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Risk factors as causes of accidents: Criterion of causality, logical structure of relationship to accidents and completeness of explanations

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Highlights

- Risk factors are causes of accidents if they can be influenced by road safety measures.
- Many human factors are impossible to change and are not causes of accidents.
- It is possible to determine when an explanation of an accident is complete.
- Coefficients in regression models do not as a rule show causal relationships.

Abstract

The causes of accidents are studied in the belief that by finding causes, accidents can be prevented by removing or controlling their causes. It follows that the risk factors that have traditionally been regarded as contributing to accidents can only be regarded as causes if it is possible to alter them by means of one or more road safety measures. Risk factors are causes if their relationship to accidents can be changed by implementing one or more road safety measures influencing the risk factors. Hence, road safety measures that could have been implemented to change risk factors identified as contributing to an accident, but have not, are also causes of accidents. Many of the human factors that have traditionally been identified as risk factors for accidents, like age, gender, driving experience, expectations or involuntary inattention are not causes of accidents, because they cannot be changed by means of any realistic road safety measure. What cannot be changed (could not have been different) is not a cause. It is possible, both in case studies and in statistical analyses, to determine when a set of factors precipitating or contributing to accidents is complete. A list of road safety measures that could have been implemented is only limited by our creativity and imagination and will therefore never be complete.

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Keywords

Cause; Risk factor; Case study; Statistical analysis; Completeness; Intervention

1. Introduction

The scientific study of causes of accidents has a history going at least 100years back. The motivation for trying to find the causes of accidents has always been the same: by finding the causes of accidents, one will learn how best to prevent them. Thus, studying causation has been regarded as necessary in order to find effective prevention. Prevention consists of removing or controlling causes.

This way of thinking is very logical; yet the following comment by Grime (1987, page 15) appears to contradict it:
"Human factors were judged to be present in about 95 percent of the accidents. This is perhaps not surprising since all accidents involve road users and it is almost always possible to think of some action which could have been taken by the road user to avoid the accident. However, when considering remedial measures, the most effective remedy is not necessarily related to the main factor and may lie in a different area. Human behaviour may often be influenced more readily by engineering means than by education or the enforcement of legislation."

Grime referred to in-depth studies of accidents, which almost always conclude that human factors are the dominant cause of accidents. But then he flatly contradicts the logic of solving a problem by removing its causes by stating that the most effective safety measures do not necessarily act on the main cause. This must be wrong and was perhaps not what he intended to say. A road safety measure can only be effective by influencing one or more risk factors for accidents (Elvik, 2004). If these risk factors cannot be identified, we cannot explain why a road safety measure is effective.

Grime is not the only one to make remarks along the lines in the quote above. It would appear that the study of accident causation on the one hand and the study of accident prevention on the other have proceeded largely as two separate disciplines with almost no exchange of knowledge between them. This appearance is deceptive, as made clear in two recent papers by Shinar (2019) and Hauer (2020). These papers argue that causation and prevention are two sides of the same coin, but that a misguided focus on what happened immediately before an accident and made it inevitable has created the misleading finding that human factors are the dominant causes of accidents.

The aims of this paper are:

1. To propose a definition of cause, that fully integrates the study of causation and prevention and treats them simply as different descriptions of the same phenomenon.
2. To apply the concept of INUS-conditions (explained below) to help decide when a list of risk factors contributing to an accident is complete, incomplete or more than complete.
3. To explain when a statistical analysis of factors associated with accidents is complete, incomplete and more than complete (overfitted).
4. To discuss how, if at all, one can decide which of the relationships in statistical analyses are causal and which are not.

2. Risk factors as causes of accidents

Definitions of cause and causation abound. In a paper discussing how to assess causality in multivariate statistical models, Elvik (2011) proposed the following definition of a cause:

A cause is any action, event or process that produces a change (the effect) that would not otherwise have occurred.

