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Some implications of an event-based definition of exposure to the risk of road accident

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ABSTRACT

This paper proposes a new definition of exposure to the risk of road accident as any event, limited in space and time, representing a potential for an accident to occur by bringing road users close to each other in time or space of by requiring a road user to take action to avoid leaving the roadway. A typology of events representing a potential for an accident is proposed. Each event can be interpreted as a trial as defined in probability theory. Risk is the proportion of events that result in an accident. Defining exposure as events demanding the attention of road users implies that road users will learn from repeated exposure to these events, which in turn implies that there will normally be a negative relationship between exposure and risk. Four hypotheses regarding the relationship between exposure and risk are proposed. Preliminary tests support these hypotheses. Advantages and disadvantages of defining exposure as specific events are discussed. It is argued that developments in

vehicle technology are likely to make events both observable and countable, thus ensuring that exposure is an operational concept.

Key words: exposure; event; learning; risk; probability

1 INTRODUCTION

Exposure is a key concept in road safety studies and many definitions of the concept have been proposed. This paper reviews some of these definitions and identifies three main classes of definitions of exposure. Following the review, the paper proposes a definition of exposure as events that have the potential of becoming accidents. Some implications of this definition of exposure are discussed. The discussion is illustrative only and intended to suggest ideas that can be pursued in further research. The main research questions discussed in this paper are:

1. What are the most common definitions of exposure?
2. Have scientific views about how best to define exposure changed over time?
3. What are the advantages and drawbacks of defining exposure as events?
4. What are the principal implications, in particular for the relationship between exposure and the number of accidents, of defining exposure as events?

2 REVIEW OF DEFINITIONS AND INDICATORS OF EXPOSURE

In an early review, Chapman (1973) defined exposure as the number of opportunities for accidents of a certain type in a given time in a given area. He added that these opportunities include cars crossing each other's path, cars following each other and cars travelling on a winding road. He illustrated studies of the relationship between exposure and accidents for head-on collisions, rear-end collisions and intersection collisions. He suggested that a count of traffic conflicts could serve as a measure of exposure. Chapman's definition of exposure, and his illustrations of it, has much in common with the event-based definition of exposure proposed later in this paper.

Brown (1981) defined the accident potential of an intersection in terms of the conflict points between the traffic movements passing the junction. Conflict points are all points where two traffic movements cross or merge. When the potential for rear-end conflicts in the approaches are included, Brown identified 36 potential conflict points in a four leg junction with two-way traffic on all approaches and no restrictions on turning movements. Based on a small sample of junctions in Johannesburg and Pretoria, Brown estimated accident rates per million conflicts for the various types of conflicts. He found that some conflict types are associated with higher accident rates than others. Similar findings were reported by Johannessen and Heir (1974) in an early Norwegian study.

Hauer (1982) discusses the relationship between traffic conflicts and exposure, and argues that the two concepts are distinct (although some definitions of exposure come close to making the concepts identical). He states that the concepts of exposure and risk can be defined by reference to the basic concepts of probability theory. Exposure can then be defined as a trial which has two possible outcomes: an accident or no accident. A trial will typically have a short duration. Exposure in a traffic system is the number of trials in that system in a given period of time. A trial, as defined and exemplified by Hauer, represents an event as defined later in this paper.

Risk and Shaoul (1982) discuss the common use of vehicle kilometres as an indicator of exposure. They note: "It is not possible to calculate a true accident probability using conventional mileage-exposure data, since no means exist by which the accident "trials" may be identified or counted. Accident rates for this reason alone cannot be taken as true probability values". While not proposing a formal definition of exposure, the examples given are all encompassed by the following definition of exposure: Exposure is any hazard, fixed or moving, that has the potential of generating an accident. The examples given by Risk and Shaoul include access points along a road, potential conflict points in junctions and any location requiring a manoeuvre to be made.

Wolfe (1982) defined exposure as the frequency of being in a given traffic situation, which number can be used as the denominator in a fraction with the number of accidents which take place in that situation as the numerator. This is intended as an operational definition of exposure. From the examples given, it is clear that Wolfe regards vehicle kilometres of travel as a useful operational definition of exposure.

Hauer, Ng and Lovell (1988) discuss how best to estimate safety in signalised intersections. They argue that the potential for accidents (exposure) is generated by the various traffic movements in an intersection and identify 15 different traffic movements that may generate accidents. Accident prediction models based on negative binomial regression were developed for all 15 movements, but only four of them were associated with a sufficient number of accidents to be regarded as statistically reliable. The definition of exposure underlying the classification is potential conflicts between traffic movements sharing space in an intersection.

