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Full Length Article

Parameters influencing pedestrian injury and severity – A systematic review and meta-analysis

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ABSTRACT

Pedestrians account for 26% of all traffic fatalities worldwide. According to in-depth collision databases, around 3500 variables can affect the outcome of a collision, making it crucial to establish the relationship between each variable and the outcome. To date, there is no method defined to assess these variables' relevance other than a statistical correlation, which can sometimes lead to reasonable conclusions, but only under specific circumstances. This article addresses this issue by first conducting a literature review to determine all relevant variables, followed by developing a variable selection criterion to select crucial variables, and then conducting a meta-analysis to quantify these relationships. Epidemiological studies published between 1990 and 2022 were examined, including 93 papers from 19 different nations that considered 904,655 pedestrian collisions. Of the 204 variables that were extracted from these studies, 152 were examined using the variable selection criterion, and 68 were found to be significant. Of these, 20 were included in the meta-analysis, which combined odds ratios to aggregate the effect of a variable across various studies, thus removing study-specific conclusions. This study makes a compelling argument that using statistical correlation by itself is insufficient to determine a variable's significance. The proposed method is an objective way to distinguish the variables for stakeholders and identify their relevance. This study offers a definitive list of the 15 characteristics that must be present in any pedestrian-to-vehicle collision databases, as well as a list of 53 variables that require additional investigation, allowing for appropriate actions for safer roads.

1. Introduction

Around the world, traffic accidents continue to be a leading source of fatalities and injuries. They account for the deaths of approximately 1.35 million people each year, and about 26% of those are pedestrians. Road traffic injuries (RTI) are now the leading cause of death for children and young adults aged 5–29 years, and the global economic burden of motor vehicle collisions and pedestrian injuries totals £26 billion [1]. Of all the road users, pedestrians are the most affected and are prone to more injuries than any other participant in a vehicle collision. Since 2019, there have been about 36,487 pedestrian casualties in Great Britain [2]. Pedestrian RTIs can be classified into three categories: primary, secondary, and tertiary. Primary RTIs are those that occur at the first contact with a vehicle, like a bumper. Secondary injuries are the ones caused by the second impact, such as windscreen or bonnet. Tertiary injuries are caused by contact with infrastructure, such as the road. The head, torso, and lower extremities are the most injured body regions for pedestrians [3]. The head is the most commonly injured body region in fatal vehicle-to-pedestrian crashes, while lower extremity injuries often result in long-term disability [4].

Research has been carried out in order to better understand and determine the variables that influence pedestrian-to-vehicle collisions and the injuries they cause. The data for these studies is either from in-depth collision databases or from generalised demographic data, for example, police and/or medical records. Statistical methods, like logistic regression and ordered probit, are the most common methods used to quantify the relationship between the variables and the severity of the injuries [5,6]. Some studies have also explored the use of advanced machine learning methods like artificial neural networks [7]. Although there is agreement that a subset of parameters like impact speed are the most influential, other parameters considered vary across each study. This is particularly important when comparing these studies, since not

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all parameters are relevant across regions. This discrepancy has led researchers to conduct region- analyses analysis and disagree with the findings of others. For example, according to Kim et al. [8] and Richards & Carroll [9], the severity of pedestrian injuries increases with age, while Kong & Yang [10], who used logistic regression to analyse 104 pedestrian accidents in China, disagreed.

The most important aspect while conducting a study to establish a relationship between variables and injury severity is to determine whether these variables are relevant, as statistically, due to the law of large numbers, almost any variable will start to display a statistical link with the dependant variable [11]. As a result, it is especially important to establish the relevance of a variable objectively before testing its statistical significance. There are several additional limitations to the previously published literature reviews. For example, they concentrate on the frequency of the parameters under consideration [12]. Others restrict the number of studies that are considered and do not assess the odds ratio (i.e., a measure of association between an exposure and an outcome). To address these limitations, this study set out to:

Step 1: Conduct a literature review and compile a list of all the variables that have been demonstrated to cause pedestrian accidents and influence the severity of resulting injuries.
Step 2: Develop a criterion for determining a variable's relevance to a vehicle-to-pedestrian collision and select relevant variables from the list compiled in step 1.
Step 3: Conduct a meta-analysis of the variables selected in Step 2, which entails comparing research based on effect size and determining if these variables have any effect on the outcome, i.e., the resulting injury severity.

2. Methods

This study sought to identify all research that investigated the association between variables and their effects on the severity of pedestrian injuries sustained in a vehicle-to-pedestrian collision from 1977 to 2021. The aim of this literature was to answer: which variables were proven to have an influence on the severity of vehicle-to-pedestrian crashes?

Once the list of variables was compiled, a criterion was developed to establish the relevance of each variable with respect to the severity of vehicle-to-pedestrian accidents. This criterion categorises each variable as a control-variable, disturbance, not important, or an output. The aim of this criterion was to evaluate the relationship between each variable and the injury severity objectively, irrespective of its statistical significance.

After the segregation, variables under control-variable and disturbance are considered for meta-analysis, which is a statistical method to combine the findings of various studies. It is usually performed when there are multiple scientific studies addressing the same question, with each producing conclusions that are expected to be biased in some way. Fig. 1 shows the steps followed in this study.

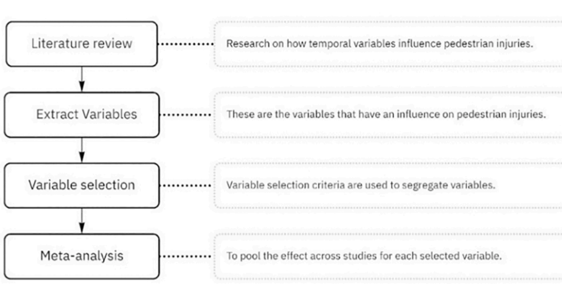


Fig. 1. Overview: Study methodology.

2.1. Literature review

2.1.1. Protocol and information sources

The literature review was conducted with the view of examining the influence of variables on the severity of pedestrian injuries. Popular databases like PedMed, Scopus, Web of Sciences, ScienceDirect, Google Scholar, and Locate were searched for published articles and reports. References to identified articles were also considered in the selection criteria.

2.1.2. Eligibility criteria

Studies were included if: (1) The study should be focused on assessing pedestrian accidents. (2) The study should have assessed the causation of the accident or the severity of the accident. (3) The study should have considered and assessed at least one parameter. (4) Investigated the severity or frequency of a vehicle-to-pedestrian collision as a result. (5) It should be published in English. Each record is assessed twice against inclusion criteria to determine if the study is to be considered for further analysis.

2.1.3. Search strategy

The search string was as follows: (*parameters* or *variables*) AND (*crashes* OR *vehicle collision* OR *injury*) AND (*influencing*) AND (*injury*).

2.2. Variable selection criterion

Despite the established statistical association between the 152 variables from the preceding section and the injuries sustained by a pedestrian in the event of a vehicle-to-pedestrian collision, this relationship may not actually exist; it may simply be a result of the law of large numbers. Consequently, a criterion that is objective and unaffected by statistical connections is required. To develop such a criterion, a system representing the interaction between vehicle and pedestrian in the event of a vehicle-to-pedestrian crash is created. The vehicle and pedestrian kinematics are two attributes of this system, and pedestrian injuries are the outcomes (Fig. 2).

The criterion is set such that the variable is evaluated based on its ability to influence the system's attributes, i.e., vehicle and pedestrian kinematics, and its output, i.e., injuries sustained. Based on this, each variable is categorised into the following groups:

1 Control-variable: if a variable can influence a system's attributes and has a direct impact on its outcome. For example, a pedestrian's age or gender.
2 Disturbance: if a variable can influence a system's attributes but has no direct impact on its outcome. They have an indirect impact on the outcome of the system by affecting a control-variable. For example, pedestrians' clothing visibility or the driver's age.
3 Not important: If a variable does not influence the system or its outcome, or if it is a derived variable, and its individual components are assessed separately, for example, body mass index (BMI), which

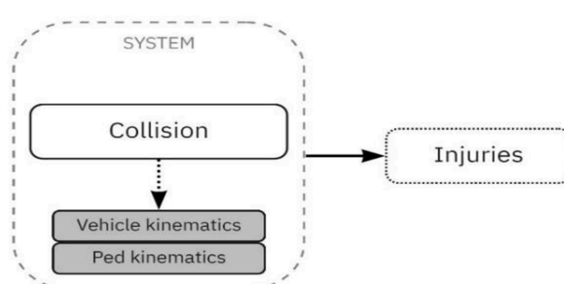


Fig. 2. Vehicle-Pedestrian collision system.

is a ratio between a pedestrian's height and weight, or a pedestrian's education level.

4 Output: If a variable quantifies or describes the output of the system. For example, Abbreviated injury score (AIS) or Injury severity score (ISS).

Each variable was assessed based on the format "Does {variable} {column header}?" (Table 1), for example, "Does {pedestrian's age} {Influence vehicle kinematics}?", leading to each column to be marked 0 (no) or 1 (yes) based on the question.

The resulting category is selected based on the following formula:

1 Control-variable: ~(A1) AND (A2 OR A3) AND (A4)
2 Disturbance: ~(A1) AND (A2 OR A3) AND ~(A4)
3 Not important: ~(A1) AND ~(A2) AND ~(A3) AND ~(A4)
4 Output: (A1) AND ~(A2) AND ~(A3) AND ~(A4)

2.3. Meta-analysis

The meta-analysis was conducted with variables that were designated as control variables or disturbances from the data selection criteria. Any variable that was not considered in at least three studies was ignored.

As the goal of this study was to determine whether a variable could cause severe injury, all the outputs were divided into the most minor and the most severe injury per study. For instance, if the source study compared the effects of minor injuries and fatalities, then the output categories would be injuries vs fatalities or if the source study considered more detailed injury scales like KABCO (K-fatal, A-incapacitating, B-non-incapacitating, C-possible, and O-no injury), then the segregation would be KABC vs O [13]. Variables were classified as discrete in some research and continuous in others. The division was made uniform across all studies for discrete variables, and the effect was changed for continuous data to reflect the trend of their discrete counterparts. For example, outcome measures were gathered from 11 studies that looked at drivers' ages to illustrate the impact of being over 65 years old. In one of the studies where the variable was continuous, the effect was taken out in a way that it reflected the impact of ageing.

Names of the authors, year of publication, data source, country of study, sample size, and outcome measure were extracted for each study (Table A1). For outcome measures, contingency tables (2×2) [14], the regression coefficients or correlation coefficient with a t-statistic, p-value, or z-statistic were extracted based on availability. These measurements were then converted to a logged odds ratio and standard error.

A series of hierarchical random-effects models were fitted for each variable [15]. Model 1 was a baseline frequentist random-effect model with no moderators. Model 2 was a Bayesian hierarchical model [16, 17]. Model 3 included the country of study as a moderator, and Model 4 used the output variable as a moderator. Publication bias was inspected visually using the funnel plot, Egger's Regression Test, Rank Correlation Test, and Vevea and Hedges Weight-Function Model. All statistical analyses were performed using R [18] packages for meta-analysis, including brms [19], metafor [20], RoBMA [21], meta [22], and weightr [23].

Residual heterogeneity was estimated and assessed by τ^2 and I^2. τ^2 is the between-study variance in the meta-analysis, which is insensitive to the number of studies and precision but hard to interpret in terms of relevance. On the other hand, the index of heterogeneity (I^2) is the percentage of variability in the effect sizes and is not influenced by sampling error. It is also considered unaffected by the number of studies, but heavily dependant on precision [24]. Higgins et al. [25] provided a rule of thumb to interpret it: 25% for low heterogeneity, 50% for moderate heterogeneity, and 75% for substantial heterogeneity. It is important to note that while studies become increasingly large, sampling error tends to zero, resulting in I^2 becomes very close to 100% [26].

As most of the studies displayed substantial or very high heterogeneity, Model 2 was used to determine its statistical significance. As the Bayesian methods create an actual sampling distribution for our parameters of interest, the exact probabilities of effect can be calculated using an empirical cumulative distribution function (ECDF), which returns the probability of effect being smaller than the given value. As the output pooled effect sizes are on Cohen's D scale, where 0.2 indicates a small effect, the ECDF function was used to calculate the probability of the effect being less than 0.1, i.e., the variable having no effect on the outcome. If this probability was less than 15%, then the pooled effect was considered to be statistically insignificant [27].

Funnel plots have long been used to assess publication bias; however, due to their reliance on visual inspection, they may be subject to error [28]. To overcome this problem, Egger et al. [29] proposed the Egger test, which quantifies funnel plot asymmetry; if this test is significant ($p < 0.05$) then there is funnel plot asymmetry, indicating publication bias. While Egger's test quantifies publication bias, it is not definitive; it is only a measure of funnel plot asymmetry. To further confirm publication bias Vevea & Woods [30] proposed a weight-function model that models publication bias using weighted distribution theory; if this test is significant ($p < 0.1$) then there is publication bias.

3. Results

The PRISMA flow diagram for reviewed studies is presented in Fig. 3. Two reviewers examined 600 search results, selecting 252 studies for analysis and 13 from the reference list. Of these, 100 were removed as they did not focus on pedestrians. 23 were not considered as they only compared methods and did not provide details on the influence of variables. Another 49 studies which did not concentrate on collision injuries were also removed. This process concluded that 93 studies met the selection criteria. The final list comprises of studies that were conducted from 1990 to 2022 and used a variety of methods to establish the influence of variables on the severity of injuries.

3.1. Characteristics of the collected studies

The shortlisted 93 studies analysed 204 different variables that affected the severity of pedestrian injuries. Of these, pedestrian age, gender, and vehicle type were the most common variables considered in 53, 44, and 41 studies, respectively. These studies included 904,655 pedestrian crashes from 19 countries. In some cases, the author did not acknowledge the significance of a variable. The reason for this could be that it had no influence on the outcome or that the influence could not be determined. 52 such variables were omitted from the list. As a result, 152 variables were taken into consideration for further research.