This definition associates a cause with a change that would not otherwise (counterfactually) have occurred. The definition is very similar to the definition proposed by Hauer (2020):

A crash cause is a circumstance or action that, were it different, the frequency of crashes and/or their severity would be different.

In other words: a cause is something that can be changed, and if it is changed, it brings about a change in the number or severity of crashes. This paper uses both the term crash and the term accident.

In the philosophy of science, a very similar definition has been proposed by Woodward (2003) (slightly abbreviated):

X is a cause of Y if (1) there is an intervention I that changes the value ofXsuch that (2) if this intervention (and no other intervention) were carried out, the value of Y, or the probability distribution of Y, would change.

IfXis a risk factor, Y is accidents and I a road safety measure, this definition states that:

A risk factor causes accidents if there exists a road safety measure that can change the value of the risk factor so that the number of accidents changes.

This definition fully integrates causation and prevention: A risk factor is a cause if it can be modified by means of a preventive measure; otherwise not. Note that not every risk factor will be a cause according to this definition. Factors that cannot be changed by some intervention are not causes. Thus, many of the human factors often listed as risk factors for accidents are not causes. This clearly includes age and gender, but also factors that cannot be (easily) manipulated such as experience or, in many cases, expectations.

This definition of a cause is regarded as fruitful when dealing with phenomena humans can influence. It is, however, not a definition that applies to, for example, laws of nature. The rotation of the earth causes daylight and darkness to alternate regularly in a predictable way. There is no doubt the relationship is causal, but humans cannot influence it. Many laws of nature are like that, but as far as societal phenomena are concerned, they are in principle subject to human intervention and modification.

3. Determining empirically when a factor is a cause

Woodward discusses when interventions can be regarded as causes by means of causal diagrams. These diagrams are shown in Fig. 1.

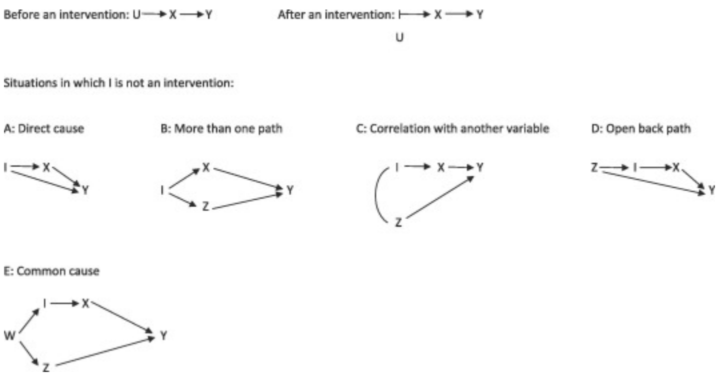

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Fig. 1. Causal diagrams for interventions. Based on Woodward (2003).

The ideal situation is shown in the upper diagram. Before intervention some factor U is associated with a risk factorXwhich is associated with accidents Y. After the intervention I, X is only influenced by I and not by U. This represents an experimental intervention in which confounding is ruled out. By confounding is meant that other variables influence the risk factor in addition to the intervention, making it difficult to identify the contribution of the intervention to changes in the risk factor.

In each of the five cases in the bottom part of Fig. 1, the variable I does not qualify as an intervention according to the restrictions proposed by Woodward (2003). In the first case (case A), the intervention is a direct cause of changes in the dependent variable. This case is unproblematic. Road safety measures always act on one or more risk factors and their influence on accidents goes through these risk factors. There is no direct path from road safety measures to accidents. In case B, two causal paths emanate from I. This could certainly be the case for some road safety measures. As an example, salting of roads (I) influences friction (X) as well as speed (Z) and both friction and speed influence the number of accidents (Y). Woodward requires that an intervention acts only by way of its intended causal path, and that it has no unintended effects following a different causal path. However, if in case B both friction and speed can be measured and their relationship to accidents determined, it is possible to identify the separate contributions of the two risk factors to the number of accidents.

