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Speed related variables for crash injury risk analysis: what has been used?

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ABSTRACT
Speed is a major risk factor in overall road safety performance. The objective of this study was to identify the most frequent explanatory variables and measures used to investigate the speed factor contribution to crash injury risk (CIR). For this purpose, a literature oriented approach was used. The analysis review, underpinned by data collected from 64 journal publications reported over the past 21 years shows that speed limit was the most frequently used variable selected by the authors to investigate speed contribution CIR. Following, speed delta-V was the second most used variable, despite the barriers to access in-depth crash quality data. Even so, the speed limit was used 3.5 times more than delta-V, possibly due to the facilitate accessibility to the roads standardize posted speed limits. However, it is unknown how much vehicles travel speed could deviate from the posted speed limit at the moment of the crash.

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KEYWORDS
Crash; injury; risk; speed; variables; vehicle

1. Introduction

Among crash risk factors, speed is recognized as a significant contributor to severe outcomes. In Europe, excessive and inappropriate speed contributes to one third of fatal collisions and is an aggravating factor in most collisions [1]. In the US, during 2016 27% of the traffic fatalities were in crashes where at least one driver was speeding [2]. An increase in the posted speed limit can raise accident injury severity by 2.3 times [3]. Several studies have attempted to determine the contribution of risk factors to crash injury severity [4–18]. Existing findings tend to be inconsistent, possibly due to the different definitions, such as for speed variations and crash type consideration or different modelling and data aggregation approaches [18]. Besides, several review articles have also been published [19–28]. However, none have focused on the different selection of variables and measures used to explore the speed risk factor.

This study, therefore, explores the wide range of variables that have been selected in previous studies to better understand what has been the most frequent choice used by the authors. The assessment of speed effect to injury risk receives in this paper special attention as it is crucial to improve road safety performance and in the medium and long-term goals to reduce the number of road traffic collisions, injuries, and deaths in which excessive or inappropriate speed is a contributory factor. The objective of this paper is to present the variety of explanatory variables and measures used to investigate the speed factor contribution to crash injury risk (CIR) based on a comprehensive review of the literature. The findings inform on the most frequent choice of variables selected for the analysis of speed factor and on the suitably of those variables. Thus enhancing future studies planning and design in the field of road safety.

2. Method

2.1. Study into context

Crash risk analysis takes into account the cause and effect relationships between three major factors: human, vehicle, and environment (which involves accident circumstances and road infrastructure). This study centres primarily on the accident risk factor analysis, with an emphasis on speed contribution to injury risk. For this purpose, an explanatory variable (or predictor variable), is the variable that is being manipulated to observe the effect on a response variable, or dependent variable, which in this context refers to crash injury level, such as a fatality or non-fatality, if using binary classification, or non-injured, minor injured, medium injured, serious injured, and fatality if using an ordered severity classification. The analysis review presented in this paper focuses on the accident explanatory variables used to model the CIR; the response variable that represents any injury severity level sustained by a vehicle's occupants.

This section provides a summary of the processes for determining the inclusion of studies, record and synthesis of variables used.

2.2. Literature search

A literature search using keywords such as accident, crash, collision, injury, speed, speeding, model, and risk, *via* two major platforms, ScienceDirect and Engineering Village, was

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Table 1. Overview of the studies by scientific journal.

Scientific journal	Studies
Accident Analysis & Prevention	47
Analytic Methods in Accident Research	4
Injury	1
International Journal of Crashworthiness	1
Journal of Safety Research	4
Journal of Transport & Health	1
Resuscitation	1
Safety Science	2
Transportation Research Part B: Methodological	1
Transportation Research Part C: Emerging Technologies	1
Transportation Research Part D: Transport and Environment	1
Σ	64

conducted until October 2018. The adopted keywords yielded an excessive number of related studies. Therefore, additional screening was adopted. The criteria for prioritising the studies to be included in this paper is outlined below.

- Report road accidents involving injuries and or fatalities to the vehicle's occupants.
- Involving accidents where at least one of the vehicles was a light vehicle.
- Availability of variables information used for the analysis.
- Published in English.
- Peer-reviewed journal articles only.