The variable selection criterion, as discussed in Section 2.2, was used to classify these 152 variables, and the results showed that 35 of them were control-variables, 33 were disturbances, 2 were outputs, and 82 were not significant. When one variable is a derivative of another, the resulting variable is deemed not important without being subjected to the criterion. One example is body mass index (BMI), which is determined by multiplying the pedestrian's weight by the square of their height, which are already under consideration. The type of vehicle is another. It was dropped because the type of vehicle is determined by the vehicle profile and because factors like vehicle height, breadth, and length of the bonnet that indicate the profile were already considered. A

Table 1
Variable selection criterion.

Does	Describe injury?	Influence Vehicle-Kinematics?	Influence Pedestrian-Kinematics?	Influence Injury?
{Variable}	A1	A2	A3	A4

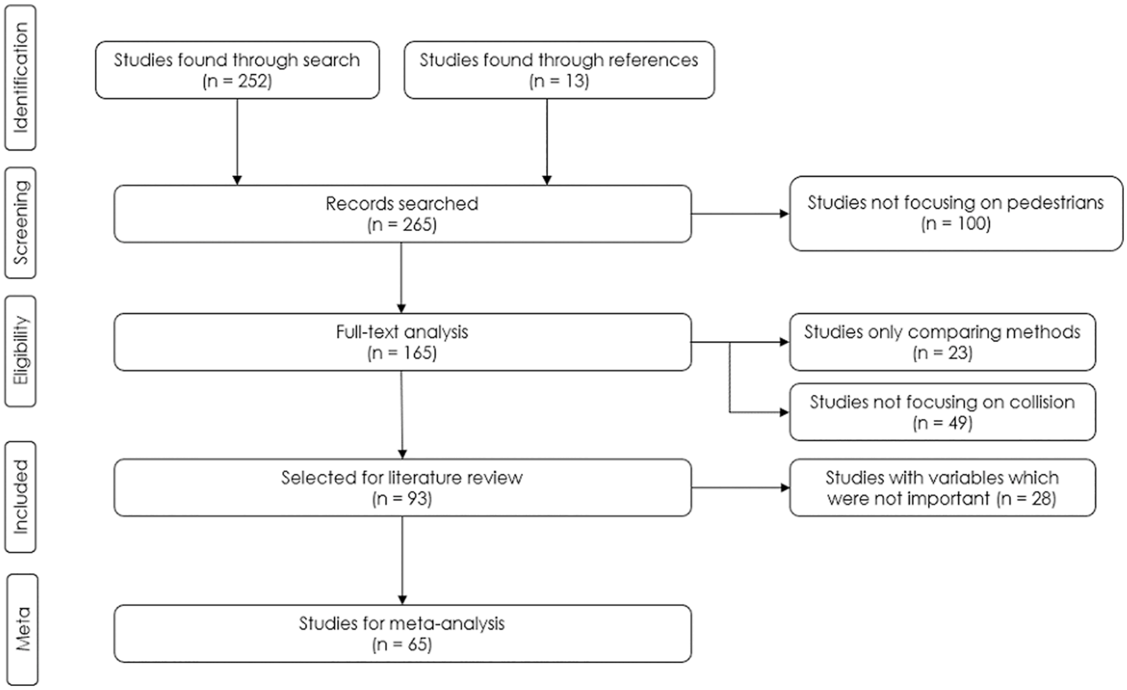


Fig. 3. PRISMA flow diagram of included studies.

detailed variable selection strategy and justification of the decision are available in Appendix B and Appendix C, respectively.

Out of the 93 studies that were chosen for the literature review, 16 were discarded because the variables considered were deemed unimportant by the variable selection criteria. Twelve articles presented their findings using injury curves and employed Finite Element (FE) models for their analysis. This made it impossible to quantify how the variables under consideration affected the outcome. The study from Li et al. [5], was dropped as their data source and sampling criteria were the same as their previous study from 2017. Kim et al. [31], Zhang et al. [32], and Zhao et al. [33], were also dropped on similar grounds. This resulted in 21 variables and 55 studies to be considered for meta-analysis (Fig. 4).

The outcomes varied from just assessing the binary outcome of fatal or not fatal to a more detailed measure of the KABCO injury scale. The data sources varied from in-depth collision databases to police and medical records. Based on the output segregation strategy explained in the methods section, 18 study outputs were "no injury vs. fatality," 2 were "no injury vs. severe injury," 6 were "minor injury vs. severe injury," and 29 were "injury vs. fatality." (Table A1)

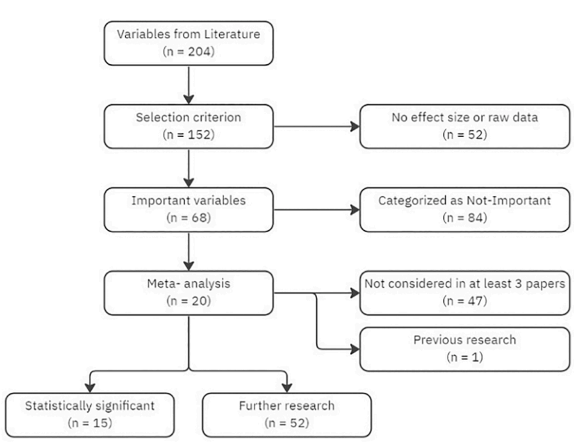


Fig. 4. Variable selection flow-chart.

3.2. *Variables, pooled effect, and publication bias*

The results of the meta-analysis are summarised in Table 2 and supporting forest plots are presented in Appendix D. For nearby infrastructure, the road network, road class type, the number of vehicles involved, and obstruction, meta-analysis was not possible since the categorisation employed in the studies that took these variables into account differed and could not be reduced to a binary category. Impact speed, which fulfilled all criteria for the meta-analysis, was excluded, as Hussain et al.'s [34] meta-analysis concluded that the severity of pedestrian injuries increases with speed. The variables evaluated by meta-analysis are listed in Table A2, together with a list of studies that took these variables into account and effect suggestions.

Area Type: Out of the 14 studies that took this factor into account, eight reported the impact of urban areas on pedestrian injury severity, while six selected the opposing effect of rural areas. To facilitate effect size pooling, all effects were converted to reflect the odds of an urban area. The pooled effects show that there is a 72% increase in the likelihood of severe injury in urban areas when compared to rural areas. Despite high heterogeneity (I^2=99.30%, τ^2=0.2871) this effect can be considered statistically meaningful as the probability of the odds being less than 10% is just 1.03%. Vevea and Hedges' weight-function model disagreed with Egger's regression test finding that there is a high funnel plot asymmetry (p = 0.081) with a p-value of 0.1524, indicating that there is no publication bias.

Control Type: For this variable, the categories were pooled into "no control" or "control present," which represents the presence of a traffic sign, traffic signal, or controlled crossing. Out of the 16 studies examining the effect of presence of control on pedestrian injury severity, half studied the effects of presence of control while the other half considered its absence. To facilitate effect size pooling, all effects were converted to reflect the odds of an absence of traffic control. The pooled effects show that presence of traffic control have very little effect of the severity of injuries, with odds being 7% with high heterogeneity (I^2=98.87%, τ^2=0.1577), and this may be because some studies chose detailed categories to divide the presence of control into types of control. While this could explain the high heterogeneity, the probability of 61.73% for the effect to be less than 10% makes it statistically insignificant. With p =

Table 2
Summary meta-analysis.

Variables	Model 1					Model 2			Egger's test	weight-function
	OR	SE	p-value	τ^2	I^2	OR	SE	ECDF	p-value	p-value
Area type	1.72	0.1507	0.0006	0.2871	99.3%	1.74	0.17	1.03%	0.081*	0.1524
Control type*	1.07	0.1044	0.5634*	0.1577	98.87%	1.06	0.12	61.73%*	0.0441*	0.0793*
Driver age*	1.08	0.1199	0.5487*	0.14	99.27%	1.1	0.14	55.4%*	0.1128	0.1581
Driver gender	1.24	0.0405	<.0001	0.0168	92.8%	1.25	0.05	1.05%	0.2858	0.4769
Driver intoxicated	2.38	0.1415	<.0001	0.15	90.79%	2.38	0.17	0.01%	0.0343*	0.0227*
Hit and run	1.26	0.0574	<.0001	0.0061	53.75%	1.25	0.11	14.03%	0.4038	0.9412
Land use	1.53	0.1068	0.0001	0.0629	89.64%	1.54	0.15	1.68%	0.302	0.2604
Lighting	1.81	0.0994	<.0001	0.2709	99.08%	1.8	0.1	0.01%	0.0122*	0.0099*
Manoeuvre	1.67	0.2093	0.0189	0.4107	98.18%	1.65	0.27	7.05%	0.7212	0.25
Number of lanes	1.48	0.089	<.0001	0.0335	92.15%	1.47	0.13	2.63%	0.0456*	0.1509
Pedestrian age	1.85	0.0803	<.0001	0.2107	99.73%	1.84	0.08	0.01%	0.0003*	0.0025*
Pedestrian behaviour	1.57	0.1239	0.0005	0.201	97.15%	1.55	0.13	0.98%	0.7993	0.586
Pedestrian clothing visibility*	4.47	1.4234	0.315*	5.7547	99.82%	2.65	1.24	22.33%*	0.0001*	0.7763
Pedestrian gender	1.14	0.0441	0.0042	0.0428	97.48%	1.15	0.05	2.85%	0.4986	0.3483
Pedestrian intoxicated	1.98	0.1349	<.0001	0.1595	95.27%	1.95	0.16	0.2%	0.9851	0.2685
Road geometry	1.37	0.047	<.0001	0.0102	81.65%	1.41	0.12	1.9%	0.3121	0.6359
Road surface condition*	1	0.1253	0.9963*	0.1519	91.42%	0.99	0.15	77.95%*	0.7473	0.7466
Road type	1.41	0.0532	<.0001	0.0198	85.55%	1.4	0.07	0.28%	0.2987	0.6623
Curb type*	1.17	0.2022	0.4477*	0.097	80.3%	1.19	0.49	42.5%*	0.0014*	0.7623
Speed limit	1.88	0.1746	0.0006	0.5475	99.9%	1.89	0.18	0.05%	0.0845	0.0036*

* These are statistically insignificant (grey)

0.0441 and $p = 0.0793$, respectively, Egger's regression test and Vevea and Hedges' weight-function model both indicate that there is a publication bias.

Driver age: The influence of older drivers (age > 60–65) compared to younger drivers was the focus of ten out of eleven studies; the other study looked at the impact of young drivers (age 24). The results were changed to reflect the impact of the driver being younger for pooling. However, the meta-analysis found that younger drivers are 8% more likely to cause serious injuries than older drivers (> 65), but with due to strong heterogeneity (I^2=99.27%, τ^2=0.14), this finding was not statistically significant. Since the likelihood that the effect would be less than 10% is 55.4%. Egger's regression test and Vevea and Hedges' weight-function model both demonstrated that there is no publication bias, with p-values of 0.1128 and 0.1581, respectively.

Driver gender: Eight of the 15 studies that considered this feature reported the influence of male drivers on the severity of pedestrian injuries, whereas seven studies explored the effect of female drivers. All effects were changed to match the probabilities of male drivers to facilitate effect size pooling. According to the pooled results, male drivers are 24% more likely than female drivers to cause a severe injury. This effect can be regarded as statistically significant despite substantial heterogeneity (I^2=92.80%, τ^2=0.0168), as the likelihood that the odds are less than 10% is just 1.05%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is no publication bias, with p-values of 0.4769 and 0.2858, respectively.

Driver intoxicated: All 12 studies examined the impact of driving while intoxicated on the severity of pedestrian injuries. According to the meta-analysis, intoxicated drivers are 2.38 times more likely to cause serious injuries than sober drivers. Despite the considerable heterogeneity (I^2=90.79%, τ^2=0.15), this conclusion is statistically significant because it was impossible (0.01% probability) for the effect to be less than 10% in this situation. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is publication bias, with p-values of 0.0227 and 0.0343, respectively.

Hit and run: Four of the five studies explored whether pedestrian injuries become more severe in hit-and-run incidents, whereas the fifth looked at the contrary. To enable pooling, the results were modified to represent hit-and-run. According to the meta-analysis, hit-and-run cases have a 26% higher likelihood of being severe with moderate heterogeneity (I^2=53.75%, τ^2=0.0061). This result was statistically significant since there was a 14.03 percent chance that the effect would be less than 10%. With p-values of 0.4038 and 0.9412, respectively, Egger's regression test and Vevea and Hedges' weight-function model both showed that there is no publication bias.

Land Use: To perform meta-analysis on this variable, it was divided into "residential" or "commercial." The studies that explored additional categories, such as parking or industry, were pooled into the "commercial" category. According to this approach, six of the nine studies looking at how land use affects the severity of pedestrian injuries looked at the effects of residential land, while the other three looked at the effects of commercial land. All effects were transformed to reflect the likelihood of residential land use to facilitate effect size pooling. When compared to commercial regions, pedestrian injuries in residential areas are 53% more severe, according to pooled effects with substantial heterogeneity (I^2=89.64%, τ^2=0.0629). The pooling of subcategories may be the cause of heterogeneity, although the pooled effect is still statistically meaningful as there is only a 1.68% chance that the effect will be less than 10%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is no publication bias, with p-values of 0.2604 and 0.302, respectively.