In case C, there is a correlation, indicated by the curved line, between the intervention (I) and some other variable (Z). According to Woodward, variable I is then not an intervention. The introduction of traffic signals corresponds to case C. Signals are only introduced if traffic volume is larger than a critical value. Their use is therefore highly correlated with traffic volume. However, if traffic volume does not change as a result of introducing traffic signals, it would still be possible to identify the causal contribution to a change in the number of accidents of introducing traffic signals. The risk factor influenced in this case would be the number of conflict points between the traffic movements passing through a junction.

In case D, a cause further back in the causal chain influences both the intervention (I) and the dependent variable (Y). An abnormally high recorded number of accidents would be an example: this will influence both the intervention (if sites with a bad accident record are selected for treatment) and the number of accidents after the intervention through regression-to-the-mean. It is possible to control statistically for regression-to-the-mean and thus eliminate it as a confounding factor (Hauer, 1997).

Finally, in case E a common cause influences both the intervention (I) and another variable (Z), both of which influence the dependent variable (Y). In this case W could be a drop in energy prices, leading to an increase in traffic volume (Z) which (directly) influenced the number of accidents. At the same time, cheaper operation of police vehicles (as a result of cheaper energy, W), could lead to increased enforcement (I), less speeding (X) and fewer accidents (Y).

The restrictions on what should count as an intervention imposed by Woodward are intended to remove confounding, i. e. avoid situations in which we cannot be sure about whether the changes in the dependent variable (Y) were caused by the intervention (I) or something else. It is, however, possible to identify and statistically control for the confounding factors in all the cases discussed by Woodward and thus establish a basis for causal inferences. Control for confounding in observational studies will always be imperfect, but it may be sufficient to support arguments in favour of a causal interpretation of a study.

4. INUS-conditions as a criterion of completeness for case studies

The association between risk factors and accidents has been studied at two levels: the case-study level (in-depth studies) and the macro-level. In case studies, the objective is to identify the risk factors that contributed to, and ultimately made inevitable, a single accident. It is not unusual for case studies to list several risk factors that were judged to contribute to the accident. In Norway, for example, multi-disciplinary teams have conducted in-depth studies of every fatal road accident since 2005. A summary report of these studies is published every year. In 2021, 76 fatal accidents were studied (Ringen, 2022). In these 76 accidents, a total of 175 contributing factors related to road users, 20 factors related to vehicles, 30 factors related to roads and 15 factors related to environmental conditions were identified. In total 240 factors contributing to 76 accidents (3.16 factors per accident) were identified, of which 72.9% were related to road users.

As mentioned above, the objective of in-depth case studies is usually to determine what factors made the accident inevitable. Is there a clear criterion for determining exactly what combination of factors made an accident inevitable, i. e. were sufficient for it to occur? Many years ago, such a criterion was proposed by John Mackie, 1965, Sosa and Tooley, 1993. He referred to it as INUS-conditions. An INUS-condition is: An Insufficient but Necessary part of a condition which is itself Unnecessary but Sufficient for the result. The letters giving these conditions their acronym have been capitalised and underlined.

As an example, Mackie uses the case of a house that burnt because of an electric short-circuit. Was the short-circuit an INUS-condition for the fire? Mackie observes that by itself, a short-circuit would not start a fire unless there was flammable material nearby. The presence of flammable material is therefore a necessary part of the condition. Mackie goes on to note that even the conjunction of a short-circuit and the presence of flammable material would not be sufficient to start a fire if the house had a sprinkler system. Thus, the absence of a sprinkler system is also part of the condition for the fire. Jointly, these three factors: (1) short-circuit, (2) flammable material, and (3) no sprinkler system were sufficient to cause the fire. They were, however, not necessary. Fires can start in many other ways, e.g. smoking in bed, lightning striking the house, a stove left on after cooking, and so on.