Studies were excluded if they complied with the following criteria: insufficient information on the crash data and/or variables description, use of driving simulator data or crash simulation data, review articles and articles with titles stating: pedestrians, motorcycles, cyclists/bikes, and heavy vehicles/trucks/buses. The selection of reference studies was based on the selection criteria and relevance to the field of factors contributing to injury severity risk in accidents involving light vehicles and independent of studies' citation indexes metrics.

2.3. Record and interpretation of explanatory variables

For each study in the literature data set, the explanatory variables used to investigate the effect of accident elements in injury risk were identified and variables were recorded. The selected studies were individually coded in a Excel template developed for this study. For a comprehensive synthesis and also to facilitate the comparison of variables used for the speed and accident type risk factors by each study, a vote-count analysis was adapted [27]. In addition to the vote-count technique, a review type analysis was undertaken to provide a comprehensive comparison of the selected variables.

3. Results

3.1. Overview

In total, 64 studies were recorded for the literature data set based on the screening criteria (explained in Section 2.2) and relevance to the field of road safety. Table 1 presents

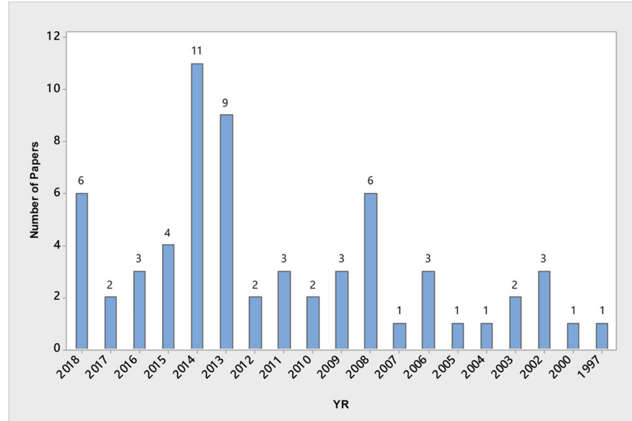

Figure 1. Number of publications per year of included studies ($N = 64$).

the number of literature studies used for the analysis review, grouped by scientific journal.

The 64 studies were selected from 11 scientific journals capturing a 21-year time period spanning from 1997 to 2018, as shown in Figure 1.

The two years with more publications were 2014 (11) and 2013 (9). The higher number of publications for these two years corroborates with [27]'s systematic review.

3.2. Summary statistics

For the accident risk factor, all the variables extracted from the literature data set were recorded as discrete data, code '1' denotes a predictor included in the reference study, otherwise '0'. Then, the sum allowed to account for the number of variables (predictors) used in each study to investigate the accident factors that included accident type (crash configuration such as rollover or head-on collision) and speed. Besides, when the speed factor was included in the reference study, the abbreviation of speed measures was chosen instead (rather than code '1'), otherwise '0'. This approach allowed to account for the source of the speed factor estimation through the literature studies, such as 'SL' indicating speed limit or 'SI' indicating speed of impact. As for the review type analysis speed was treated as a categorical variable, the proportion of studies is used rather than the mean. Table 2 presents the summary statistics for the explanatory variables used to model the accident risk factors across the literature studies. In general, to investigate accident risk factors around four variables (3.67, SD 1.83) were used in literature studies. To explore the effect of crash type, studies used 3 variables (3.00, SD 1.85). The most common observed measure to explore the effect of speed risk factor was SL (Mode SL) as exhibited in Table 2.

3.3. Explanatory variables used to analyse the speed risk factor

The variables extracted through the literature studies were used to derive a list of explanatory variables, or predictors in the broader sense, to be used for CIR factors analysis. Table 3 presents the outcome of the coded studies for the

Table 2. Summary statistics of accident explanatory variables used across the studies ($N = 64$).