Lighting condition: The categories were combined into "dark" or "light" for this variable. Darkness is made up of dawn, dusk, and night without illumination, whereas light is made up of daylight and night with lighting. Four of the 31 studies looked at how lighting conditions affected the severity of pedestrian injuries, while the other 27 looked at the effects of darkness. All effects were modified to reflect the likelihood of a lack of light to facilitate effect size pooling. The pooled effects demonstrate that pedestrian injuries in the absence of illumination were more severe, with odds of 81% and considerable heterogeneity (I^2=99.08%, τ^2=0.2709). However, this conclusion can be statistically significant as it was impossible (0.01% probability) for the effect to be less than 10%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is publication bias, with p-values of 0.0099 and 0.0122, respectively.

Manoeuvre: This variable was split into two groups for our analysis: "straight," i.e., no manoeuvre by the driver, and "manoeuvre," which comprised all driving manoeuvres like turning, slowing down, and breaking. Out of 12, three examine the impact of manoeuvres, while the remaining nine examine the effects of none. The severity of pedestrian injuries decreases by 40% if the driver is making any manoeuvre. The pooled effect showed high heterogeneity (I^2=98.18%, τ^2=0.4107), but the effect can still be regarded as statistically significant because there is only a 7.05% chance that it will be less than 10%. With p-values of 0.7212 and 0.25, respectively, Egger's regression test and Vevea and Hedges' weight-function model both showed that there is no publication bias.

Number of lanes: Out of the 5 studies that took this factor into account, four explored the effect of ≥2 lanes on pedestrian injury severity, and the other considered single lane as an effect category. To facilitate effect size pooling, all effects were converted to reflect the odds of ≥2 lanes. The pooled effects show that there is a 48 percent increase in the likelihood of severe injury on multiple lanes compared to single lanes. Despite high heterogeneity (I^2=92.15%, τ^2=0.0335) this effect can be considered statistically meaningful as the probability of the odds being less than 10% is only 2.63%. Vevea and Hedges' weight-function model disagreed with Egger's regression test finding that there is a high funnel plot asymmetry ($p = 0.0456$) for publication bias with a p-value of 0.1509, indicating that there is no publication bias.

Pedestrian's Age: The goal of the study was to divide this variable into older and younger groups. Of the 40 studies that investigated the effects of a pedestrian's age, 25 chose an effect variable with a cut-off of >65, and six others placed the bar at 45–60. Two studies compared the effects of ageing up to the age of 19, while one study focused on children under the age of five. The remaining 5 studies used age as a continuous variable and reported that getting older increased the likelihood of injury. We can examine the effect of age on severity between older and younger all 25 studies compared the likelihood of suffering a severe injury when comparing an older age to a younger age. All effects were changed to older age representations for meta-analysis. The pooled effect states that the likelihood of getting a severe injury increases by 85% with a pedestrian's age. All though this result had high heterogeneity (I^2=99.73%, τ^2=0.2107), the results can still be considered statistically meaningful as there is no possibility (0.01% probability) that the effect would be less than 10%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is publication bias, with p-values of 0.0003 and 0.0025, respectively.

Pedestrian's Behaviour: For this variable, the research paper focused only on comparing the effects of pedestrians walking on the road versus walking along the road. Of the 16 studies, 14 explored the effects of pedestrians walking in the road, and the other two focused on pedestrians walking along the road. All the effects were converted to represent the odds of walking on the road. The pooled effect indicated that there is a 57% chance of a pedestrian being severely injured while walking on the road when compared to walking off the carriageway. The heterogeneity was high (I^2=97.15%, τ^2=0.201), but the effect can still be regarded as statistically significant because there is only a 0.98% chance that it will be less than 10%. With p-values of 0.7993 and 0.586, respectively, Egger's regression test and Vevea and Hedges' weight-function model both showed that there is no publication bias.

Pedestrian's Clothing Visibility: All three studies exploring the effect of pedestrian clothing visibility analysed the condition that the clothes were not in contrast with the background. The pooled effect indicated that the pedestrian is about four times more likely to suffer severe injuries if the clothing is not in contrast with the background, but with strong heterogeneity (I^2=99.82%, τ^2=5.7547), this finding was not statistically significant as the likelihood that the effect would be less than 10% is 22.33%. Vevea and Hedges' weight-function model disagreed with Egger's regression test's finding that there is a little funnel plot asymmetry ($p = 0.0001$) for publication bias with a p-value of 0.7763, indicating that there is no publication bias.

Pedestrian's Gender: Fifteen of the 28 studies that considered this feature reported the influence of male pedestrians on the severity of their injuries, whereas twelve studies explored the effect on female pedestrians. All effects were changed to match the probabilities of a male pedestrian to facilitate effect size pooling. According to the pooled results, male pedestrians are 14% more likely than their female counterparts to sustain a severe injury. This effect can be regarded as statistically significant despite substantial heterogeneity (I^2=97.48%, τ^2=0.0428), as the likelihood that the odds are less than 10% is just 2.85%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is no publication bias, with p-values of 0.3483 and 0.4986, respectively.

Pedestrian Intoxicated: All 11 studies examined the effect of intoxication on the severity of pedestrian injuries. According to the meta-analysis, intoxicated pedestrians are almost twice as likely to sustain serious injuries than sober pedestrians. Despite the considerable heterogeneity (I^2=95.27%, τ^2=0.1595), this conclusion was statistically significant as it was almost impossible (probability of 0.2%) for the effect to be less than 10%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is no publication bias, with p-values of 0.9851 and 0.2685, respectively.

Road geometry: For this variable, the research paper focused only on comparing the effects of road geometry, including horizontal and vertical grade, with no road geometry, i.e., a straight, level road. Of the 8 studies, 6 explored the effects of no road geometry, and the other two focused on vertical geometry. All effects were changed to match the probabilities of road geometry being present to facilitate effect size pooling. According to the pooled results, accidents on inclined roads cause 37% more severe injuries when compared to collisions on level roads. This effect can be regarded as statistically significant despite substantial heterogeneity (I^2=81.65%, τ^2=0.0102), as the likelihood that the odds are less than 10% is just 1.9%. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is no publication bias, with p-values of 0.6359 and 0.3121, respectively.

Road surface condition: The influence of a bad or wet road surface was the focus of six out of thirteen research studies; the other studies considered road conditions to be good or dry. The results were changed to reflect the effects of collisions on a bad road surface for pooling. The meta-analysis found that road surface condition has no influence on the severity of injuries sustained by the pedestrian. With strong heterogeneity (I^2=91.42%, τ^2=0.1519), this finding was not statistically significant as the likelihood that the effect would be less than 10% is 77.95%. Egger's regression test and Vevea and Hedges' weight-function model both demonstrated that there is no publication bias, with p-values of 0.7473 and 0.7466, respectively.

Road type: Eight of the ten studies explored whether pedestrian injuries become more severe in collisions on dual carriageways, while the rest looked at collisions on single carriageways. To enable pooling, the results were modified to consider the effects on dual carriageways. According to the meta-analysis, incidents on dual carriageways have a 41% higher likelihood of being severe with high heterogeneity (I^2=85.55%, τ^2=0.0198). This result was statistically significant since there was only a 0.28% chance that the effect would be less than 10%. With p-values of 0.2987 and 0.6623, respectively, Egger's regression test and Vevea and Hedges' weight-function model both showed that there is no publication bias.

Curb type: Two studies examined the effect of shoulders being curbed on the severity of pedestrian injuries; one considered the un-curbed shoulder. The effects were converted to represent the odds of a curbed shoulder for meta-analysis. The pooled effect indicated that the pedestrian is 17% more likely to suffer severe injuries if the shoulder is curbed. With strong heterogeneity (I^2=80.3%, τ^2=0.097), this finding was not statistically significant as the likelihood that the effect would be less than 10% is 42.5%. Vevea and Hedges' weight-function model disagreed with Egger's regression test's finding that there is a high funnel plot asymmetry ($p = 0.0014$) for publication bias with a p-value of 0.7623, indicating that there is no publication bias.

Speed limit: The goal of the study was to divide this variable into higher and lower speed limits. Of the 20 studies that investigated the effects of a speed limit, seven chose an effect variable with a cut-off of >50, and eight others placed the bar at 40. Two studies compared the effects of speeding up to 30. The remaining 3 studies used the speed limit as a continuous variable and reported that higher limits increased the likelihood of injury. We can examine the effect of speed limit on severity between higher and lower limits all 20 studies compared the likelihood of suffering a severe injury when comparing a higher speed limit to a lower. The pooled effects demonstrate that pedestrian injuries in high-speed limit zones result in more severe injuries, with odds of 88% and considerable heterogeneity (I^2=99.9%, τ^2=0.5475). However, this conclusion is statistically significant, as it was impossible (probability of 0.05%) for the effect to be less than 10% in this situation. Vevea and Hedges' weight-function model and Egger's regression test both demonstrated that there is publication bias, with p-values of 0.0036 and 0.0845, respectively.

4. Discussion

This literature review identified 93 studies and collected 204 variables that might have an influence on the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, such as vehicle speed, speed limit, pedestrian's age, gender, lighting conditions, type of road, intoxication of the pedestrian, or the driver. Even though they all show a statistical correlation with the assessed outcome, these variables may not actually have any relevance. Because of the law of large numbers, given enough data, every variable will start to demonstrate a relationship with the outcome. Therefore, before considering any statistical analysis, it is imperative to determine their relevance.

This is the first study of its kind to collect variables assessed in the literature, analyse them for their relevance, and conduct a meta-analysis to quantify and aggregate their effects on the outcome. The variables are segregated based on their relevance via a variable selection criterion, and the criterion found that out of 152 variables that have statistically proven influence on the severity of pedestrian injury, only 68 are relevant, which is about 50%.

Only 25 of the 68 relevant variables were considered in at least three studies, allowing us to undertake a meta-analysis. Of these 25, five variables precluded the use of a meta-analysis. Only 15 of the 20 factors included in the meta-analysis's pooled effects were statistically significant enough to support any conclusions. There was a high level of residual heterogeneity amongst the effect sizes in the final model (I^2 >

60%). As the data was grouped and sampled based on the criteria set by this study, this might be the cause of high heterogeneity. Models 3 and 4 did show that the injury type as a moderator did address the heterogeneity in some cases where there were sufficient data, but unfortunately this exercise could not be performed on all variables as the number of studies was already low. It is important to note that while studies become increasingly large, sampling error tends to zero, resulting in an I^2 very close to 100% [26]. Thus, a Bayesian model with the ECDF function was employed to revalidate the pooled effect and verify its statistical significance.

The goal of this study was to demonstrate that expert knowledge-based, objective criteria must be utilised to eliminate any variable that was not pertinent to the study, assess the influence of variables on the severity of pedestrian injuries, and then use statistical analysis to quantify this influence. The variable selection criterion does this precisely by classifying the variables into control variables and disturbances, in addition to deciding whether a variable is important or not. Some factors, such as the area type, speed limit, and type of road, may have an evident association with one another, but this is only a portion of the interdependent variables; it is impossible to identify all variables that are interdependent. We believe that acknowledging this interdependence between the variables and considering these dependencies while modelling the output would be a better strategy.

Another indication that the criterion selection is in line with the statistical correlation is that the justification provided during the variable selection process is in line with the findings of the meta-analysis. For example, results showed that inadequate lighting conditions would increase the chances of severe pedestrian accidents by 81%, and this might be the case where the driver is not able to see the pedestrian and fails to make the necessary manoeuvre, which is proven to reduce the severity of injuries sustained by 40%. It is also important to note that these are only indicators that the justification is consistent with the statistical relationship, not proof that these variables behave in this manner.

5. Conclusion

This systematic analysis found 93 articles that examined the impact of variables on the severity of pedestrian injuries between 1990 and 2022. They examined a total of 904,655 pedestrian incidents and came from 19 different countries. In total, 204 distinct factors were examined in the analyses of these 93 papers. This is the first review of its kind to assess the relevance of a variable regardless of its statistical association using a variable selection criterion and then combine odds ratios from numerous studies using meta-analysis. This rigorous criterion's objective is to determine whether a variable is relevant to the outcome. It is clear that not all variables that display statistical correlation are significant or relevant because 82 out of the 204 variables did not meet the criterion.

We strongly recommend that at least the 68 variables examined in this study, which have been objectively and statistically demonstrated to be significant, be included in any study or database that tries to collect and analyse vehicle-to-pedestrian collisions. Based on what they represent, the 68 variables were grouped into four groups: pedestrian, vehicle, infrastructure, and environmental. These groups each had 11, 21, 28, and 8 variables, respectively. These 68 variables are split in 15 characteristics that must be present in any pedestrian-to-vehicle collision databases, as well as a list of 53 variables that require additional investigation, allowing for appropriate actions for safer roads. Which group of variables the stakeholders should concentrate on is also largely determined by the variable selection criterion. While lawmakers or city planners focus on disturbances, automakers and designers should consider the control-variables.

6. Limitations

Although the list of studies considered in this systematic review is extensive, it does not include all published studies; therefore, some key variables might be missing from the database. While the variable selection criterion is designed to be generic and capable of segregating a wide range of variables, it is important to note that the criterion is biased towards the evaluator's opinion on the variable. One way to avoid this is to revalidate the scoring by two independent researchers.

Due to the insufficient information in the original article, 12 studies were not considered, and, due to the time constraints of the project, the authors of these studies were not contacted. The statistical models used in this meta-analysis assume that effect size is independent between studies. On a few occasions, studies were based on the same database, and a substantial portion of these studies were from the United States. These studies vary based on different inclusion criteria, thus making it difficult to determine the complete dataset. The influence of double counting was also ignored for this study.

A total of 43 variables that seem to be important had to be dropped, as very few studies considered them, limiting the ability to assess them in a meta-analysis. There was a high level of residual heterogeneity amongst the effect sizes in the final model ($I^2 > 60\%$). This may have been influenced by unaccounted for differences between the included studies. Although the data was derived from 19 countries, most of the studies were based on data from the United States. Even though a Bayesian meta-analysis was performed to assess the statistical significance of the pooled effects, its findings are open for interpretation.