Hauer (1995) notes that estimates of exposure tend to be used for two purposes: (1) to control for differences in traffic volume, so that the number of accidents can be compared between locations with different traffic volume; (2) to identify locations that have a higher than normal number of accidents for a given traffic volume. In both these uses of exposure, it serves as the denominator when estimating an accident rate (number of accidents per million units of exposure; usually per million vehicle kilometres). These uses of exposure are correct only if the number of accidents is proportional to the amount of exposure: twice the exposure, twice the number of accidents. However, many studies have found that the relationship between exposure and the number of accidents is non-linear. This invalidates the traditional use and interpretation of accident rates.

Persaud and Mucsi (1995) provide very clear examples of the non-linear relationship between traffic volume (average hourly volume) and the number of accidents. The shape of the relationship between hourly traffic volume and the number of accidents varies depending on the time of the day (day or night) and the type of accident used as dependent variable (single vehicle accidents or multi vehicle accidents). It is therefore clear that estimates of the relationship between traffic volume and the number of accidents based on averages or totals can be misleading.

This point is further elaborated by Mensah and Hauer (1998). They discuss two problems of averaging arising in the estimation of the relationship between accidents and traffic flow. The first type of averaging is called argument averaging. An example of argument averaging is the use of AADT to measure traffic volume, rather than an estimate of the traffic volume at the time of the accident, which could be quite different from AADT, since traffic volume varies throughout the day, week and months of the year. Mensah and Hauer develop closed-form estimators for the size of the bias associated with argument averaging for four of the most common functional forms used to relate accidents to traffic volume. The second type of averaging is called function averaging. It occurs when a single function is estimated for a relationship, which in reality is best represented by two or more functions that differ in shape. Using a single function will then generate bias. Mensah and Hauer illustrate the potential size of this bias, but do not develop closed-form expressions to estimate the typical size of the bias. The analysis of Mensah and Hauer constitutes a strong argument for using disaggregate measures of exposure, as well as using specific types of accidents as dependent variable.

Qin, Ivan and Ravishanker (2004) develop exposure measures for various types of accident that are intended to be linear, i.e. the rate of accidents per unit of exposure will be independent of the amount of exposure. They identify four types of accident: single vehicle, multi vehicle same direction (rear-end), multi vehicle opposite direction (head-on), and multi vehicle intersecting direction (angle). For each type of accident, an exposure function was developed. The function had the same form for all types of accident:

Exposure = ${V_i}^{\alpha V_k} \cdot {L_i}^{\alpha L_k}$

Where V denotes traffic volume (AADT) on section i, L is the length of section i, αV and αL are estimated coefficients, and k is accident type k. The models developed clearly showed that the assumption that the number of accidents is proportional to section length, normally made when using vehicle kilometres of travel to measure exposure, is not valid. The coefficients for section length where less than one for all types of accident. Thus, all else equal, short road sections may not have the same number of accidents per unit of length as long road sections. The study controlled for lane width, shoulder width and speed limit, but there could be other differences between short and long road sections, such as the number of intersections or access points, parking regulations, and pedestrian and cyclist volume.

Oh, Park and Ritchie (2006) developed a measure of the risk of rear-end collision based on stopping distances. Based on data collected by inductive loop detectors that continuously monitor traffic, it is possible to estimate the distance between vehicles following each other in the same travel lane. When both distance and speed are known, stopping distance can be estimated, given a certain driver reaction time. It is then possible to estimate the proportion of vehicles keeping an unsafe following distance, i.e. a distance shorter than the estimated stopping distance. Drivers keeping such a short distance may, however, never discover the high risk involved in doing so: if the need to brake never arises, the driver may experience what Fuller (1991) referred to as a learning trap: risky behaviour is reinforced by the absence of feedback revealing the risk involved to the driver.