The logical structure of INUS-conditions implies that their relation to accidents is probabilistic. Each accident must by logical necessity have had some sufficient conditions for it to occur, but none of the elements of a sufficient condition are necessary, and each of the conditions that jointly were sufficient was not sufficient by itself.

It is interesting that Mackie included the absence of a safety measure among the conditions for an accident. This makes his conception of accident causation analogous to that proposed for risk factors in this paper (a risk factor is a cause if it can be influenced by a safety measure). The next section illustrates how the INUS-condition criterion can be applied to identify the combination of factors that were sufficient (but not necessary) to bring about an accident.

5. An in-depth study of an accident

Many years ago, in-depth studies of road accidents were made in the county of Østfold in Norway (Muskaug, 1988). One of the accidents was described as follows:
"Single vehicle accident in which the tractor of a tractor-trailer combination overturned when making a left turn at an intersection. The intersection has good sight distances. During the left turn, the tractor overturned and ended in the ditch on the right-hand side of the road into which the left turn was made. The accident did not result in personal injury. No other road users were present at the intersection when the accident occurred. "

After analysing the sequence of events leading to the accident, and interviewing the driver, the panel of experts pointed to the following *potentially* contributing factors:

1. The radius of the curve where the left tum was made is only 10–15 m, making it very difficult to negotiate with a tractor-trailer combination.

2. The primary road curves through the intersection. This means that left-turning vehicles are subjected to an inverse super-elevation when making the left turn (i. e. instead of a superelevation where the right-hand side wheels are elevated, the super-elevation in this case resulted in the left-hand side wheels being elevated).

3. The maximum safe speed for avoiding overturning for vehicles with the same size and weight as the vehicle involved in the accident was estimated to be around 21 km/h.
4. The driver did not choose an optimal driving path when making the left tum. He made a relatively sharp turn, with a radius of about 10 m, instead of making a turn with a curve radius closer to 15 m.
5. When the driver noticed that the vehicle was about to overturn, he tried to avoid this by steering to the right. This did not prevent the vehicle from overturning, as the right tum manoeuvre was obstructed by a rock of about 25 kg which was located in front of the front wheel of the trailer.
6. The driver was comparatively inexperienced and did not perceive the curve as hazardous. He did not know that the vehicle was likely to overturn at such a low speed. He had negotiated the curve successfully on several previous occasions.

In total, six potentially contributing factors were listed. To identify the risk factors constituting the INUS condition of the accident, we must ask: Does the list include a combination of risk factors that jointly were sufficient to bring about the accident? Does the list include risk factors that cannot be regarded as causes, because no intervention could change them?

The first risk factor listed is curve radius. This is certainly a risk factor that can be modified and should therefore be regarded as a contributing cause. The second risk factor listed is an inverse super-elevation, which is also a factor that can be modified. The third risk factor (maximum speed) may be interpreted as a high centre of gravity increasing the probability of overturning. Again, this factor can be changed by, for example, changing the track width or height of the vehicle. The fourth factor, the choice of turning radius, could also have been different. Had the driver chosen a larger turning radius, the accident would have been less likely to occur.

As for the fifth risk factor, it is not regarded as contributing to the outcome. When the driver tried to prevent the vehicle from overturning, it had already started to do so, and it is doubtful if a more successful right-turn could have prevented it from overturning. This is obviously a judgment. But even if we suppose that by turning right, the driver had been able to prevent the vehicle from overturning, this would probably not have prevented an accident. By turning right, the driver was turning to the edge of the road and might not have been able to stop before going into the ditch.

The sixth risk factor, driver inexperience, is judged as irrelevant as it could not have been different.

This leaves the following risk factors: curve radius, inverse super-elevation, high centre of gravity and choice of driving path. The combination of these forms the INUS condition. If one of them is left out, the accident would most likely not have happened. Once the risk factors forming causes have been identified, the next step of analysis is to identify road safety measures that may influence these risk factors and assess the possibility of implementing these measures. Table 1 shows some potential measures.