In contrast to standard meta-analysis and systematic reviews, this research first identified the pertinent studies, extracted variables from the studies, and then performed meta-analysis using the available data. If, in the future, a focused systematic review and meta-analysis are carried out for each variable under consideration, the heterogeneity should be addressed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Appendix A

(Table A1, A2)

Table A1
Characteristics of included studies.

Seq	Study	Country	Time	Samp Size	Data-Source	Output Min vs Max injury
1	Holubowycz, 1995 [35]	Australia	1981–1992	617	PTIC, RAH	Injury: Fatal
2	Li et al., 2019 [5]	Germany	2000–2015	184	GIDAS	Injury: Fatal
3	Zajac & Ivan, 2003 [6]	United States	1989–1998	278	ConnDOT	No Injury: Fatal
4	Sze & Wong, 2007 [36]	Hong Kong	1991–2004	73,746	TRADS	Injury: Fatal
5	Kim et al., 2008 [8]	United States	1997–2000	5808	Police report, NC	No Injury: Fatal
6	Kong & Yang, 2010 [10]	China	2003–2009	104	IVAC	Injury: Severe injury
7	Richards & Carroll, 2012 [9]	United Kingdom	2000–2010	500	Multiple	Injury: Severe injury
8	Badea-Romero & Lenard, 2013 [37]	-NA-	-NA-	-NA-	-NA-	-NA-
9	Islam & Jones, 2014 [38]	United States	2006–2010	1463	CARE	Injury: Severe injury
10	Li et al., 2017 [39]	-NA-	-NA-	-NA-	-NA-	-NA-
11	Yin et al., 2017 [40]	NA	NA	315	Primary data	Injury: Fatal
12	Huang et al., 2018 [41]	-NA-	-NA-	-NA-	-NA-	-NA-
13	Nishimoto et al., 2019 [42]	Australia	1990–2016	6868	TRAS	Injury: Severe injury
14	Su et al., 2021 [43]	-NA-	-NA-	-NA-	-NA-	-NA-
15	Chang et al., 2022 [44]	Korea	2012–2019	147,026	TAAS	No Injury: Fatal
16	Pitt et al., 1990 [45]	United States	1977–1980	1035	PICS	Injury: Fatal
17	Zhao et al., 2014 [33]	China	2006–2011	121	Primary data	Injury: Fatal
18	Ballesteros et al., 2004 [46]	United States	1955–1999	2942	MAARS, MTR	Injury: Fatal
19	Li et al., 2015 [47]	-NA-	-NA-	-NA-	-NA-	-NA-
20	Untaroiu et al., 2009 [48]	-NA-	-NA-	-NA-	-NA-	-NA-
21	Lefler & Gabler, 2004 [49]	-NA-	-NA-	-NA-	-NA-	-NA-
22	Matsui, 2005 [50]	-NA-	-NA-	-NA-	-NA-	-NA-
23	Lee & Abdel-Aty, 2005 [51]	United States	1999–2002	4351	FTCRD	No Injury: Fatal
24	Eluru et al., 2008 [52]	United States	2004	60,000	GES	No Injury: Fatal
25	Miles-Doan, 1996 [53]	United States	1988–1990	27,231	STAMIS	Injury: Fatal
26	Al-Ghamdi, 2002 [54]	Saudi Arabia	1997–1999	638	RTPD	Injury: Fatal
27	Kim et al., 2010 [31]	-NA-	-NA-	-NA-	-NA-	-NA-
28	Aziz et al., 2013 [55]	United States	2002–2006	4666	NYCDOT	No Injury: Fatal
29	Sasidharan & Menéndez, 2014 [56]	Switzerland	2008–2012	12,659	ASTRA	No Injury: Fatal
30	Haleem et al., 2015 [57]	United States	2008–2010	3038	FDOT, CAR	Injury: Severe injury
31	Sun et al., 2019 [58]	United States	2006–2015	14,236	LADOTD	No Injury: Fatal
32	Hussain et al., 2019 [34]	NA	NA	37,257	Meta-Analysis	No Injury: Fatal
33	Anderson et al., 1997 [59]	-NA-	-NA-	-NA-	-NA-	-NA-
34	Abdel-Aty et al., 2007 [60]	-NA-	-NA-	-NA-	-NA-	-NA-
35	Pour-Rouholamin & Zhou, 2016 [61]	United States	2010–2013	14,538	ICD	Injury: Severe injury
36	M. Kim et al., 2017 [62]	Korea	2011–2013	137,470	TAAS	No Injury: Fatal
37	Lalika et al., 2022 [63]	United States	2016–2018	913	SFADB	Injury: Fatal
38	Olowosegun et al., 2022 [64]	United Kingdom	2010–2018	5156	STATS19	Injury: Fatal
39	Nasri et al., 2022 [65]	Australia	2010–2019	10,040	VicRoads	Injury: Fatal
40	Yao et al., 2008 [66]	-NA-	-NA-	-NA-	-NA-	-NA-
41	Mohamed et al., 2013 [67]	United States	2002–2006	6896	NYCDOT	Injury: Fatal
42	Mohamed et al., 2013 [68]	Canada	2003–2006	5820	SAAQ	Injury: Fatal
43	Clifton et al., 2009 [69]	United States	2000–2004	4695	MMVAR	No Injury: Fatal
44	Han et al., 2018 [70]	-NA-	-NA-	-NA-	-NA-	-NA-
45	Mokhtarimousavi et al., 2020 [71]	United States	2010–2014	10,146	HSIS	No Injury: Severe injury
46	Song et al., 2020 [72]	United States	2007–2018	27,091	NCDOT	No Injury: Severe injury
47	Helmer et al., 2010 [73]	United States	1994–1998	376	PCDS	Injury: Fatal
48	Iragavarapu et al., 2015 [74]	-NA-	-NA-	-NA-	-NA-	-NA-
49	Chen et al., 2015 [75]	-NA-	-NA-	-NA-	-NA-	-NA-
50	Gunji et al., 2012 [76]	-NA-	-NA-	-NA-	-NA-	-NA-
51	Lyons & Simms, 2012 [77]	-NA-	-NA-	-NA-	-NA-	-NA-
52	Roudsari et al., 2004 [78]	United States	1994–1998	542	PCDS	Injury: Fatal
53	Špička et al., 2016 [79]	-NA-	-NA-	-NA-	-NA-	-NA-
54	Ishikawa et al., 1994 [80]	-NA-	-NA-	-NA-	-NA-	-NA-
55	Matsui et al., 1999 [81]	-NA-	-NA-	-NA-	-NA-	-NA-
56	Watanabe et al., 2012 [82]	-NA-	-NA-	-NA-	-NA-	-NA-
57	Islam & Hossain, 2015 [83]	United States	2010–2012	2305	CARE	No Injury: Fatal
58	Kitali et al., 2017 [84]	United States	2009–2013	1397	FDOT	Injury: Fatal
59	Pelet-Del-Toro et al., 2019 [85]	-NA-	-NA-	-NA-	-NA-	-NA-
60	Hosseinian et al., 2021 [7]	Iran	2017–2019	6123	TTP	Injury: Fatal
61	Simms & Wood, 2006 [86]	-NA-	-NA-	-NA-	-NA-	-NA-
62	Wang et al., 2019 [87]	Germany	2000–2012	404	GIDAS	Injury: Fatal
63	Darus et al., 2022 [88]	Malaysia	2009–2014	2518	RMP	Injury: Fatal
64	Liu et al., 2002 [89]	-NA-	-NA-	-NA-	-NA-	-NA-
65	Zhang et al., 2008 [32]	-NA-	-NA-	-NA-	-NA-	-NA-
66	Yasmin et al., 2014 [90]	United States	2002–2006	4701	NYCDOT	Injury: Fatal
67	Zhao et al., 2013 [91]	-NA-	-NA-	-NA-	-NA-	-NA-
68	Y. Han et al., 2019 [92]	-NA-	-NA-	-NA-	-NA-	-NA-
69	Y. Zhang et al., 2021 [93]	-NA-	-NA-	-NA-	-NA-	-NA-
70	Moradi et al., 2019 [94]	-NA-	-NA-	-NA-	-NA-	-NA-
71	Peng et al., 2012 [95]	-NA-	-NA-	-NA-	-NA-	-NA-
72	Simms & Wood, 2006a [96]	-NA-	-NA-	-NA-	-NA-	-NA-
73	Y. Han et al., 2012 [97]	-NA-	-NA-	-NA-	-NA-	-NA-
74	Jang et al., 2010 [98]	United States	2002–2007	5084	SWITRS	No Injury: Fatal

(*continued on next page*)

Table A1 (*continued*)

Seq	Study	Country	Time	Samp Size	Data-Source	Output Min vs Max injury
75	Ma et al., 2018 [99]	United States	2011–2012	2614	IDOT	Injury: Fatal
76	Rosén et al., 2011 [100]	-NA-	-NA-	-NA-	-NA-	-NA-
77	Tang et al., 2020 [101]	-NA-	-NA-	-NA-	-NA-	-NA-
78	Chakraborty et al., 2019 [102]	India	2011–2016	342	KTP	Injury: Fatal
79	Wenjun et al., 2017 [103]	-NA-	-NA-	-NA-	-NA-	-NA-
80	Uddin & Ahmed, 2018 [104]	United States	2009–2013	3184	HSIS	No Injury: Fatal
81	Rodionova et al., 2021 [105]	Russia	2015–2021	13,888	K-DTP	Injury: Fatal
82	Malin et al., 2020 [106]	Finland	2014–2017	281	Police report	Injury: Fatal
83	Šarić et al., 2021 [107]	Croatia	2015–2018	7155	TADS	No Injury: Fatal
84	Kamboozia et al., 2020 [108]	Iran	2014–2019	484	Police report	Injury: Fatal
85	Tao et al., 2022 [109]	-NA-	-NA-	-NA-	-NA-	-NA-
86	Neal-Sturgess et al., 2002 [110]	-NA-	-NA-	-NA-	-NA-	-NA-
87	Rezapour & Ksaibati, 2022 [111]	United States	2010–2019	811	WYDOT	No Injury: Fatal
88	Rella Riccardi et al., 2022 [112]	United Kingdom	2016–2018	67,356	STATS19	Injury: Fatal
89	Guo et al., 2021 [113]	United States	2006–2016	856	Colorado	No Injury: Fatal
90	Mokhtarimousavi, 2019 [114]	United States	2010–2014	8573	California	No Injury: Fatal
91	Zhu, 2021 [115]	Hong Kong	2016–2018	3054	HKTD	Injury: Fatal
92	Pour et al., 2016 [116]	Australia	2004–2013	9872	CrashStats	Injury: Fatal
93	Pineda-Jaramillo et al., 2022 [117]	-NA-	-NA-	-NA-	-NA-	-NA-

*Studies marked -NA- were not parts of meta-analysis.

Table A2
Variable with study list.

Variables	Study ID
Area type	15, 23, 25, 31, 35, 38, 46, 57, 58*, 63, 80, 82, 88, 90
Control type	4, 5, 9, 23, 28*, 29*, 30, 35, 37, 41*, 46*, 63, 75, 81, 88*, 91*
Driver age	5, 13, 29*, 35, 37, 39, 41*, 45, 80*, 88, 92*
Driver gender	5, 13, 16*, 29, 35, 36, 37, 39, 41, 75, 81, 88, 89, 90, 92*
Driver intoxicated	3, 5, 16, 24, 35, 36, 45, 46, 57, 80, 89, 90
Hit and run	46, 63, 75, 89, 91
Land use	3, 5, 9, 16*, 28, 41, 46, 57, 63
Lighting	3, 5, 9, 13, 23, 25, 28, 29, 30, 31, 35, 37, 38, 39, 41, 42, 45, 46, 57, 58, 63, 66, 80, 81, 82, 83, 84, 88, 89, 90, 91
Manoeuvre	5, 16*, 25, 28*, 37, 41, 42, 45*, 47, 58, 88, 89
Number of lanes	4, 28, 35, 41, 80
Ped Age	1, 2, 3, 4, 5, 6, 7, 9, 13, 16, 17, 23, 24, 26, 28, 29, 30, 31, 35, 36, 37, 39, 41, 43, 46, 47, 52, 57, 58, 60, 62, 66, 74, 75, 80, 83, 84, 88, 92
Ped behaviour	4, 5, 9, 16*, 17*, 28, 29, 30, 31*, 39, 41, 47, 57, 58, 88, 90
Ped clothing visibility	35, 43, 60
Ped gender	1, 4*, 9*, 13, 16, 17, 23*, 24, 25, 26, 28, 29, 31, 35, 36*, 37, 39, 41, 43, 46, 57, 58, 75*, 81*, 84*, 88, 89, 92
Ped intoxicated	1, 3, 23, 24, 25, 29, 31, 43, 46, 74, 89
Road geometry	5, 13, 28, 29, 46, 63, 84, 89
Road surface condition	3, 28, 30*, 35, 37, 38*, 45, 58, 63, 75*, 81, 82*, 84*
Road type	4, 5, 13, 15, 35, 37, 46, 63, 75, 88
Shoulder type	37, 58*, 63
Speed limit	3, 4, 13, 18, 24, 25*, 29, 30, 31, 37, 38, 39, 58, 63, 80, 82, 83, 88, 92

[*] Are the studies that reported the opposite effect compared to others in the group.

