tends to combine observed crash data with prior historical crash data or with data from similar sites to account for variations in crash frequency [76]. The Approach relies on the definition of prior and posterior distribution. The prior distribution is based on historical crash data to evaluate crash count at a specific site level [79, 80]. When data for a specific location are unavailable, similar sites could also be considered. The posterior distribution is obtained through Bayes' Theorem by combining the prior distribution (that gives the number of crash that happens) and the likelihood that accidents could happen on observed crash data [79, 80]. The expected crash frequency, evaluated as the mean of the posterior distribution, provides a more accurate estimate.

3.3 Pedestrian Crash Severity Models

Crash severity refers to the damages a pedestrian or road user may have when a crash occurs [81]. It could be classified into levels according to the degree of lesions [82, 83]. Pedestrian crash severity models can predict the outcome of a crash and evaluate the probability of the accident itself. From the analysed literature, the idea of classification performed is shown in Table 3. Pedestrian crash severity models are often used to perform pattern recognition tasks [84–86], Variable importance Analysis [87–103], and model development [85, 86, 104–111]. For each of the tasks described in Table 3, econometric and Machine Learning Approaches could be implemented to achieve the purposes of the task.

Regarding the pattern recognition task, Latent Class Analysis (LCA) [84], Association Rules, and Classification Tree [85, 86] are often used to solve the proposed model: the first technique belongs to the Econometric field, the other to the Machine Learning Approach. LCA is an econometric technique that aims to find subgroups that share features in the dataset [112], while association rules is a data mining technique that aims to find relationships among variables [113]. The Decision Tree algorithm split the observation into several leaves, with the aim (similar to LCA) to find groups as homogeneous as possible [85].

The decision tree method is not only used for pattern recognition tasks but also for performing variable importance analysis and model development. The reason why it is divided into Variable Importance and Model Development Tasks is that some models (especially some machine learning algorithms) cannot be implemented to find relationships between dependent and independent variables. Logistic Regression Models and their evolutions and tree-based models, such as Decision Tree and Random Forest, can be used to achieve both tasks. Other models among the Machine learning algorithms (Neural Network, Support Vector Machine, k-nearest neighbour, Bagging, Boosting, XGBoost, Naïve Bayes) are only used to model development.

Table 3. Classification of the pedestrian crash severity studies according to the spatial unit.

Task	Approach	Models	References
Pattern Recognition	Econometric	Latent Class Analysis	[84]
	Machine Learning	Association Rules	[85, 86]
		Classification Tree	[85, 86]
Variable Importance Analysis	Econometric	Logistic Regression	[84, 87–90, 93–95, 100, 101]

(*continued*)

Table 3. (*continued*)

Task	Approach	Models	References
		Mixed/Random Parameter Logit	[85, 86, 102, 103]
		Multivariate Logit	[91]
		Ordered Logit	[86, 95]
		Partial Proportional Odds	[95, 96]
		Ordered Probit	[99]
	Machine Learning	Decision Tree	[85, 86, 104–106]
		Random Forest	[85, 86, 107, 108]
Model Development	Econometric	Logistic Regression	[84, 87–90, 93–95, 100, 101]
		Mixed/ Random Parameter Logit	[85, 86, 102, 103]
		Multivariate Logit	[91]
		Ordered Logit	[86, 95]
		Partial Proportional Odds	[95, 96]
		Ordered Probit	[99]
		Linear Discriminant Analysis	[104]
		Quadratic Discriminant Analysis	[104]
	Machine Learning	Decision Tree	[85, 86, 105–107]
		Random Forest	[85, 86, 108, 109]
		Bagging	[106]
		Boosting	[106]
		Support Vector Machine	[86, 110]
		XGBoost	[109, 111]
		Naïve Bayes	[109]
		K-nearest Neighbour	[108]
		Neural Network	[98, 100, 108]

4 Discussion and Conclusions

The classification proposed here aims to answer the research questions shown in Sect. 2. As it emerges from the previous sections, by analysing the studies collected, the discriminant on which the classification is based is the output of the model. Studies based on identifying the contributory factors with the implementation of statistical techniques identify the first category, which is named Risk Factor Analysis. Studies that aim to predict the number of pedestrian accidents use models from the statistical field and are classified as Pedestrian Crash Frequency Models, while the last category aims to predict the severity of crashes involving pedestrians by using econometric and Machine Learning Models, and these models are classified as Pedestrian Crash Severity Models.

As it is shown in the analysis, the main dataset needed to study pedestrian accidents (Research Question 1) depends on the output of the model. If the purpose is to study with statistical techniques the contributory factor, the pedestrian crash dataset is enough to perform such type of analysis and evaluate the severity of accidents with Pedestrian Crash Severity Models. If the objective of the analysis is frequency forecasting, more datasets are needed.

The availability of some datasets over others also regulates the typology of methods that could be implemented (Research Question 2). Regarding Risk Factor Analysis, Descriptive Statistics, Statistical Approach, GIS-based Approach, and Economic-based Approach could be implemented (see Table 1); for Pedestrian Crash Frequency Models, mainly Empirical Bayes Approach and Statistical Models are the predominant methods used (see Table 2); while for Pedestrian Crash Severity Models, Econometric and Machine Learning Methods are the most used approaches (see Table 3).

But which are the main research gaps? From the analysis of the selected studies, the datasets used to create crash frequency models are very detailed and take into account, for instance, traffic and pedestrian flows, which are some data difficult to retrieve. This highly detailed framework is not present when the objective is to evaluate the severity of pedestrian accidents. When Pedestrian Crash Severity Models are applied, national datasets provided by agencies that collect such types of data are used. Despite the high number of features that are collected, some information regarding some variables that are related to the severity of the involved pedestrians (such as pedestrian and vehicular flows and speeds) is not available.

Alongside this aspect, Machine Learning Models that are strongly utilized in predicting the severity of pedestrian crashes are not implemented as regression methods to evaluate and forecast the pedestrian crash frequency. In addition to that, among the Pedestrian Crash Frequency studies, there is a limited number of studies that focus on predicting crash frequency for pedestrian crossings.

In conclusion, this paper aims to give a brief overview of methods and models that could be implemented in pedestrian safety. Based on the availability of some datasets or others and the study's objective, several models could be used to perform the analysis. In a complex field of analysis in which every day new methods and technologies are applied, this paper aims to give a guide and also a tutorial for the first steps in pedestrian accident modelling. A deep dive with selecting only a few papers and highlighting their limitation and innovative elements is a future development of this paper.

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