Variable	Total count	Range	Mode	Mean (SD)	Proportion
Accident factors	236	0- 6	5	3.67 (1.83)	–
Accident type	192	0- 5	5	3.00 (1.85)	–
Speed	44	–	SL	–	44/64

SL: speed Limit.

two aspects covered in this paper, accident type and speed risk factors, and it is used for cross-comparison of explanatory variables selected in the literature studies. The definition of speed abbreviation codes can be found in Table 3. The literature review analysis results show that 38% (24/64) of the studies covered the five accident types listed in Table 3, such as the work published by Hassan and Al-Faleh [50] and Torrao et al. [66]. On the other hand, 8% (5/64) of the studies focused only on one accident type, e.g. Gårder [49], Conroy et al. [43], and Tolouei et al. [10] exclusively focused on head-on collisions. A possible explanation for prioritizing this accident type could be the fact that head-on collisions are known to have the highest fatality risk [78].

Speed is a scalar quantity measured in units of distance divided by time (e.g. kilometres per hour) and the magnitude of the velocity, which is the speed with a direction. Although in the literature the term speed is widely used but explored using a variety of measures. Figure 2 shows the different measures used to examine the speed contribution to road injuries. The literature studies aimed at capturing the effect of this risk factor by investigating the average speed, speed limit, speed impact, and speed ratio or delta-V contribution to the CIR.

Although 69% (44/64) of studies included the speed risk factor, the majority of those (64%, 28/44) used speed limit, as presented in Table 3 and Figure 2. Other speed related measures used with decreasing frequency through the literature were: delta-V (8/44), speed impact and speed ratio (both with the proportion of 3/44), average speed (2/44) and standard deviation of speed (1/44).

4. Discussion

Vehicle's speed is recognised as a major factor linked to severe road injuries and 69% of the studies included this risk factor. This section provides a discussion of the measures used to examine the speed contribution to injury risk by grouping the literature approaches according to their approaches.

4.1. Approaches to examine the speed risk factor

4.1.1. Speed limit

The first approach group refers to the studies that included the speed limit as the measure to investigate the effect of speed in injury risk and it accounts for the largest group in the literature dataset. Speed limit was the most frequent measure (44%), as shown in Tables 2 and 3. Several authors used the legal speed limit as a 'proxy' of a vehicle's speed at the moment of a crash [4,13,47,48,57,66,72]. One possible reason for the highest proportion (28/64) of studies using speed limit measures might be the easily reachable

Table 3. Accident factor explanatory variables used for CIR analysis in the literature studies.

Publication reference		Accident type				
	Speed	Ran off	Rollover	Head-on	Sideswipe	Rear End
[29]	SR*	0	0	0	0	0
[30]	SI*	1	1	0	0	0
[17]	SL	0	0	0	0	0
[31]	SL	1	1	1	1	1
[15]	SL	0	1	0	0	0
[32]	0	1	1	0	0	0
[33]	0	1	1	0	0	0
[34]	SI	1	1	0	0	0
[35]	0	1	1	0	0	0
[36]	ΔV	1	0	0	0	0
[4]	SL	0	0	1	1	1
[5]	0	1	1	1	1	1
[37]	ΔV	0	1	1	1	1
[38]	SL	1	1	1	1	1
[39]	SL	0	0	1	1	1
[40]	SL	1	1	1	1	1
[41]	0	0	0	0	0	0
[42]	SL	0	0	1	1	1
[18]	MS/L	0	0	0	0	0
[6]	AV	0	0	0	0	0
[43]	ΔV/BES	0	0	1	0	0
[44]	SL	0	0	1	1	1
[45]	0	1	1	1	1	1
[16]	0	0	0	1	1	1
[46]	SL	0	0	1	1	1
[47]	SL	0	0	0	0	0
[48]	SL	0	0	1	1	1
[49]	0	0	0	1	0	0
[50]	SL	1	1	1	1	1
[51]	SL	0	0	0	0	0
[52]	SL, SR	0	0	1	1	1
[53]	SL	1	0	1	1	0
[54]	SL	1	1	0	0	0
[55]	SI	1	1	1	1	1
[8]	ΔV	1	0	1	1	1
[56]	0	1	1	0	0	0
[57]	SL	1	1	1	1	1
[58]	0	1	1	1	1	1
[59]	SL	1	1	1	1	1
[60]	0	1	1	1	1	1
[61]	0	1	1	1	1	1
[7]	SL	1	1	1	1	1
[62]	0	1	1	1	1	1
[13]	SL	0	0	0	1	0
[9]	ΔV	1	1	1	1	1
[63]	BES	1	1	1	1	1
[64]	ΔV	0	0	1	1	1
[65]	0	1	1	1	1	1
[10]	VC	0	0	1	0	0
[66]	SL	1	1	1	1	1
[67]	SL	1	1	1	1	1
[68]	0	1	1	1	1	1
[69]	0	1	1	1	1	1
[11]	0	1	1	1	1	1
[70]	0	1	1	1	1	1
[14]	0	1	0	0	0	0
[71]	SL	1	1	0	0	0
[72]	SL	0	0	1	1	1
[73]	SL	1	1	1	0	0
[74]	SL	0	0	0	0	0
[75]	0	1	1	0	0	0
[76]	StS	0	0	0	0	0
[77]	SR*	0	0	1	1	1
[78]	SL	1	1	1	1	1