Appendix B

Does	Describe injury	Influence Veh-Kinematics	Influence Ped-Kinematics	Influence Injury	
Age	0	0	1	1	Control Variable
age effect	0	0	0	0	not important
Behaviour	0	0	1	1	control variable
BMI	0	0	0	0	Not Important
Clothing visibility	0	1	0	0	Disturbance
Face direction angle	0	0	1	1	Control Variable
Gait	0	0	1	1	Control Variable
Gender	0	0	1	1	Control Variable
Education	0	0	0	0	Not Important
Height	0	0	1	1	Control Variable
Hip height	0	0	0	0	Not Important
IMD decile	0	0	0	0	Not Important
Injury location	1	0	0	0	Output
Intoxicated	0	0	1	1	Control Variable
ISS	1	0	0	0	Output
Job	0	0	0	0	Not Important
Language	0	0	0	0	Not Important
Nationality	0	0	0	0	Not Important
Number of pedestrians involved	0	0	1	1	Control Variable
Ratio height shoulder / ground rear hood op.	0	0	0	0	Not Important
Ratio body height / ground rear hood opening	0	0	0	0	Not Important

(*continued on next page*)

(*continued*)

Does	Describe injury	Influence Veh-Kinematics	Influence Ped-Kinematics	Influence Injury	
Ratio body height / ground base windshield	0	0	0	0	Not Important
Ratio body height / hood length	0	0	0	0	Not Important
Size	0	0	0	0	Not Important
Speed	0	0	1	1	Control Variable
Weight	0	0	1	1	Control Variable
Age	0	0	0	0	Not Important
Bonnet angle	0	0	1	1	Control Variable
Bonnet leading edge angle	0	0	1	1	Control Variable
Bonnet leading edge height	0	0	1	1	Control Variable
Normalised Bonnet leading edge height	0	0	0	0	Not Important
Bonnet end depth	0	0	0	0	Not Important
Bonnet length	0	0	1	1	Control Variable
Bonnet stiffness	0	0	1	1	Control Variable
Bumper bottom Height	0	0	0	0	Not Important
Bumper central Height	0	0	0	0	Not Important
Normalised Bumper central Height	0	0	0	0	Not Important
Bumper lower depth	0	0	0	0	Not Important
Bumper lower height	0	0	0	0	Not Important
Normalised Bumper lower height	0	0	0	0	Not Important
Bumper upper depth	0	0	0	0	Not Important
Bumper upper height	0	1	1	1	Control Variable
Normalised Bumper upper height	0	0	0	0	Not Important
Bumper stiffness	0	0	1	1	Control Variable
Bumper wrap around	0	0	0	0	Not Important
Driver age	0	1	0	0	Disturbance
Driver gender	0	1	0	0	Disturbance
Driver home area	0	0	0	0	Not Important
Driver IMD Decile	0	0	0	0	Not Important
Driver intoxicated	0	1	0	1	Control Variable
Driver Job	0	0	0	0	Not Important
Driver License Condition	0	1	0	0	Disturbance
Driver nationality	0	0	0	0	Not Important
Driver journey purpose	0	0	0	0	Not Important
Ground to base of windshield (wrap)	0	0	0	0	Not Important
Ground to top of windshield (wrap)	0	0	0	0	Not Important
Impact location	0	1	1	1	Control Variable
Impact Speed	0	1	1	1	Control Variable
Impact Speed (squared)	0	0	0	0	Not Important
kinetic energy	0	0	0	0	not important
Manoeuvre	0	1	1	1	control variable
Number of vehicles involved	0	1	1	1	Control Variable
Rear hood opening distance	0	0	0	0	Not Important
Registration year	0	0	0	0	Not Important
Speed Ratio (Impact speed/Speed limit)	0	0	0	0	Not Important
Travel speed	0	1	0	0	Disturbance
Vehicle Engine (CC)	0	1	0	0	Disturbance
Vehicle propulsion	0	0	0	0	Not Important
Vehicle type	0	0	0	0	Not Important
Weight	0	1	1	1	Control Variable
Windscreen Angle	0	0	1	1	Control Variable
Windscreen stiffness	0	0	1	1	Control Variable
Year of manufacture	0	1	0	1	Control Variable
Area type	0	1	1	0	Disturbance
Clear roadway width	0	1	0	0	Disturbance
Control type	0	1	0	0	Disturbance
Crosswalk type	0	1	0	0	Disturbance
Hazard	0	1	1	0	Disturbance
Intersection type	0	1	1	0	Disturbance
Land Use	0	1	1	0	Disturbance
Near by infrastructure	0	1	1	0	Disturbance
Node type	0	1	1	0	Disturbance
Number of lanes	0	1	1	0	Disturbance
Number of roads	0	1	1	0	Disturbance
Obstruction	0	1	1	0	Disturbance
On-street parking	0	1	1	0	Disturbance
Park lane	0	1	1	0	Disturbance
Pavement type	0	1	1	1	Control Variable
Pavement surface condition	0	0	1	1	Control Variable
Road class type	0	1	0	0	Disturbance
Road geometry	0	1	0	0	Disturbance
Road marking	0	1	1	0	Disturbance
Road Network	0	1	0	0	Disturbance
Road surface condition	0	1	1	1	Control Variable
Road surface material	0	1	1	1	Control Variable
Road type	0	1	0	0	Disturbance
Road width	0	0	1	0	Disturbance

(*continued on next page*)

(*continued*)

Does	Describe injury	Influence Veh-Kinematics	Influence Ped-Kinematics	Influence Injury	
Shoulder type	0	0	1	0	Disturbance
Special circumstance	0	1	1	0	Disturbance
Speed limit	0	1	1	0	Disturbance
Traffic aids	0	0	0	0	Not Important
Traffic congestion	0	1	1	0	Disturbance
Population age	0	0	0	0	Not Important
Accident Location	0	0	0	0	Not Important
Accident type	0	1	1	1	Control Variable
Alcohol involvement	0	0	0	0	Not Important
Average annual daily traffic	0	0	0	0	Not Important
Contributory factor	0	0	0	0	Not Important
Day of week	0	0	0	0	Not Important
Direction of impact	0	1	1	1	Control Variable
Education	0	0	0	0	Not Important
Ethnicity	0	0	0	0	Not Important
Fault	0	0	0	0	Not Important
First harmful event	0	1	1	1	Control Variable
Household income	0	0	0	0	Not Important
Household size	0	0	0	0	Not Important
Humidity	0	1	1	1	Control Variable
Lighting	0	1	1	0	Disturbance
Month	0	0	0	0	Not Important
Population	0	0	0	0	Not Important
Road Density	0	0	0	0	Not Important
Time of day	0	0	0	0	Not Important
Visibility	0	0	0	0	Not Important
Weather	0	0	0	0	Not Important
Temperature	0	1	1	1	Control Variable
Year	0	0	0	0	Not Important
Zone area (km2)	0	0	0	0	Not Important
Ambulance Rescue	0	0	0	0	Not Important
Avenue	0	0	0	0	Not Important
Borough/District	0	0	0	0	Not Important
Camera distance	0	1	0	0	Disturbance
Camera land use	0	0	0	0	Not Important
Contrecoup pressure	0	0	0	0	Not Important
Coup pressure	0	0	0	0	Not Important
Cumulative strain damage measure	0	0	0	0	Not Important
Dilatational damage measure	0	0	0	0	Not Important
Distance from GPO	0	0	0	0	Not Important
Hit and run	0	1	0	0	Disturbance
Number of bus stops	0	0	0	0	Not Important
Number of hotels	0	0	0	0	Not Important
Number of metro exits	0	0	0	0	Not Important
Number of non-signalized intersections	0	0	0	0	Not Important
Number of restaurants	0	0	0	0	Not Important
Number of schools	0	0	0	0	Not Important
Number of shopping malls	0	0	0	0	Not Important
Number of signalized intersections	0	0	0	0	Not Important
Percentage of trucks	0	0	0	0	Not Important
Shear stress	0	0	0	0	Not Important
Total crashes	0	0	0	0	Not Important
Trip generation (per day)	0	0	0	0	Not Important
Von Mises stress	0	0	0	0	Not Important
Walking frequency (per day)	0	0	0	0	Not Important

Appendix C

Pedestrian

Age – Control-variable

Lockhart et al. (2005) prove that age affects the dynamic equilibrium responsible for recovery in a slip-fall event, implying that older pedestrians' kinematics are impacted as they age. When compared to the 20 to 29 age group, Yamada & Evans (1970) discovered that the mechanical qualities of all bones reduced by 1% in the 30 to 39 age group and by 22% in the 70 to 79 age group, implying that injury severity increased with age. As a result, the age of pedestrians is classified as a control-variable.

Age Effect – Not important

Although some studies have found this variable to have an influence on severity of pedestrian injuries, this variable is omitted for this study since it captures the effect of age, and we have already considered age.

Behaviour – Control-variable
Crossing the street, lying down on the road, walking, and running have all been shown to influence pedestrian kinematics. Several studies have demonstrated a link between pedestrian behaviour, kinematics, and the severity of resulting injuries in the event of a vehicle-to-pedestrian collision. As a result, pedestrian behaviour is a control-variable.

BMI. (Body Mass Index) – Not important
Although some studies have found this variable to have an influence on severity of pedestrian injuries, this variable has been excluded since it is a combination of height and weight, both of which are assessed separately.

Clothing visibility – Disturbance
Several researchers have found a statistical correlation between clothing visibility and injury severity. We disagree, while a pedestrian's clothes may impact vehicle kinematics, it has no bearing on the severity of an injury. The driver may miss the pedestrian and fail to make the necessary maneuvers to prevent a collision if the pedestrian's attire does not contrast with the background. We feel that other variables, such as vehicle speed, offer a better explanation for differences in injury severity than garment visibility. As a result, the visibility of pedestrians' clothing is classified as disturbance.

Face direction angle – Control-variable
It is demonstrated by various FE models that the resulting impact location and rotation of the pedestrians' heads alter depending on the initial face direction at collision, demonstrating its influence on kinematics. The injuries differ depending on the impact site and rotation, as detailed in the previous section. As a result, the face direction angles of pedestrians are classed as control-variable.

Gait – Control-variable
The impact of pedestrian gait on kinematics is well understood, and this variation in kinematics also modifies the contact points between the pedestrian and the vehicle, resulting in injuries. As a result, pedestrian gaits are designated as control-variable.

Gender – Control-variable
McLean et al. (2004) discovered that females exhibit less hip and knee flexion, hip and knee internal rotation, and hip abduction than their male counterparts, demonstrating the kinematic differences between genders. They also found that these differences in joint kinematics point to higher knee valgus in women, which may raise the risk of anterior cruciate ligament (ACL) injury. As a result, it is categorised as control-variable.

Education – Not important
Although several studies have identified a statistical correlation between a pedestrian's educational level and the severity of injuries incurred in the case of a vehicle-to-pedestrian collision, we believe it has no bearing on the pedestrian's kinematics or injuries. It could be argued that education is linked to socioeconomic status in some circumstances, resulting in a lower quality of life, which may have an impact on the severity of injury cases, but for our analysis, we are interested if education has an independent effect on pedestrian-to-vehicle collision, which it does not. As a result, a pedestrian's level of education is considered irrelevant.

Height – Control-variable
Yanaoka et al. (2016) conducted experiments that revealed a clear link between pedestrian height, kinematics, and injuries in the event of a vehicle-to-pedestrian collision. As a result, pedestrian height is designated as control-variable.

Hip height – Not important
A study by C. Gordon et al. (1989) provided a correlation between a pedestrian's hip height and total height. This variable is redundant because we are considering the pedestrian's height.

IMD. decile – Not important
The Index of Multiple Deprivation, a measure of relative deprivation, has no proven influence on the kinematics of the vehicle or the pedestrian and the severity of the injuries sustained.

Intoxicated – Control-variable
According to an article called The Influence of Alcohol on Physiologic Processes and Exercise, alcohol consumption reduces strength and impairs motor skills. Slow reaction time and judgement are thought to produce changes in pedestrian kinematics. Johnston & McGovern (2004) found that alcohol-related injuries are more severe because alcohol thins the blood, allowing the blood to rush to the injury site and cause quicker bleeding. As a result, intoxication amongst pedestrians is regarded as a control-variable.

Job – Not important
Although several studies have identified a statistical correlation between a pedestrian's job and the severity of injuries incurred, we believe it has no bearing on the pedestrian's kinematics or injuries. It could be argued that job is linked to socioeconomic status in some circumstances, resulting in a lower quality of life, which may have an impact on the severity of injury cases, but for our analysis, we are interested if job has an independent effect on pedestrian-to-vehicle collision, which it does not. As a result, a pedestrian's level of education is considered irrelevant.

Language – Not important
Even though numerous studies have identified a statistical association between the pedestrian's language and the severity of the injuries experienced, we do not believe it has any effect on the vehicle's or pedestrian's kinematics or the severity of the injuries sustained. It could be argued that the pedestrian's ability to understand and follow traffic restrictions is hampered by the language, but this is immaterial in and of itself.

Nationality – Not important

While there may be a statistical correlation between the pedestrian's nationality and the severity of the injury, we feel that nationality is unimportant and has no bearing on vehicle-to-pedestrian collisions. Although pedestrians from other nations may be unaware of traffic laws, this can cause misunderstandings and accidents, as well as physical variations owing to demographics. The pedestrian's nationality has no effect on the kinematics of the impact or the severity of the injuries.

Number of pedestrians involved – Control-variable

The number of pedestrians involved in a collision with a vehicle is control-variable since it affects the pedestrians' kinematics as well as the injuries they incur. Pedestrians may collide with each other during or after the collision, causing the kinematics to change. This may also cause injuries other than the contact with the vehicle as well as the infrastructure.

Ratio height shoulder / ground rear hood op – Not important

As it is derived from variables that are assessed individually, it is excluded.

Ratio body height / ground rear hood opening – Not important

As it is derived from variables that are assessed individually, it is excluded.

Ratio body height / ground base windshield – Not important

As it is derived from variables that are assessed individually, it is excluded.