Lassarre, Papadimitriou, Yannis and Golias (2007) develop a microscopic measure of pedestrian exposure to risk. The starting point is that pedestrians are principally exposed to risk when crossing the road. The possibility of crossing the road at an unregulated location depends on whether there are sufficient gaps in traffic or not. A closed-form solution is developed to assess the risk involved in crossing at a given location. The risk is a function of time taken to cross (which, in turn, depends on lane width and walking speed), traffic volume, the length of vehicles and the speed of vehicles. When risk at each potential crossing location in a defined road network has been estimated, the next stage of analysis is to model pedestrian choice of crossing location. For this purpose, random utility functions are developed. Estimates made for Paris and Athens (Papadimitriou, Yannis and Golias 2012) indicate that the model makes sensible predictions, i.e. few pedestrians are predicted to cross the road at the most hazardous locations.

Zhang, Ivan and Ravishanker (2008) develop a new measure of exposure to the risk of rear-end collisions, vehicle time spent following. The time spent following is the time another vehicle is in front of a case vehicle and neither free choice of speed (i.e. choice not influenced by the speed chosen by other vehicles) nor overtaking is possible. The measure is therefore best suited for two-lane roads with a relatively high traffic volume. Zhang et al. find that the number of same direction collisions is proportional to vehicle time spent following, implying that this measure of exposure, at least in their data set, satisfies the linearity property required of accident rates.

Elvik, Erke and Christensen (2009) criticise the use of summary measures of exposure, such as vehicle kilometres of travel, in road safety research and point out that summary measures of exposure cannot be interpreted as countable trials in the sense of probability theory. Thus, common operational definitions of exposure and risk bear no clear relation to the concepts of trials and probability that historically were the foundations of accident research. They introduce the concept of an elementary unit of exposure, defining it in terms of specific events that are limited in space and duration. Four such events are defined: encounters (vehicles passing each other in opposite directions), simultaneous arrivals in junctions, lane changes, and braking events. Elvik (2010A) discussed the shape of the relationship between the number of these events and the number of accidents, suggesting that it will normally be negative.

Miranda-Moreno, Strauss and Morency (2011) investigate the use of disaggregate exposure measures for accidents involving cyclists at signalised intersections. They define twelve traffic movements for motor vehicles in four-leg signalised intersections and four movements for cyclists. The product of the conflicting flows is estimated and negative binomial regression models developed in order to find the relationship between volume and the number of accidents involving cyclists and motor vehicles. A non-linear relationship was found, with the number of accidents increasing far less than proportional to the conflicting volumes, showing that there is a so-called "safety-in-numbers" effect for accidents involving cyclists and motor vehicles.

Paefgen, Staake and Fleisch (2014) note that vehicle kilometres of travel is not a homogeneous measure of exposure. Kilometres driven in the dark involve a different risk from those driven during daytime, kilometres driven in urban areas involve a different risk from those driven in rural areas, and so on. Based on data recorded by in-vehicle-data-recorders, used as part of a pay-as-you-drive insurance experiment, they developed a logistic regression model to investigate how the probability of becoming involved in an accident depends on time of the day, day of the week, road type, speed, and monthly mileage. Unsurprisingly, they found that the probability of accident involvement did not depend only on the number of kilometres driven, but also on characteristics of the environment (day/night, urban/rural, etc.). Unfortunately, the study did not control for driver characteristics.

The main lessons that can be learnt from the studies reviewed above are:

1. There are three main conceptions of exposure: activity-based (kilometres, entering vehicles), event-based (potential conflicts, turning movements), and behaviour-based (time spent following, pedestrian crossing behaviour).
2. Activity-based definitions of exposure are the oldest and simplest in terms of data requirements. It is increasingly recognised that in their aggregate form, these measures of exposure are unsuitable for controlling for the effects of exposure on the number of accidents.
3. Research has found that accidents are not proportional to AADT or road length, which are the principal inputs when estimating vehicle kilometres of travel. Accident rates based on an assumption of proportionality between vehicle kilometres and the number of accidents are highly likely to be biased and misleading.
4. Recent research has increasingly focused on event-based or behaviour-based definitions of exposure. These are microlevel indicators, by which exposure is typically observed in a single junction or for a single trip.
5. Advances in data collection technology make it increasingly realistic to observe and count events or choices of behaviour that represent a potential for accidents to occur.

3 EXPOSURE AS EVENTS

Based on the previous studies of Elvik, Erke and Christensen (2009) and Elvik (2010A), the following definition of exposure to the risk of a traffic accident is proposed (Elvik 2014):

Exposure is the occurrence of any event in traffic, limited in space and time, that represents a potential for an accident to occur by bringing road users close to each other in time and/or space or by requiring the road user to act to avoid leaving the roadway.