SI: speed of Impact; SI*: self-reporting speed; SL: speed Limit; SR: speed/Limit speed; SR*: speed ratio for two-vehicle collisions; ΔV: delta-V: change in vehicle velocity associated with the impact force following the crash; VC: velocity change of the vehicles during the collision ($\Delta v1$ and $\Delta v2$) based on the mass ratio and closing speed of the vehicles; AV: average speed for all lanes and over 6 min; StS: standard deviation of speed; BES: estimation if the speed at the time of impact, based on an examination of the vehicle and crash data at the scene; and MS/L: mean speed by lane.

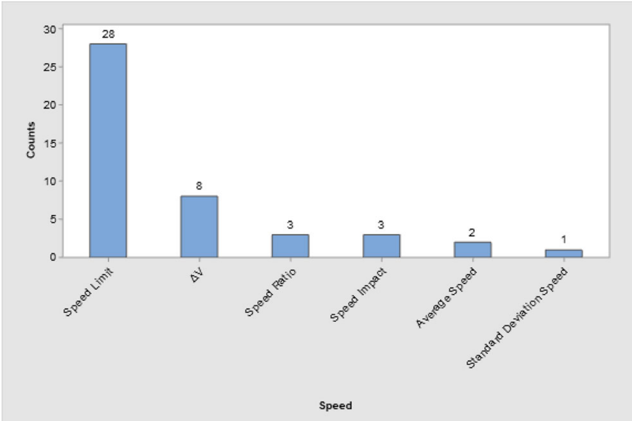

Figure 2. Variables used for the speed risk factor analysis with application to CIR investigation.

information. Another possible reason might be linked to the authors' study design for which speed limit could be pertinent for the research objectives. Anarkooli et al. [15] found a positive association between speed and the likelihood of fatal, serious, and slight injuries; stating that 'one can conclude that the posted speed limit can be used as a proxy to a vehicle's travel speed in which the actual pre-crash speed of the vehicle is unknown'. This correlation could be understood for the cases where the vehicles are more or less travelling closer to the speed limit at the moment of the crash. However, this is not necessarily always the case. On the other hand, if another vehicle is involved in the collision, the resulted impact speed would be affected. Speed limit violations are very common, either intentionally, or unintentionally, typically 40% to 60% of the drivers exceed the posted limit in the European roads [79]. Therefore, for those cases where the vehicle involved in a crash was speeding, the approach of using the speed limit as a 'proxy' of a vehicle's speed may potentially be leading to biased estimates. Thus, careful consideration is needed thorough examination of models results using as input variable speed limit data.