Ratio body height / hood length – Not important

As it is derived from variables that are assessed individually, it is excluded.

Size – Not important

As it is derived from variables that are assessed individually, it is excluded.

Speed – Control-variable

The study by Simms & Wood (2006) found that pedestrian speed has a substantial impact on the pedestrian's head contact location and contact load on the vehicle, making it a control-variable.

Weight – Control-variable

Capodaglio et al. (2021) concluded from their research that obese adult had less knee flexion and a greater knee ab-adduction angle throughout the gate cycle, altering kinematics. According to another study by Stroud et al. (2018), non-obese patients have a lower risk of abdominal, thoracic, or extremity injuries compared to obese adults. As a result, the patient's weight is classified as a control-variable.

Vehicle

Age – Not important

The age of a vehicle can be inferred by the year it was manufactured; the vehicle age variable is considered unimportant.

Bonnet angle – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the bonnet angle. As a result, the bonnet angle has been designated as a control-variable.

Bonnet leading edge angle – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the bonnet leading edge angle. As a result, the bonnet leading edge angle has been designated as a control-variable.

Bonnet leading edge height – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the bonnet leading edge height. As a result, the bonnet leading edge height has been designated as a control-variable.

Normalised Bonnet leading edge height – Not important

As it is derived from variables that are assessed individually, it is excluded.

Bonnet end depth – Not important

As it is derived from variables that are assessed individually, it is excluded.

Bonnet length – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the bonnet length. As a result, the bonnet length has been designated as a control-variable.

Bonnet stiffness – Control-variable

Several studies have found that the vehicle's front profile stiffness is important in pedestrian-to-vehicle collisions. As a result, bonnet stiffness has been designated as a control-variable.

Bumper bottom Height – Not important

Internal calculations and experiments have determined that this parameter is not essential and has little bearing on injuries or kinematics, even though numerous studies have found it to influence the kinematics of the pedestrian following the collision. As a result, bumper bottom height is considered not important.

Bumper central Height – Not important

Internal calculations and experiments have determined that this parameter is not essential and has little bearing on injuries or kinematics, even though numerous studies have found it to influence the kinematics of the pedestrian following the collision. As a result, bumper central height is considered not important.

Normalised Bumper central Height – Not important

As it is derived from variables that are assessed individually, it is excluded.

Bumper lower depth – Not important

Internal calculations and experiments have determined that this parameter is not essential and has little bearing on injuries or kinematics, even though numerous studies have found it to influence the kinematics of the pedestrian following the collision. As a result, bumper lower depth is considered not important.

Bumper lower height – Not important

Internal calculations and experiments have determined that this parameter is not essential and has little bearing on injuries or kinematics, even though numerous studies have found it to influence the kinematics of the pedestrian following the collision. As a result, bumper lower height is considered not important.

Normalised Bumper lower height – Not important

As it is derived from variables that are assessed individually, it is excluded.

Bumper upper depth – Not important

Internal calculations and experiments have determined that this parameter is not essential and has little bearing on injuries or kinematics, even though numerous studies have found it to influence the kinematics of the pedestrian following the collision. As a result, bumper upper depth is considered not important.

Bumper upper height – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the bumper upper height. As a result, the bumper upper height has been designated as a control-variable.

Normalised Bumper upper height – Not important

As it is derived from variables that are assessed individually, it is excluded.

Bumper stiffness – Control-variable

Several studies have found that the vehicle's front profile stiffness is important in pedestrian-to-vehicle collisions. As a result, the bumper stiffness has been designated as a control-variable.

Bumper wrap around – Not important

As it is a derived variable; it is excluded from analysis.

Driver age – Disturbance

Although it has been determined that the driver's age is statistically significant when compared to the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, this may not actually be the case because the driver's age may be associated to careless driving, which may lead to more severe injuries, but the driver's age by itself has no relation to the severity of a pedestrian's injury.

Driver gender – Disturbance

Although it has been determined that the driver's gender is statistically significant when compared to the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, this may not actually be the case because the driver's gender may be associated to careless driving, which may lead to more severe injuries, but the driver's gender by itself has no relation to the severity of a pedestrian's injury.

Driver home area – Not important

Although studies have discovered a statistical correlation between a driver's home area and the seriousness of the pedestrian's injury, we are of the opinion that this may not be the case because the driver's home area has no effect on the kinematics of the vehicle or the pedestrian, thereby having no bearing on the outcomes of injury. As a result, the driver's home area is considered not important.

Driver IMD Decile – Not important

The Index of Multiple Deprivation, a measure of relative deprivation, has no proven influence on the kinematics of the vehicle or the pedestrian and the severity of the injuries sustained.

Driver intoxicated – Disturbance

It has been determined that the driver's intoxication is statistically significant when compared to the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, but this may not actually be the case because the driver's intoxication may be associated with careless driving and a delayed reaction to collision conditions, which results in higher severity of pedestrian injuries, making it a disturbance.

Driver Job – Not important

Although studies have discovered a statistical correlation between a driver's Job and the seriousness of the pedestrian's injury, we are of the opinion that this may not be the case because the driver's home area has no effect on the kinematics of the vehicle or the pedestrian, thereby having no bearing on the outcomes of injury. As a result, the driver's Job is considered not important.

Driver License Condition – Disturbance

Although it has been determined that the driver's license condition is statistically significant when compared to the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, this may not actually be the case because the driver's license condition may be associated with careless driving or not being aware of traffic rules, which results in higher severity of pedestrian injuries, thus making it a disturbance.

Driver nationality – Not important

Although studies have discovered a statistical correlation between a driver's nationality and the seriousness of the pedestrian's injury, we are of the opinion that this may not be the case because the driver's home area has no effect on the kinematics of the vehicle or the pedestrian, thereby having no bearing on the outcomes of injury. As a result, the driver's nationality is considered not important.

Driver journey purpose – Not important

Although it has been determined that the driver's journey purpose is statistically significant when compared to the severity of pedestrian injuries in the event of a vehicle-to-pedestrian collision, this may not actually be the case because it has no influence on the event and should be considered not important.

Ground to base of windshield (wrap) – Not important

As it is derived from variables that are assessed individually, it is excluded.

Ground to top of windshield (wrap) – Not important

As it is derived from variables that are assessed individually, it is excluded.

Impact location – Control-variable

Numerous research has looked at this question and shown a relation between stiffness and injury mechanism and impact location geometry. The location of the pedestrian impact is thus categorised as a control-variable.

Impact Speed – Control-variable

Various researchers have proved the relationship between impact speed and the severity of injuries sustained by pedestrians. As a result, impact speed is classified as control-variable.

Impact Speed (squared) – Not important

As it is derived from variables that are assessed individually, it is excluded

Kinetic energy – Not important

As it is derived from variables that are assessed individually, it is excluded .

manoeuvre – Control-variable

The kinematics of the vehicle and the pedestrian are affected by the manoeuvre of the vehicle, such as breaking or steering, which also determines the severity of the injuries experienced by the pedestrian. The manoeuvre of the vehicle is thus classified as a control-variable.

Number of vehicles involved – Control-variable

The number of vehicles involved in a collision with a pedestrian is control-variable since it affects the pedestrians' kinematics as well as the injuries they incur. Vehicles may collide with each other during or after the collision, causing the kinematics to change. This may also cause injuries other than the contact with the vehicle as well as the infrastructure.

Rear hood opening distance – Not important

As it is derived from variables that are assessed individually, it is excluded .

Registration year – Not important

As the registration year of the vehicle does not affect its kinematics or its stiffness, this variable is excluded from the study.

Speed Ratio (Impact speed/Speed limit) – Not important

As it is derived from variables that are assessed individually, it is excluded .

Travel speed – Disturbance

Travel speed indicates pre-impact conditions, as we are interested in crash configuration it is classified as a disturbance. It can be argued that impact speed can be derived from travel speed and can influence the kinematics of the vehicle, but this condition is already being assessed.

Vehicle Engine (CC) – Disturbance

The performance of a vehicle can be correlated with its engine capacity, and this may enable the vehicle to go at a higher speed, which in turn results in a higher impact speed, seriously injuring people. While a vehicle's engine capacity may have an impact on the kinematics of the vehicle, it has no control over how seriously the pedestrian may be injured. Vehicle engine capacity variable is therefore categorised as disturbances.

Vehicle propulsion – Not important

The efficiency and power of vehicle propellant fuels may vary, however since engine specifications control how the vehicle performs, this variable is not thought to be important.

Vehicle type – Not important

Numerous studies have discovered a statistical relationship between vehicle type and the severity of pedestrian injuries, but we do not think this is the case since vehicle type approximates the combination of other variables that describe vehicle geometry. This is considered not important.

Weight – Control-variable

The vehicle's weight governs the vehicle's kinematics and dictates how much energy is transferred from the vehicle to the pedestrian, making it a control-variable.

Windscreen Angle – Control-variable

Several studies have found that the vehicle's front profile is important in pedestrian-to-vehicle collisions. One of the factors influencing the front profile is the windscreen angle. As a result, the windscreen angle has been designated as a control-variable.

Windscreen stiffness – Control-variable

Several studies have found that the vehicle's front profile stiffness is important in pedestrian-to-vehicle collisions. As a result, the windscreen stiffness has been designated as a control-variable.

Year of manufacture – Control-variable

The year the vehicle was manufactured can be used to identify the attributes of the body materials and safety performance of the vehicle, which directly affect the severity of the pedestrian injury, making it a control-variable.

Infrastructure

Area type and Clear roadway width – Disturbance

Due to lesser traffic density in rural areas or on open roads, automobiles may go faster and injure pedestrians more severely. Serious pedestrian injuries are not caused by the type of area or the clear roadway width; they are caused by increased speeds and aggressive driving. Therefore, these are considered disturbances.

Control type and Crosswalk type – Disturbance

The presence of a junction control or crosswalk will affect how the vehicle and pedestrians proceed since they may need to slow down for safety reasons or by law. The slower speed means that when a vehicle impacts a pedestrian, the severity of the injuries is less severe. The severity decreased because of decreasing speed rather than a control type or crossing type. Therefore, these are considered disturbances.

Hazard and Intersection type – Disturbance

The type of intersection or the presence of a hazardous environment can influence how a vehicle and a pedestrian behave, which may result in a slower speed or greater caution and a lower severity vehicle-to-pedestrian collision. The severity decreased because people were driving more slowly or exercising caution, not because there were any intersections or hazardous situations. Therefore, these are considered disturbances.

Land Use and Nearby infrastructure – Disturbance

The movement of the vehicle and the pedestrians will be impacted by the nearby train station, school zone, or residential zone, as they may slow down to navigate or be required by law. When a vehicle hits a pedestrian, the severity of the injuries is reduced because of the slower speed. Decreasing speed and not nearby infrastructure or land use is what caused the severity to decrease. These are therefore regarded as disturbances.

Node type, Number of lanes and Number of roads – Disturbance

A road with more lanes or one that is in the midst of a block may cause vehicles to become less alert to pedestrians crossing the road in the middle, allowing them to travel at higher speeds and injuring pedestrians more severely. Increased speeds and aggressive driving are to blame for serious pedestrian injuries, not the number of lanes, roadways, or node type. These fit the definition of disturbance.

Obstruction, On-street parking, and Park Lane – Disturbance

The movement of the vehicle and the pedestrians will be impacted by obstruction, on-street parking, or the presence of a parking lane, as they may slow down to navigate. When a vehicle hits a pedestrian, the severity of the injuries is reduced because of the slower speed. Decreasing speed and not parking is what caused the severity to decrease. These are therefore regarded as disturbance.

Pavement type – Control-variable

Unpaved or gravel pavement has an impact on both the movement of vehicles and pedestrians, as well as the severity of injuries sustained by pedestrians hitting the surface following a collision between a vehicle and a pedestrian. Pavement type is therefore regarded as a control variable.

Pavement surface condition – Control-variable

One of the most crucial factors for pedestrian injury causation in the case of a vehicle-to-pedestrian collision is the tertiary impact, or the impact between the pedestrian and the road infrastructure. The type of pavement surface condition governs the severity of injuries sustained. Thus, pavement surface condition is therefore categorised as a control-variable.

Road class type – Disturbance

Vehicles move at higher speeds on some types of roads, such as highways versus town roads, and drivers' being less vigilant may result in a higher severity of pedestrian injuries. A road class type variable is therefore categorised as a disturbance.

Road geometry – Disturbance

The geometry of the road, i.e., being curved or up or down hill, affects the kinematics of the vehicle by increasing or decreasing the speed of the vehicle, thus affecting the severity of the impact with a pedestrian. As a result, road geometry is classified as a disturbance.

Road marking – Disturbance

We believe that the behaviour of pedestrians and the driver of the vehicle changes based on road marking. They can get more vigilant, thus reducing the severity of injuries caused by vehicle-to-pedestrian collisions. The change in injury severity is due to the change induced by the road markings, making it a disturbance.

Road Network – Disturbance

We believe that the kinematics of the pedestrian and the vehicle change based on whether there is an intersection or not, and this may change how they behave, thus affecting the severity of the injuries sustained. The change in injury severity is due to the change induced by the road network, making it a disturbance.

Road surface condition – Control-variable

One of the most crucial factors for pedestrian injury causation in the case of a vehicle-to-pedestrian collision is the tertiary impact, or the impact between the pedestrian and the road infrastructure. The type of road surface condition governs the severity of injuries sustained. Thus, road surface condition is categorised as a control-variable.

Road surface material – Control-variable

One of the most crucial factors for pedestrian injury causation in the case of a vehicle-to-pedestrian collision is the tertiary impact, or the impact between the pedestrian and the road infrastructure. The type of road surface material governs the severity of injuries sustained. Thus, road surface material is categorised as a control-variable.