Table 1. Causal analysis of truck overturning when turning left in an intersection.

INUS conditions	**Curve radius**	**Super-elevation**	**Centre of gravity**	**Choice of path**
Potential road safety measures	A: Changing angle between roads to increase curve radius	D: Straighten curve on through-road	F: Widen track width of truck	H: Inertial steering wheel based on gyro sensor
	B: Widen side-road to allow for larger turning radius	E: Warning sign about lack of super-elevation	G: Lower height of truck	I: Intelligent speed adaptation based on gyro sensor
	C: Converting junction into roundabout			J: Driver training (e. g. in a simulator)
Number of measures	3	2	2	3

It is assumed that none of the measures listed have been implemented. A total ten measures are listed. A few of them deserve comments. If the truck had been equipped with a gyro recording spatial acceleration, this might have been integrated with the steering wheel to prevent the driver from making turns that would exceed the critical values of acceleration with respect to overturning. The gyro could also have been integrated with intelligent speed adaptation, keeping speed below the critical value for overturning.

Driver training in controlled conditions could have a potential for preventing this kind of accident. In a simulator, a vehicle could overturn safely when a critical speed or turning radius was reached, and by repeatedly driving through a sharp curve, the driver could learn how large the turning radius, and how low speed must be to avoid overturning.

If the study of risk factors is regarded as the study of possibilities for prevention, any study should include a list of potential road safety measures that can influence the risk factors. It will not always be the case that all these measures can be implemented, but those who have the power to decide on their use should at least be required to justify why a certain measure was not used. Such a requirement would clarify the responsibility of system designers for the safety of the road system as defined according to the Safe System approach to road safety. Note that the measures listed in Table 1 are related to all elements of the system: drivers, roads and vehicles.

6. A statistical criterion of completeness

In case studies, the completeness of the list of risk factors constituting a sufficient condition for the accident can be determined according to whether they form part of an INUS-condition or not. How can the completeness of multivariate statistical models of factors that are associated with accidents be determined?

A statistical model is complete when the residual term of the model contains random variation only. If a model is developed using negative binomial regression, which is the most common statistical technique in modern accident models, this means that the value of the overdispersion parameter should be zero. A model is incomplete, in the sense of not explaining all systematic variation in the number of accidents, if the overdispersion parameter is positive. A model is overfitted if the residual terms have a smaller value than the mean number of accidents in the data serving as the basis for the model. This criterion for overfitting is based on the assumption that random variation in the number of accidents is described by the Poisson distribution, in which the variance equals the mean. Hence, if residual variance is smaller than the mean, part of the random variation has been "explained" in addition to any systematic variation.

One might think that the completeness of a statistical analysis depends on how many variables it includes. Accidents are influenced by very many variables, and the more of these a statistical analysis can include, the more complete it ought to be. This intuition is wrong. A model can be "more than complete", i. e. overfitted even if it includes just a single independent variable.

Commandeur et al. (2013) fitted a model to the natural logarithm of the annual count of traffic fatalities in Norway from 1970 to 2009. Year was the only independent variable. The model was fitted using state-space time-series analysis and tracked the annual fluctuations in the number of fatalities quite closely. The mean value of the time series was 363.6. Residual variance was 259.3, which is smaller than the mean value, indicating an overfitted model.

A model which includes quite a few independent variables may, on the other hand, not explain all systematic variation in the number of accidents. Elvik et al. (2013) fitted a model including 24 independent variables in order to estimate the effects on accidents of changes in the use of studded tyres in major cities in Norway. The Elvik-index of goodness-of-fit (Fridstrøm et al., 1995) for the model based on data for 2002–2009 was 0.919, indicating that just under 92% of the systematic variation in the number of accidents was explained.