An event involving more than one road user can be viewed as a potential traffic conflict (Laureshyn, Svensson and Hydén 2010), i.e. the event may develop into a conflict, but need not do so. Some factors that may influence the likelihood that an event develops into a conflict and subsequently to an accident are discussed later in the paper. An event involving a single road user is covered by the definition if the event requires the road user to take immediate action to avoid leaving the roadway.

Events have limited duration and spatial extent. Their beginning and end can be defined precisely enough to allow events to be counted. Risk is defined as the proportion of events that have an accident as the outcome. The following elementary types of events are proposed:

1. Encounters, i.e. vehicles or road users passing each other in opposite directions of travel with no physical barrier to separate them
2. Simultaneous arrivals at points where conflicts between road users may arise (junctions, pedestrian crossings, railway level crossings)
3. Turning movements in junctions (involving conflicting traffic movements between road users who did not necessarily arrive at the same time)

4. Braking events
5. Lane changes on multilane roads
6. Overtakings, i.e. one vehicle passing another vehicle travelling in the same direction
7. Negotiating horizontal curves
8. Other events, such as an animal suddenly entering the road in front of a road user, or a weather event, which will typically last longer than other events.

An event typically lasts a few seconds. For some of the events listed above, their number can be calculated from summary measures of exposure, like AADT. In the future, however, it is likely that motor vehicles will have technology that can recognise the events and be able to count them if technology for this purpose is part of the event-recognising systems. There is already on the market vehicle technology that monitors braking (intelligent cruise control), lane-keeping and blind spots when changing lanes. These systems are probably only the beginning of more comprehensive, integrated systems that can monitor most aspects of traffic. To redefine exposure in terms of specific events is therefore future-oriented and allows for a vastly more detailed study of exposure than current summary measures, like vehicle kilometres.

4 LEARNING FROM REPEATED EVENTS

When exposure is defined as events, it follows naturally to think about exposure as a process of learning. The shape of the relationship between exposure and risk is therefore influenced by the efficiency of learning that repeated experience of given events provides. Developing hypotheses about this relationship can benefit from the insights gained in the study of learning curves (Ohlsson 1996, Ritter and Schooler 2001, Duffey and Saull 2003, Anzanello and Fogliatto 2011, Howard 2014).

It is reasonable to assume that events differ with respect to their potential for learning. In some cases, a single exposure to an unwanted event may be sufficient to prevent its repetition. Thus, a novice driver who neglects to check the blind zone when attempting to change lane, and to his or her great surprise discovers that there is a car in the blind zone, will probably find the experience so unpleasant, and the nature of the mistake so obvious, that it is unlikely to be repeated. This is a case of single-trial learning.

Other events are more subtle and give fewer clues about how to manage them. Judging speed and distance can be difficult and it may not always be clear whether there is time enough to turn left in front of an oncoming car or not. In general, the reliability of human task performance increases if a task is simple and performed often. Table 1, which is taken from Reason (1997), shows error probabilities for various tasks.

Table 1 about here

It is seen that reliability is very high (i.e. the probability of committing errors very low) for routine tasks performed frequently and at a pace permitting errors to be recovered before the task is completed. While a similar table of the reliability in performing tasks as a road user cannot be presented, it seems clear that the reliability of human performance is very high for many tasks encountered in traffic. Moreover, accident rates, however imprecise they may be as a measure of risk, tend to higher in complex traffic environments than in simpler environments (Elvik 2006, 2010B). This suggests that learning from events is not equally easy for all events. Studies of learning curves (Anzanello and Fogliatto 2011) show that the shape of these curves is influenced by, among other things, individual motivation to learn, the number of times a task has been performed and task complexity. Based on this, it is suggested that at least the following characteristics of events (and possibly additional characteristics) may influence the potential for learning:

1. The complexity of the event: Simple actions and tasks are easier to learn than more complex actions and tasks.
2. The frequency of the event: Events that occur often give more opportunities for learning than events occurring rarely.
3. The similarity of repeated instances of the event: Events that are completely identical each time are easier to remember and learn than events that differ in some of their characteristics.
4. How quickly an event unfolds: Events that require very fast action are more difficult to manage successfully than those that develop more slowly.

It is hypothesised that to the extent that road users learn from events how to prevent them from developing into accidents, there will be a negative relationship between exposure (the number of events experienced) and risk (the probability that an event results in an accident).