Others have considered the effect of excessive speed, which was defined on the basis that the vehicle was travelling above the posted speed limit. Ulfarsson and Mannering [67] developed a multivariate multinomial logit model of injury severity by considering a driver's speed violation, with the risk factor represented by the exceeded reasonable speed or speed limit. Similarly to Anarkooli et al. [15] and Ulfarsson and Mannering [67], Fountas et al. [47] modelled the speed factor using speed excess; coded as '1' if a vehicle's speed exceeded a safe level or speed limit and '0' otherwise. This approach seems more realistic than simply using the speed limit values as it may benefit the analysis for the cases where excess speed was involved. However findings may be limited if not quantifying the extent to which the vehicle was travelling above the speed limit, such as 5% or 25% deviation from the posted speed limit.

4.1.2. Speed derivative measures

The second approach group refers to the studies that used speed measures calculated based on crash reports and other available information. Three studies used computations of speed estimations and these are identified under the speed ratio series, in Figure 2. Abdel-Aty [29] focused on the injury severity of drivers involved in traffic crashes in the vicinity of toll plazas and estimated the speed factor as the ratio of running speed at the time of a crash and post speed at the location of the crash. To model the effect of speed factor to injury risk, Huang et al. [52] used the speed limit and relative speed, calculated by the sum of the estimated speeds of the colliding vehicles or absolute value of the difference between the estimated speeds of the colliding vehicles, for head-on and rear-end crashes, respectively. On the other hand, Zeng and Huang [77] modelled the speed factor as the speed ratio of two vehicles involved in a collision. Christoforou et al. [6] used a random parameter ordered probit model to explore the influence of speed and traffic volume on the injury level sustained by the vehicle's occupants using the average speed as the explanatory variable. This approach used speed data recorded over six min intervals, ending 12 min before a crash. The speed value reflected an average speed for all road lanes over six min (in km/h) and not the vehicle's travelling speed at the time of the crash. An interesting approach for estimating the speed involved in a crash was presented by Yu and Abdel-Aty [76] that included hierarchical Bayesian binary probit models to analyse crash injury severity on high-speed roadway segments with real-time traffic data in the US. These authors used the space mean speeds captured by the automatic vehicle identification (AVI) system on roadways as the explanatory variables. The AVI traffic data provided average segment speeds at one and two min intervals, according to the roadway segment. The mean, standard deviation, and coefficient of variations of the AVI speed at six min intervals were calculated and used as explanatory variables in the crash injury severity analysis to represent the traffic flow conditions when the crash occurred. Crashes were assigned to the AVI segments based on mile markers posted along the road. The crash data were then matched with the AVI speed information. Yu and Abdel-Aty's [76] suggested that a large variance of speed prior to crash occurrence would increase crash severity. By using the AVI systems information the authors were able to account for more realistic estimates on the speed between the miles markers where a crash occurrence was registered. However vehicle's speed may change over a short segment, the use of average speeds may be a deterrent when there is dispersion for the set of speed values. Authors recognised that 'Large variance of speed prior to the crash occurrence would increase crash severity' [76]. In addition, the authors also mentioned that seat belt information was not included. The absence of seat belt use by a vehicle's occupants could magnify the speed contribution to severity risk, compared with other crashes that have involved similar speeds and vehicle characteristics but where the vehicle's occupants wore seat belts. Choudhary et al. [18] explored the relationships between speed variations and crashes on a freeway segment in the UK using crash data obtained from STATS 19 from 2013 to 2015, and supplemented this data with traffic volume and mean speeds by lane for the study segment area. Results suggested that the crash rates increased as the speed variations within the lanes increased, especially at higher traffic volumes. Thus, this study also contributes to reinforcing the need to account for speed variations in crashes data analysis.