Road type – Disturbance

Vehicles move at higher speeds on some types of roads, such as two-lane vs single-lane ones, and driver's being less vigilant, may result in a higher severity of pedestrian injuries. Road type variable is therefore categorised as a disturbance.

Road width – Disturbance

Road width may cause pedestrians to rush when crossing the street, increasing crossing speed, which affects pedestrian kinematics and injury severity. This makes road width variable a disturbance.

Shoulder type – Disturbance

Shoulder type variable, such as being curbed or paved, is classified as disturbance as pedestrians may be careless while on the paved shoulder, thus affecting only the kinematics of the pedestrian and not the severity of the injuries.

Special circumstance – Disturbance

Special circumstances, such as busy pathways or bus routes, may appear to have an impact on the severity of pedestrian injuries. However, this may not always be the case. If there are no other vehicles on the path, buses may drive more quickly, causing serious pedestrian injuries. Special situations are hence categorised as disturbance.

Speed limit – Disturbance

Although there may be a correlation between the speed limit and the severity of pedestrian injuries, we classify this relation as a disturbance because we think that the speed limit affects vehicle kinematics through influencing the impact speed rather than pedestrian injuries on their own.

Traffic aids – Not important

Unfortunately, although other studies have concluded that there is a statistical relationship between traffic aid and the severity of pedestrian injuries, they did not include any information about what this variable represents, thus making it difficult to analyse. As a result, it is not considered important.

Traffic congestion – Disturbance

Although some studies have found a statistical correlation between traffic congestion and the severity of pedestrian injuries, this may not be the case because, prior to the impact, traffic congestion may cause the vehicle to slow down and make pedestrians more cautious, which may result in a reduction in severity. By itself, traffic congestion has no influence on pedestrian injuries, making it a disturbance.

Environment

Population age – Not important

Population age is a measure of the demographics of the area where a vehicle-pedestrian collision happens, but because each of these incidents is unique, population age has no bearing on how serious the accidents are. The age of the population is thus not thought to be significant.

Accident Location – Not important

Although the location of the event affects how severe a vehicle-pedestrian collision is, this information is already acquired in more detail from variables in the infrastructure section, therefore the location of the accident is not seen to be crucial.

Accident type – Control-variable

The configuration of the interaction between the vehicle and the pedestrian is described by the accident type variable. This arrangement controls both the kinematics of the encounter and the injuries the pedestrian sustains as a result accident type is regarded as a control-variable.

Alcohol involvement – Not important

It is evident that alcohol involvement is known to cause severe injuries in the event of a vehicle-to-pedestrian collision. But this information is acquired in detail by other variables. As a result, this variable is considered non-important.

Average annual daily traffic – Not important

Average annual daily traffic is a measure of the demographics of the area where a vehicle-pedestrian collision happens, but because each of these incidents is unique, average annual daily traffic has no bearing on how serious the accidents are, thus not thought to be significant.

Contributory factor – Not important

The contributing factor is a blatant signal of who might have caused the accident, and as it lacks information on the severity of the pedestrian's injuries, thus it is considered not important.

Day of week – Not important

There may be a correlation between the day of the week and the severity of the injuries experienced by the pedestrian in vehicle-to-pedestrian collisions since certain days may see more accidents than others, and some of these accidents may cause serious injuries. The day of the week, however, does not affect the kinematics of vehicles, pedestrians, or injuries, thus we contend that this is purely a statistical link and has no consequence on the seriousness of injuries. As a result, this variable is considered non-important.

Direction of impact – Control-variable

The direction of impact variable describes the configuration of the interaction between the vehicle and the pedestrian. This configuration not only governs the kinematics of the interaction but also the resulting injuries sustained by the pedestrian. Thus, direction of impact is considered a control-variable.

Education – Not important

Although several studies have identified a statistical correlation between an educational level and the severity of injuries incurred in the case of a vehicle-to-pedestrian collision, we believe it has no bearing on the pedestrian's kinematics or injuries. It could be argued that education is linked to socioeconomic status in some circumstances, resulting in a lower quality of life, which may have an impact on the severity of injury cases, but for our analysis, we are interested if education has an independent effect on pedestrian-to-vehicle collision, which it does not. As a result, education is considered irrelevant.

Ethnicity – Not important

While there may be a statistical correlation between the nationality and the severity of the injury, we feel that nationality is unimportant and has no bearing on vehicle-to-pedestrian collisions. Although pedestrians from other nations may be unaware of traffic laws, this can cause misunderstandings and accidents, as well as physical variations owing to demographics. Nationality has no effect on the kinematics of the impact or the severity of the injuries.

Fault – Not important

The fault is a blatant sign of who might have caused the accident, and as it lacks information on the severity of the pedestrian's injuries, it is considered not important.

First harmful event – Control-variable

The first harmful event variable describes the configuration of the interaction between the vehicle and the pedestrian. This configuration not only governs the kinematics of the interaction but also the resulting injuries sustained by the pedestrian. Thus, the first harmful event is considered a control-variable.

Household income – Not important

Although several studies have identified a statistical correlation between a household income and the severity of injuries incurred, we believe it has no bearing on the pedestrian's kinematics or injuries. It could be argued that income is linked to socioeconomic status in some circumstances, resulting in a lower quality of life, which may have an impact on the severity of injury cases, but for our analysis, we are interested if income has an independent effect on pedestrian-to-vehicle collision, which it does not. As a result, household income is considered irrelevant.

Household size – Not important

Although there may be a statistical link between household size and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable household size is therefore unimportant.

Humidity – Control-variable

In their investigation, Kalankesh et al. (2015) found that low humidity and high temperatures increased the likelihood of trauma deaths because they caused changes in blood pressure. It is also known to cause changes in vehicle performance. Thus, humidity is regarded as a control-variable.

Lighting – Disturbance

Several researchers have found a statistical correlation between lighting conditions and injury severity. We disagree, believing that, while a lighting condition may impact vehicle kinematics, it has no bearing on the severity of an injury. The driver may miss the pedestrian and fail to make the necessary maneuvers to prevent a collision if the pedestrian is not visible due to bad lighting. We feel that other variables, such as vehicle speed, offer a better explanation for differences in injury severity than lighting condition. As a result, the lighting condition is classified as a disturbance.

Month – Not important

Although there may be a statistical link between the month of the year and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable months are therefore unimportant.

Population – Not important

Although there may be a statistical link between population and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable population is therefore unimportant.

Road Density – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Time of day – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Visibility – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Weather – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Temperature – Control-variable

In their investigation, Kalankesh et al. (2015) found that low humidity and high temperatures increased the likelihood of trauma deaths because they caused changes in blood pressure. It is also known to cause changes in vehicle performance. Thus, temperature is regarded as a control-variable.

Year – Not important

Although there may be a statistical link between year and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable years are therefore unimportant.

Zone area (km2) – Not important

Although there may be a statistical link between zone area and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable zone area is therefore unimportant.

Others

Ambulance Rescue – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Avenue – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Borough/District – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Camera distance – Disturbance

The placement of a camera may encourage motorists to follow the law, lessening the severity of pedestrian injuries. It is obvious that following the rules rather than the camera's presence is what has caused the severity to decrease. As a result, it is categorised as a disturbance.

Camera land use – Not important

Although there may be a statistical link between camera land use and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable camera land use is therefore unimportant.

Contrecoup pressure – Not important

Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Coup pressure – Not important

Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Cumulative strain damage measure – Not important

Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Dilatational damage measure – Not important

Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Distance from GPO – Not important

Although there may be a statistical link between distance from GPO and the seriousness of a pedestrian injury, we do not think it affects the kinematics of the pedestrian or the vehicle or the injuries that ensue. Variable distance from GPO is therefore unimportant.

Hit and run – Disturbance

The most serious vehicle-to-pedestrian collisions are frequently tied to hit-and-run incidents. As a result, the statistical association. Hit-and-run accidents merely serve as a gauge of the severity of the collision and have no bearing on the injuries they cause.

Number of bus stops – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of hotels – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of metro exits – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of non-signalized intersections – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of restaurants – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of schools – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of shopping malls – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Number of signalized intersections – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Percentage of trucks – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Shear stress – Not important

Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Total crashes – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Trip generation (per day) – Not important

As it captures the same information as another variable which is assessed, it is excluded.

Von Mises stress – Not important

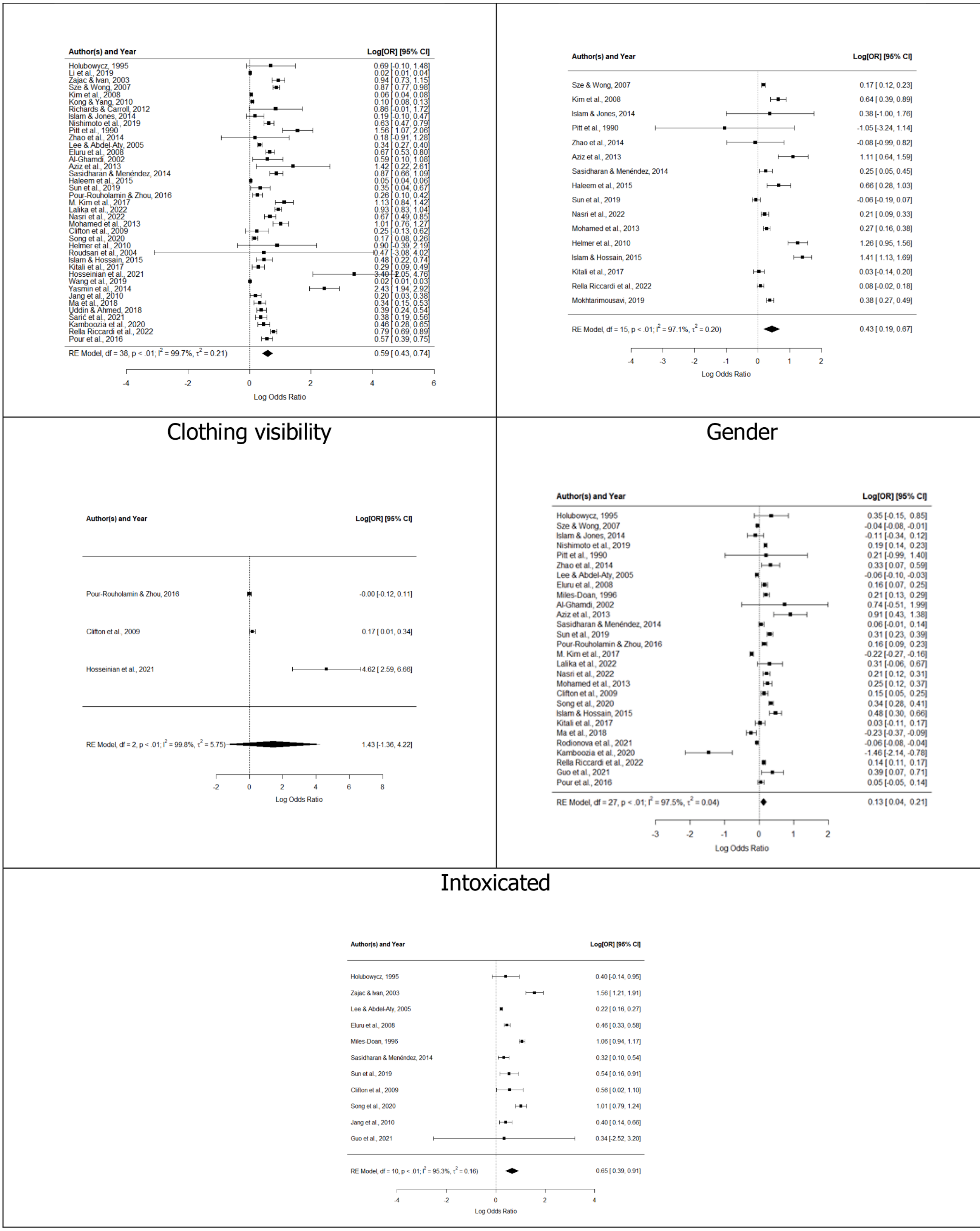
Despite being an excellent indicator of the severity of the injuries incurred, this variable was left out since it cannot be extracted at the scene of the collision and required a complex computational process.