5 A HYPERBOLIC RISK FUNCTION (PERFECT LEARNING)

Learning from traffic events can be fast or slow. Some road users will learn to perform certain tasks virtually without error, other road users will continue to have a high error rate (Bjørnskau and Sagberg 2005, Sagberg and Bjørnskau 2006). With respect to traffic exposure as a process of learning, it is proposed, as a benchmark, to define perfect learning as a hyperbolic risk function, i.e. a hyperbolic curve having exposure (number of events) as abscissa and accident rate per event as ordinate. Figure 1 shows such a curve. The hyperbolic risk function is termed perfect learning because it implies that the expected number of accidents is independent of exposure, i.e. larger exposure will always be perfectly compensated for by a lower accident rate. This is indicated by the numerical example given in Figure 1.

Figure 1 about here

This, obviously, is a limiting condition not likely to be observed in practice. One may, however, use the hyperbolic risk function as a benchmark for developing an estimator of the efficiency of learning. This is the primary use of the hyperbolic risk function. Perfect learning is represented by the hyperbolic risk function; actual learning is represented by the actual risk function, having the number of events as its argument (abscissa) and relative risk as the outcome (ordinate). The ratio of actual learning to perfect learning is an estimator of the efficiency of learning.

To illustrate these notions, the accident prediction models developed by Persaud and Mucsi (1995) will be applied. These models were of the form:

$E(m) = \alpha LTF^{\beta}$

E(m) is an estimate of the long-term expected number of accidents. L is segment length, T is period of the day (day, night or 24 hours), F is traffic flow (AADT), and

α and β are coefficients to be estimated. The model applying to multi vehicle accidents during 24 hours (coded model 111 by Persaud and Mucsi) will be applied. The coefficient for traffic volume in this model was 1.123. This implies that the number of accidents increases more than in proportion to AADT.

There are many types of multi vehicle accidents, but for the purposes of the illustration below, the coefficient estimated by Persaud and Mucsi will be assumed to apply to head-on collisions. Head-on collisions are directly related to one of the events listed above, encounters. The number of encounters on a road is equal to:

$$\text{Number of encounters} = \left(\frac{AADT}{2}\right)^2$$

If AADT is known, the number of encounters expected to occur at any point on the road can be estimated for any period of time. If, for example, AADT increases from 1,000 to 10,000 (a factor of 10), the number of encounters increases from 250,000 to 25,000,000 (a factor of 100). This has major implications for the shape of the relationship between exposure and accident rate. If the rate of accidents (number of accidents divided by AADT) is plotted as a function of AADT, using the coefficient of 1.123, it will slope upwards. If, on the other hand, the rate of accidents is plotted as a function of the number of encounters (number of accidents divided by number of encounters), it will slope downwards. This is shown in Figure 2.

Figure 2 about here

If the number of head-on collisions expected to occur at the lowest AADT is set equal to 1, the relative rate of head-on collisions per encounter will decrease. At AADT 1,000, the relative rate of head-on collisions per encounter (250,000 encounters at AADT 1,000; 62,500 encounters at AADT 500) will be 0.545 according to the accident prediction model, but 0.25 according to the perfect learning curve, since the number of encounters is four times greater. The ratio of actual risk reduction (1 – 0.545 = 0.455) to the risk reduction implied by perfect learning (1 – 0.25 = 0.75) is the estimator of the efficiency of learning: 0.455/0.750 = 0.607.

6 SOME PRELIMINARY HYPOTHESES

Based on the discussion above, the following tentative hypotheses about the relationship between exposure and risks are proposed:

Hypothesis 1:

There is a negative relationship between the amount of exposure (the number of events of a given type experienced per unit of time) and the risk of accident (the number of accidents per unit of exposure).

This is a general hypothesis. It describes a statistical regularity. It is, as such, similar to other relationships in accident research and exceptions from the relationship cannot be ruled out, as noted in the example of single-trial learning mentioned above. However, it is hypothesised that in the normal case, the relationship between exposure and risk is negative. The hypothesis is consistent with well-known learning curves showing that tasks are performed more quickly and with fewer errors the more times they have been performed (Ritter and Schooler 2001).

Hypothesis 2:

Frequent events are associated with more effective learning than events occurring less often. More effective learning is evidenced in a more strongly negative relationship between exposure and risk than less effective learning.