4.1.3. Estimates of actual speed involved in the crash

The third approach group refers to the studies that have accounted for the estimates of speed involved in the crash to examine the risk of injury sustained by a vehicle's occupants. Three studies (5%) included the speed of impact: Kockelman and Kweon [55], Abu-Zidan and Eid [30], and Behnood and Mannering [35], as shown in Table 3. Abu-Zidan and Eid [30] developed a general linear model for the effect of injury factors where the speed variable measure used was impact speed. However, this study reported that the speed data was based on self-reporting by patients. Although interviews are a scientifically valid approach, patients may not precisely remember the actual driving conditions at the moment of the crash, nor the speedometer reading. In addition, patients may intentionally hide relevant information, especially when speeding is involved. The actual speeds involved during the collision are identified amongst the most important factors for injury risk [8,29,34,55,80–82]. Nonetheless, data of the vehicle's speed at the moment of an accident are non-existent in the majority of the studies, especially those based on police record reports. Police reports are a major source of crash data worldwide, yet variables are often missing and detailed information is marginal. Issues related to crash quality data have been well addressed [20,23,24,28]. Concerns derive mainly from difficulties in data linkage due to inconsistencies in databases, severity misclassification, inaccuracies and incompleteness of crash contributory factors [23].

4.1.4. Delta-V

The fourth and last approach group refers to the studies that investigated the speed contribution factor using a more complex measure. This explanatory variable, Delta-V has been defined as the: 'change in vehicle velocity associated with the primary direction of the force of the crash event' [8] or 'longitudinal means of the cumulative change in velocity, as recorded by the EDR of the vehicle, along the longitudinal axis, starting from crash time zero and ending at 0.25 s, recorded every 0.01 s' [83,84]. In a study conducted in Sweeden, Ydenius [73] analysed 422 frontal vehicle crashes from 1992 to 2006 to investigate how vehicle crash severity varies in frontal crashes for different posting speed limits, road friction. Ydenius's [73] results showed a significantly higher delta-V on 90 km/h roads compared with 70 km/h roads, 4.6 ± 4.1 km/h. In addition, average delta-V was significantly higher on 90 km/h roads compared with 50 km/h roads, 7.0 ± 5.9 km/h. The highest average crash severity was found on 90 km/h roads, both regarding delta-V and mean acceleration. Despite the usefulness of the delta-V quality data value for investigating the effect of the speed factor in injury risk, only 13% (8/64) of the studies used this variable, as presented in Table 3 and Figure 2. This is due to the limited access to data sources with records for this important predictor. Kononen et al. [8] used the National Automotive Sampling System – Crashworthiness Data System for the calendar years 1999–2008, in the US. The authors developed a logistic regression model to predict the risk of serious injuries for the vehicle model year 2000 and newer vehicles, which models training phase benefited by accessing a large database with extensive information for crash related circumstances, including specific data for delta-V. Kononen et al.'s [8] findings identified delta-V, seat belt use, and crash direction as the most important predictors of serious injury.

Sobhani et al. [64] considered the factors contributing to speed change, which was estimated using the speed limit at the scene of the crash, principal direction of force (referring to angled and side crashes), weight of the opponent and subject vehicles, and area of most significant damage. Sobhani et al.' [64] study suggested that the ratio of mass of bullet vehicle over mass of subject vehicle and speed at the scene of the crash had a positive effect on the injury severity score. In this study, the actual speed of an opponent's vehicle before a crash was not available. To overcome this shortcoming, the authors used the speed limit at the scene of the crash as a surrogate variable for the speed of the bullet vehicle before a crash. Conroy et al. [43] focused on vehicles with deformation along the frontal plane in head-on crashes and a principal direction of force equal to 12 o'clock. In this study, when delta-V data was not available, the barrier equivalent speed (BES) was used to determine the change in velocity due to the impact. The BES was calculated for multi-vehicle crashes when there was insufficient information regarding the second vehicle to calculate delta-V. Conroy et al.'s [43] findings suggested that when controlling for intrusion, vehicle body type, vehicle curb weight, age, safety belt use, and delta-V, the type of damage distribution across the frontal plane may be important to consider when analysing drivers' injuries in head-on motor vehicle crashes.