Walking frequency (per day) – Not important

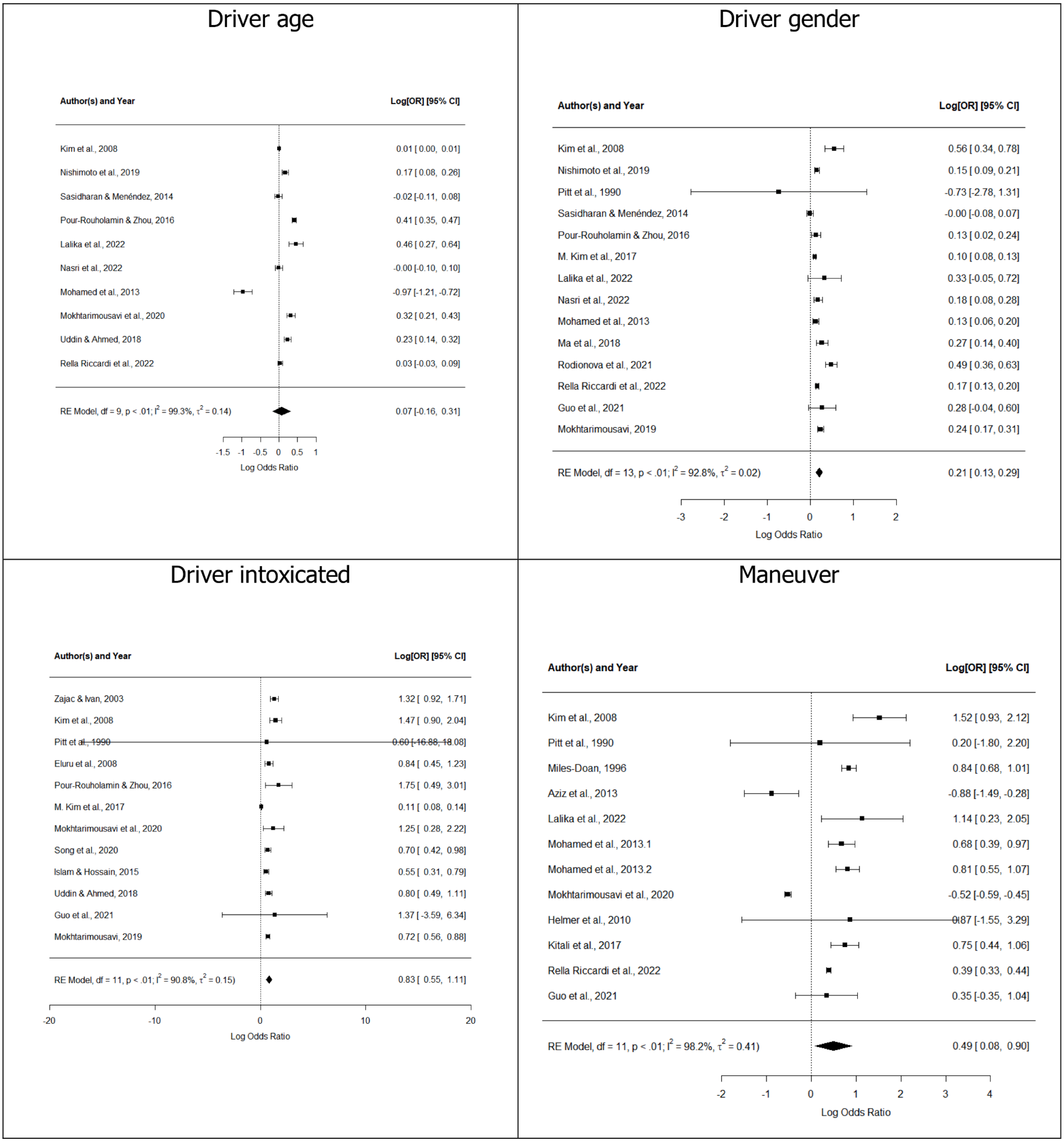
As it captures the same information as another variable which is assessed, it is excluded.

Appendix D

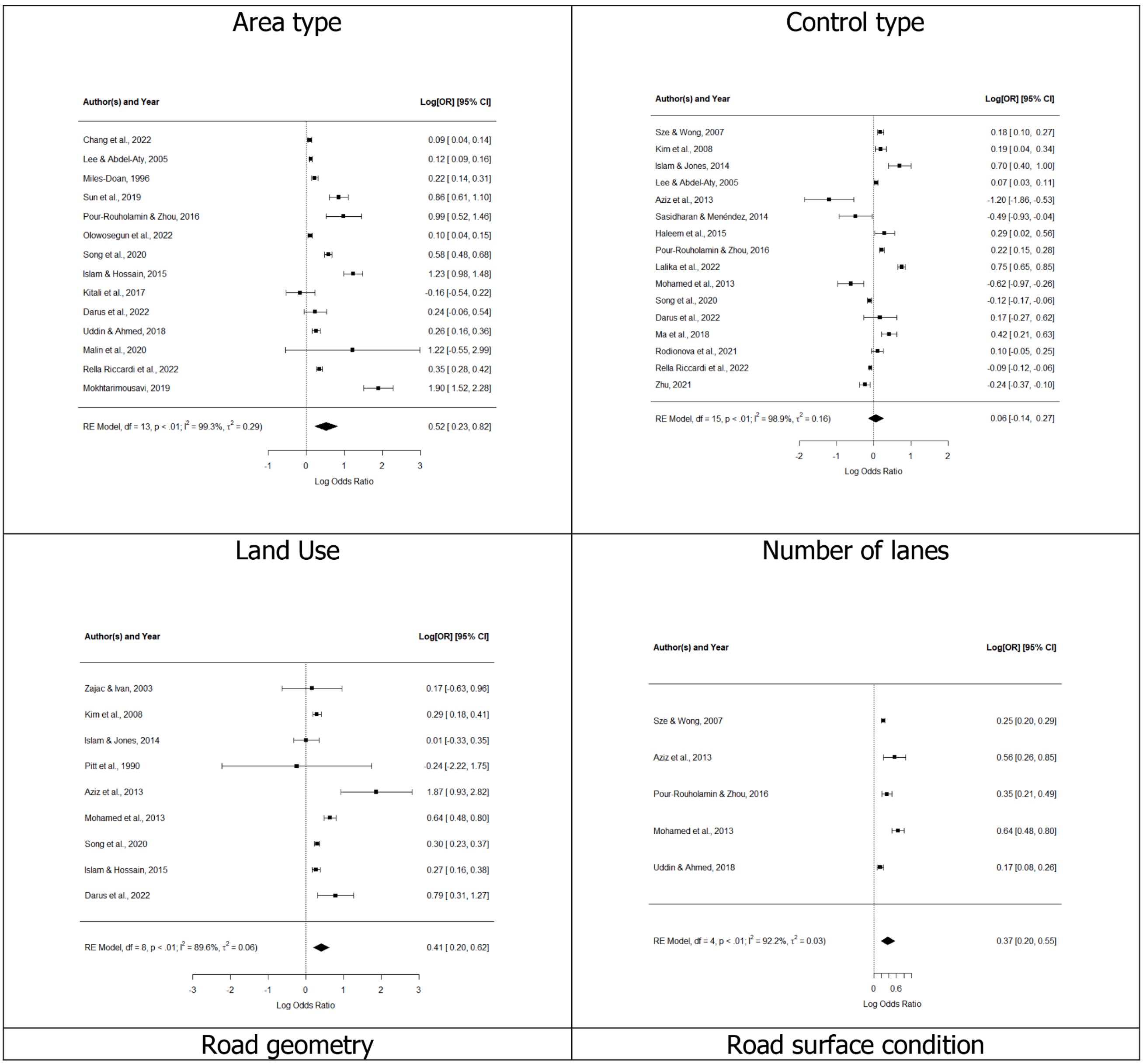
Pedestrian



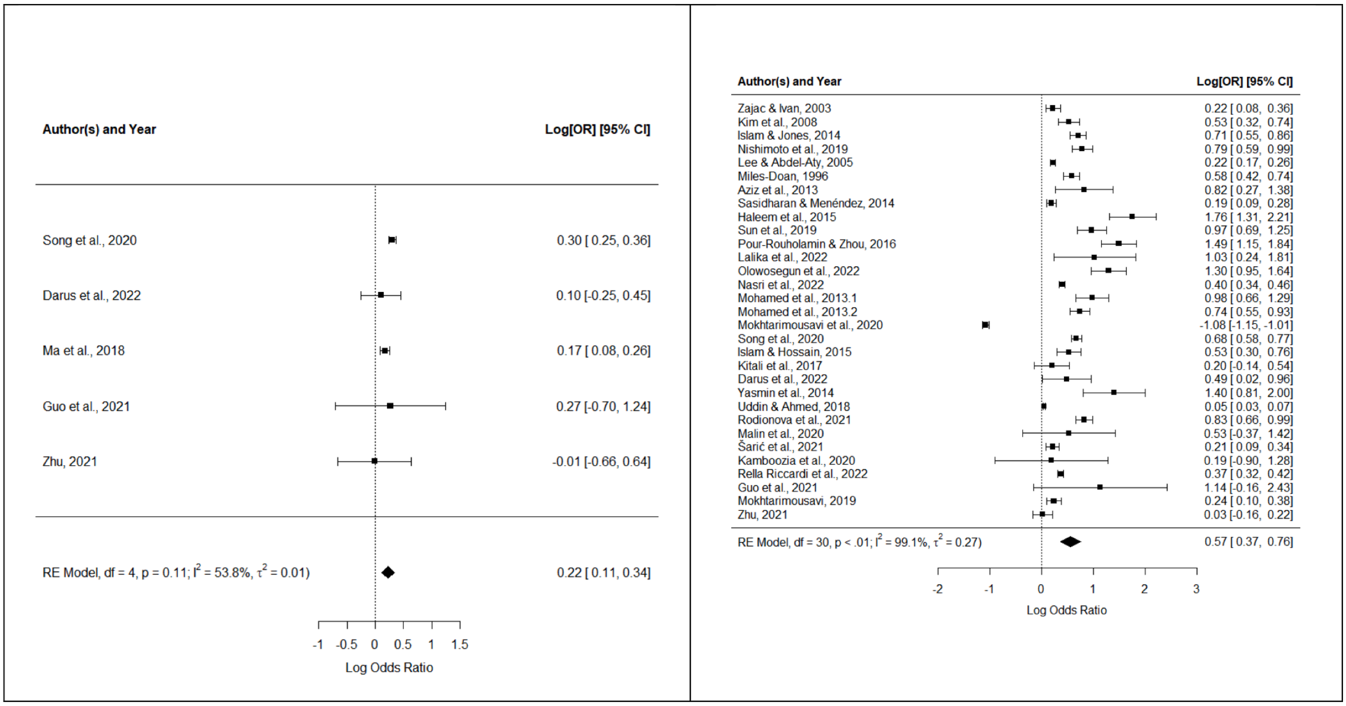
Vehicle


Driver age
Author(s) and Year
Log[OR] [95% CI]
Kim et al., 2008 0.01 [0.00, 0.01]
Nishimoto et al., 2019 0.17 [0.08, 0.26]
Sasidharan & Menéndez, 2014 -0.02 [-0.11, 0.08]
Pour-Rouholamin & Zhou, 2016 0.41 [0.35, 0.47]
Lalika et al., 2022 0.46 [0.27, 0.64]
Nasri et al., 2022 -0.00 [-0.10, 0.10]
Mohamed et al., 2013 -0.97 [-1.21, -0.72]
Mokhtarimousavi et al., 2020 0.32 [0.21, 0.43]
Uddin & Ahmed, 2018 0.23 [0.14, 0.32]
Rella Riccardi et al., 2022 0.03 [-0.03, 0.09]
RE Model, df = 9, p < .01; I² = 99.3%, τ² = 0.14) 0.07 [-0.16, 0.31]
-1.5 -1 -0.5 0 0.5 1
Log Odds Ratio
Driver gender
Author(s) and Year
Log[OR] [95% CI]
Kim et al., 2008 0.56 [0.34, 0.78]
Nishimoto et al., 2019 0.15 [0.09, 0.21]
Pitt et al., 1990 -0.73 [-2.78, 1.31]
Sasidharan & Menéndez, 2014 -0.00 [-0.08, 0.07]
Pour-Rouholamin & Zhou, 2016 0.13 [0.02, 0.24]
M. Kim et al., 2017 0.10 [0.08, 0.13]
Lalika et al., 2022 0.33 [-0.05, 0.72]
Nasri et al., 2022 0.18 [0.08, 0.28]
Mohamed et al., 2013 0.13 [0.06, 0.20]
Ma et al., 2018 0.27 [0.14, 0.40]
Rodionova et al., 2021 0.49 [0.36, 0.63]
Rella Riccardi et al., 2022 0.17 [0.13, 0.20]
Guo et al., 2021 0.28 [-0.04, 0.60]
Mokhtarimousavi, 2019 0.24 [0.17, 0.31]
RE Model, df = 13, p < .01; I² = 92.8%, τ² = 0.02) 0.21 [0.13, 0.29]
-3 -2 -1 0 1 2
Log Odds Ratio
Driver intoxicated
Author(s) and Year
Log[OR] [95% CI]
Zajac & Ivan, 2003 1.32 [0.92, 1.71]
Kim et al., 2008 1.47 [0.90, 2.04]
Pitt et al., 1990 0.60 [-16.88, 18.08]
Eluru et al., 2008 0.84 [0.45, 1.23]
Pour-Rouholamin & Zhou, 2016 1.75 [0.49, 3.01]
M. Kim et al., 2017 0.11 [0.08, 0.14]
Mokhtarimousavi et al., 2020 1.25 [0.28, 2.22]
Song et al., 2020 0.70 [0.42, 0.98]
Islam & Hossain, 2015 0.55 [0.31, 0.79]
Uddin & Ahmed, 2018 0.80 [0.49, 1.11]
Guo et al., 2021 1.37 [-3.59, 6.34]
Mokhtarimousavi, 2019 0.72 [0.56, 0.88]
RE Model, df = 11, p < .01; I² = 90.8%, τ² = 0.15) 0.83 [0.55, 1.11]
-20 -10 0 10 20
Log Odds Ratio
Maneuver
Author(s) and Year
Log[OR] [95% CI]
Kim et al., 2008 1.52 [0.93, 2.12]
Pitt et al., 1990 0.20 [-1.80, 2.20]
Miles-Doan, 1996 0.84 [0.68, 1.01]
Aziz et al., 2013 -0.88 [-1.49, -0.28]
Lalika et al., 2022 1.14 [0.23, 2.05]
Mohamed et al., 2013.1 0.68 [0.39, 0.97]
Mohamed et al., 2013.2 0.81 [0.55, 1.07]
Mokhtarimousavi et al., 2020 -0.52 [-0.59, -0.45]
Helmer et al., 2010 0.87 [-1.55, 3.29]
Kitali et al., 2017 0.75 [0.44, 1.06]
Rella Riccardi et al., 2022 0.39 [0.33, 0.44]
Guo et al., 2021 0.35 [-0.35, 1.04]
RE Model, df = 11, p < .01; I² = 98.2%, τ² = 0.41) 0.49 [0.08, 0.90]
-2 -1 0 1 2 3 4
Log Odds Ratio

Infrastructure



Environment



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