7. Causality in statistical models

Hauer (2010) and Elvik (2011) discuss whether coefficients estimated in statistical models can be given a causal interpretation. Hauer argues as follows regarding this issue:
"Suppose … that two regressions that differ in some variables yield roughly the same θ for a treatment. The interpretation of such a consistency depends on the 'state of nature'. If θ depends only weakly on all variables included in one regression but not the other, then the consistency could be viewed as genuine. However, if θ depends strongly on the not-in-common variables, then the noted consistency should carry little causal weight."

As discussed by Hauer, θ is not a regression coefficient. It is an accident modification factor obtained by comparing the number of accidents predicted without a certain treatment to the number of accidents predicted with a certain treatment. Hauer explains that if different regression models find different values of a coefficient referring to some treatment, one cannot know why the coefficients are different if the models include different variables. In general, the value of a regression coefficient estimated for a specific variable will depend on which other variables are included in a model.

Elvik (2011) applies the criteria of causality proposed in epidemiology as a checklist to assess whether a certain coefficient can be given a causal interpretation. The idea is that the more of these criteria (strength of association, clear causal direction, control for confounding, theoretical plausibility, etc.) a certain coefficient can be judged to satisfy, the more defensible it is to interpret it as showing a causal relationship. However, the checklist is merely a heuristic device and cannot demonstrate causality.

To guide further discussion, it is useful to keep in mind that the definition of a cause proposed in section 2 of the paper is counterfactual: A cause is an intervention, which, were it carried out, would make a difference to the number of accidents by changing the value of one or more risk factors associated with accidents. The key issue is therefore how one can introduce – or remove – an "intervention" in a statistical model to see what happens.

The main manipulation available within a statistical model is to vary the set of variables included and assess the stability of a coefficient for a variable included in all model specifications. This means that analysts should test a number of different model specifications and report the results of all of them. As an example, Elvik (2016) developed seven different models in a study of accidents in pedestrian crossings in Oslo and some of its suburbs. The coefficient for the natural logarithm of pedestrian volume in these seven models was: 0.062; 0.054; 0.054; 0.075;

0.071; 0.061; 0.066. These values are close to each other and do not display any consistent tendency to decrease or increase in value as more variables were added to the models. Unfortunately, no model was developed leaving out pedestrian volume, but keeping the other variables to see whether their coefficients changed values.

For the moment, a conservative conclusion would be that regression coefficients estimated in models based on cross-sectional data cannot be interpreted as showing causal relationships. However, while researchers may live well with this conclusion, practitioners may be in a situation where the only knowledge they can base their decisions on comes from regression models based on cross-sectional studies. Except for a single study (Srinivasan et al., 2018), this is the case for horizontal curve radius. There is a single before-after study showing that by increasing the radius of horizontal curves, the number of accidents is reduced. However, a single study is usually not regarded as sufficient evidence for the effects of a treatment, as the representativeness of its results remains unknown until one or more replications of it are published.

To decide, for example, to increase the radius of a horizontal curve based on the relationship between radius and the number of accidents found in cross-sectional studies is, effectively, to treat this relationship as causal. It may be inevitable to do so, but it should, at least ideally, only be done if the following conditions are fulfilled:

1. There should be several cross-sectional studies with consistent findings. To give an example, Elvik (2023) identified 47 cross-sectional studies of the relationship between horizontal curve radius and the number of accidents. All of these found that a smaller radius was associated with a higher number of accidents.

2. The relationship found in cross-sectional studies should not be sensitive to the number of variables included in the studies, i.e. it should hold up equally well in studies including many variables as in studies including few variables.

3. The variable a coefficient refers to should not be clearly endogenous. By endogenous is meant that it is a treatment which is introduced at high-risk locations. Horizontal curve radius may contain an element of endogeneity to the extent that sharp curves are straightened out as a result of a bad accident history. However, this element is not likely to be very strong, as the radius of many horizontal curves is to large extent determined by the terrain and major changes in radius are difficult to implement.