Bose et al. [36] developed a computational methodology to predict injury risk for motor vehicle crash victims: a framework for improving Advanced Automatic Crash Notification systems using Crash Injury Research Engineering Network (CIREN) data. Similar to Conroy et al. [43], the approach to determine the crash kinematics was also based on the equivalent barrier impact speed, which was determined using the crash information and vehicle event data records (EDR) [36]. Later, to investigate the determinant factors in severe motor vehicle accidents, Shannon et al. [63] accounted for the speed at the time of impact using the BES, which was available from the CIREN database, estimated by technicians who examined both vehicles and scene data. Shannon et al. [63] concluded that the vehicle's relative speed at the time of impact significantly influenced the level of injuries sustained. It is worth mentioning that despite there being six late publications (articles published in 2018), none of these studies included delta-V. Difficulties in accessing quality data for in-depth crash investigation could be possibly a major reason. This finding is consistent with Tolouei et al. [10], who found the main difficulty in investigating the relationship between injury risk and speed was the lack of information regarding the speed of the vehicles prior to a crash, which is required together with the mass of the vehicles to calculate speed variation.

4.2. Limitations

First, the literature studies data set includes publications from 1997 to 2018. Therefore, temporal instability may exist due to significant differences across crash-data years. Time-varying unobserved heterogeneity is likely to exist amongst the population of crashes due to unmeasurable factors such as differences in individual behaviour (e.g. risk-taking behaviour), crash involved vehicles (e.g. variations in crashworthiness and safety features), and road infrastructure and environmental factors (e.g. average annual daily traffic and weather conditions) [35,75,85,86]. Second, the analysis review focused on 64 literature studies, and generalizations to other publications in the literature should be taken with care. Larger sample size would be beneficial for mapping the abundance of speed measures used in the studies of the road safety field.

4.3. Considerations

Although speed factor is recognized as a major factor for severe crash injuries occurrences, in-depth crash analysis is a very complex matter due to the underline relationships among risk factors: human, vehicle, and environment/crash circumstances. This paper was only centered on the last, with an emphasis on speed contribution to road injury risk. However, to develop a more comprehensive and integrated analysis of crash injury contributory risk factors, it would be fundamental to include the contribution of human factors, vehicle(s) factors and crash circumstances factors. In this complex matter, speeding and inappropriate speed may be linked to driver behaviour, which is a human risk factor. One aspect that is observed for some drivers' psychological profile is sensation seeking, which is the attitude associated with the willingness to perform risky behaviors, including risky driving and speeding [87]. In addition, there is also the inevitable contribution of vehicle occupants' physiological characteristics such as gender and age that could explain differences in the injury level sustained following a crash. The complexity of this matter makes the subject of another author's work where the accident risk factor is analysed simultaneously with vehicle risk factor and is published elsewhere [88].

5. Conclusions and future research

This paper aimed to present a comprehensive review of literature studies' approaches to select speed associated variables and measures used in the complex matter of crash injury risk (CIR) factors analysis. There is often a rationale for variable selections and combinations, which are dependent on the aim, study design, funding, and data accessibility. Hence any attempt to compare research results introduces a multitude of source variations, such as crash population characteristics and environment. This paper contributes to the literature by mapping speed related variables across 64 prior review papers for a period of 21 years. The results testify the abundance of variables measures used to assess the impact of speed risk factor, such as speed limit, average speed, standard deviation of speed, speed of impact and delta-V. From those, the speed limit was the most frequent measure used in the studies (28/64). It is unclear if the use of speed limit (the most used measure) was due to easy data accessibility or due to sparse information on the crash circumstances. Whether measures were appropriate depends on what the authors were attempting to capture and how closely they aligned their interpretation with what was measured. Despite significant research, there are opportunities to improve the approaches investigating speed risk factor contribution to road injuries. Besides, the road speed assessment framework operates on the principles that the posted speed limit should be guided by whether the accident rate on a section of road is above or below the respective 35 or 60 injury accident thresholds [89]. Still, efforts are needed to improve the understanding by users of the risks involved on different types of roads and the speed limits which apply and why self-compliance is important.

Future research on analysing CIR factors should not seek ideal measures (which are largely impossible) but focus on the best way to measure important variables to increase model accuracy and reliability and well as knowledge transferability for road safety assessment and the automobile industry.

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