8. Discussion

The traditional approach to the study of accident causes has focused on what happened immediately before the accident and made it inevitable. The conclusion has typically been that actions that were taken, or not taken, by road users precipitated the accident. Studies conforming to this model are still published. A recent study by Wang et al. (2022), for example, concluded that human factors were causes of 98.13% of accidents.

Many of the human factors that have been found to affect the risk of accident involvement, like age, gender, driving experience, expectations regarding road user behaviour, or involuntary inattention should not be regarded as causes of accidents. The reason for this, is that these factors cannot be modified by means of road safety measures acting on them. Age and gender are immutable, and driving experience accumulates at a constant rate that cannot be influenced by any road safety measure. Expectations are formed based on experience, and may have very strong inductive support, in the sense that thousands of nearly identical repetitions of an event have been experienced before, unpredictably, the event suddenly develops differently from the thousands of previous occasions.

Risk factors are causes of accidents only if there exist one or more road safety measures that can change the value of the risk factors (e. g. make it less dark, make it less slippery, change sight distance, shorten braking distance, etc.) and, by doing so, change the number of accidents. This definition of cause fully integrates the study of causation and prevention of accidents. The study of causation only makes sense if it is a study of prevention. Therefore, any analysis of accident causation should include a list of road safety measures that could have been implemented but have not.

It may seem strange to speak about the absence of something as a cause, but this is only because we have not become accustomed to it. A junction which is not a roundabout has a 3.33 times higher risk of fatal accidents and a 1.67 times higher risk of injury accidents than a roundabout. Not being a roundabout is thus an important risk factor.

The estimates of risk were obtained as follows: Elvik (2017) found that converting a junction into a roundabout reduces the number of fatal accidents by about 70%. Hence, risk is $1/0.3=3.33$ times higher before conversion. Likewise, the number of injury accidents is reduced by about 40%, making risk $1/0.6=1.67$ times higher before conversion.

By viewing the study of accident causation and accident prevention as the same thing, interest in prevention is stimulated. This may in turn stimulate an innovative use of road safety measures. It will also increase the demand for knowledge about the effects of road safety measures. Within the safe system model of road safety management, system designers fail to live up to their responsibility for safety by not demanding a continuous updating and development of knowledge about road safety measures. This does obviously not imply that, for example, every road should have road lighting, or every junction be converted into a roundabout. It only implies that decisions about the use of road safety measures become better informed by knowledge and thereby hopefully more successful in contributing to the prevention of accidents.

9. Conclusions

The following main conclusions can be drawn from the study reported in this paper:

1. The study of accident causation and accident prevention can be fully integrated and viewed as studying the same problem.

2. A risk factor is a cause of an accident if there exists at least one road safety measure that can change the value of the risk factor and thereby change the number of accidents.

3. It is possible to determine, both in case studies and in statistical analyses, when a list of contributing risk factors is complete, incomplete or more than complete.

4. Regression coefficients estimated in statistical analyses do not ordinarily represent causes; however, an application of them to estimate impacts on accidents of changes in the variables the coefficients apply to may be inevitable and can be justified under restrictive assumptions.

CRediT authorship contribution statement

Rune Elvik: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

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.

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Recommended articles

Data availability

Data will be made available on request.

References

Commandeur et al., 2013 J.J.F. Commandeur, F.D. Bijleveld, R. Bergel-Hayat, C. Antoniou, G. Yannis, E. Papadimitriou
On statistical inference in time series analysis of the evolution of road safety
Accid. Anal. Prev., 60 (2013), pp. 424-434
View PDF View article View in Scopus ↗ Google Scholar ↗

Elvik, 2004 R. Elvik
To what extent can theory account for the findings of road safety evaluation studies?
Accid. Anal. Prev., 36 (2004), pp. 841-849
View PDF View article View in Scopus ↗ Google Scholar ↗

Elvik, 2011 R. Elvik
Assessing causality in multivariate accident models
Accid. Anal. Prev., 43 (2011), pp. 253-264
View PDF View article View in Scopus ↗ Google Scholar ↗

Elvik, 2016 R. Elvik
Safety-in-numbers: estimates based on a sample of pedestrian crossings in Norway
Accid. Anal. Prev., 91 (2016), pp. 175-182
View PDF View article View in Scopus ↗ Google Scholar ↗

Elvik, 2017 R. Elvik
A synthesis of studies of access point density as a risk factor for road accidents
Accid. Anal. Prev., 107 (2017), pp. 1-10

View PDF View article View in Scopus Google Scholar

Elvik et al., 2013 R. Elvik, L. Fridstrøm, J. Kaminska, S.F. Meyer
Effects on accidents of changes in the use of studded tyres in major cities in Norway: A long-term investigation
Accid. Anal. Prev., 54 (2013), pp. 15-25
View PDF View article View in Scopus Google Scholar

Elvik, 2023 Elvik, R. 2023. Vegers linjeføring og trafikksikkerhet. Rapport 1933. Oslo, Transportøkonomisk institutt.
Google Scholar

Fridstrøm et al., 1995 L. Fridstrøm, J. Ifver, S. Ingebrigtsen, R. Kulmala, L.K. Thomsen
Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts
Accid. Anal. Prev., 27 (1995), pp. 1-20
View PDF View article View in Scopus Google Scholar

Grime, 1987 G. Grime
Handbook of road safety research
Butterworths, London (1987)
Google Scholar

Hauer, 1997 E. Hauer
Observational before-after studies in road safety
Pergamon Press, Oxford (1997)
Google Scholar

Hauer, 2010 E. Hauer
Cause, effect and regression in road safety: A case study
Accid. Anal. Prev., 42 (2010), pp. 1128-1135
View PDF View article View in Scopus Google Scholar

Hauer, 2020 E. Hauer
Crash causation and prevention
Accid. Anal. Prev., 143 (2020), Article 105528
View PDF View article View in Scopus Google Scholar

Mackie, 1965 Mackie, J.L., 1965. Causes and conditions. American Philosophical Quarterly, 2/4, 245-264. Reprinted in Sosa and Tooley (1993), 33-55.
Google Scholar

Muskaug, 1988 Muskaug, R. 1988. Ulykkeskommisjon for tunge kjøretøy i Østfold. Kommisjonens rapporter. TØI notat 878, konfidensielt. Oslo, Transportøkonomisk institutt.
Google Scholar

Ringen and 2022 Ringen, S. 2022. Dybdeanalyser av dødsulykker i vegtrafikken 2021. Statens vegvesens rapporter 487. Oslo, Statens vegvesen, Vegdirektoratet.
Google Scholar

Shinar, 2019 D. Shinar
Crash causes, countermeasures, and safety policy implications
Accid. Anal. Prev., 125 (2019), pp. 224-231
View PDF View article View in Scopus Google Scholar

Sosa and Tooley, 1993 Sosa, E., Tooley, M. 1993. (Eds). Causation. Oxford, Oxford University Press.
Google Scholar

Srinivasan et al., 2018 R. Srinivasan, D. Carter, C. Lyon, M. Albee
Before-after evaluation of the realignment of horizontal curves on rural two-lane roads
Transp. Res. Rec., 2672 (2018), pp. 43-52
CrossRef View in Scopus Google Scholar

Wang et al., 2022 X. Wang, Q. Liu, F. Guo, S. Fang, X. Xu, X. Chen

Causation analysis of crashes and near crashes using naturalistic driving data

Accid. Anal. Prev., 177 (2022), Article 106281

Google Scholar ↗

Woodward, 2003 J. Woodward

Making things happen. A theory of causal explanation

New York, Oxford University Press (2003)

Google Scholar ↗

Cited by (0)