Perhaps the most frequent event of all those listed above is an encounter. It is also a very simple event. It does not require any particular action from the driver, except for staying within his or her driving lane. This implies that repeated events should be associated with a sharp decline in risk per event, which is tantamount to highly effective learning.

Hypothesis 3:

Complex events are associated with less effective learning than simple events. A complex event requires simultaneous attention to several information elements at the same time and must be performed within a short time.

An example of a complex event is turning left into a main road in a four leg junction from a minor road with yield signs. In this situation, the driver entering the main road must give way to many other traffic movements and need to pay attention to all of these. Differences in accident rates between simple and complex turning movements in junctions have been found by Johannessen and Heir (1974), Brown (1981) and Hauer, Ng and Lovell (1988).

Hypotheses 4:

Events that have significant duration and/or require major behavioural adaptation to maintain a low level of risk, will have a less negative relationship to risk (accidents per event) than events not lasting long or not requiring major behavioural adaptation.

It may be to stretch concepts to refer to more long-lasting events as events. An encounter lasts a few seconds, turning left in a junction may last a few seconds, waiting for a pedestrian to cross the road may also take a few seconds. Most of the events that constitute exposure as defined in this paper last only a few seconds at the maximum. Adverse weather, on the other hand, may last for hours. Adverse weather is an event that makes driving more demanding and difficult, but drivers do not fully adapt their behaviour to adverse weather or slippery roads (Eisenberg 2004, Theofilatos and Yannis 2014). This is not a matter of not learning, but of deliberately trading off safety against mobility and accepting a somewhat higher level of risk, which costs less in terms of increased travel time than fully adapting to difficult driving conditions.

7 REVIEW OF SELECTED EMPIRICAL STUDIES

The hyperbolic risk function depicting perfect learning can be written as a power function with an exponent of –1:

$$Y = X^{-1}$$

By using power functions with negative exponents to model the relationship between exposure and risk, the value of the exponent can be compared in order to test the hypotheses proposed above.

7.1 The relationship between driving distance and accident rate

Several studies have noted a negative relationship between the annual distance driven by a driver and his or her accident rate (Hakamies-Blomqvist et al. 2002, Fontaine 2003, Langford et al. 2006, Alvarez and Fierro 2008). Figure 3 is based on these four studies and combines their results. Since the absolute accident rates are not likely to be comparable, they were converted to relative accident rates. In each study, the accident rate for drivers with the longest annual driving distance was set equal to 1. In all studies, drivers were divided into three groups with respect to annual driving distance:

1. Short, which is less than 3,000 km per year. The typical mean distance of drivers in this group is around 1,500 km per year.
2. Medium, which is between 3,000 and 14,000 km per year. A typical mean in this group is around 8,000 km per year.
3. Long, which is more than 14,000 km per year. A typical mean in this group is around 22,000 km per year.

Figure 3 about here

There is a clear negative relationship between driving distance and accident rate. A power function best fits the data and indicates a risk elasticity of –0.681. Drivers with the shortest annual driving distance have an accident rate which is up to 10 times higher than drivers with the longest annual driving distance. The samples studied included both middle-aged drivers and older drivers. The tendency for accident rate to decline as driving distance increases therefore appears to be general. It applies to all drivers, not just to novice drivers (Sagberg 1998) for whom a risk curve like the one shown in Figure 3 could reasonably be interpreted as a learning curve. A similar relationship, based on 250-mile bins for driving distance (i.e. 0-250, 251-500, etc.), was reported by Ferreira and Minikel (2012). Mannering (1993) gives further support for the non-linear relationship between distance driven and accident involvement. He found, among other things, that the longer male drivers have been driving without an accident, the lower is their probability of having an accident soon.

It should be added, however, that kilometres driven per year, like all summary estimators of exposure is imprecise and likely to be confounded. Thus, it is known that older drivers tend to restrict their driving to easier situations, such as driving only in daytime, in light traffic and on familiar roads. Such a behavioural adaptation would tend to reduce their accident rate independently of the number of kilometres driven per year. It could, as an un-intended by-product also slow down their rate of learning, by reducing the frequency of involvement in events providing opportunities for learning. A power function like the one shown in Figure 3 fits well to the data in each of the four studies that were combined, but the value of the exponent varies substantially, suggesting that there are individual differences in learning. Ideally speaking the number of events drivers are involved in should have been used as the estimator of exposure. This number is not known, although it is reasonable to think that the number of events increases at a faster rate than kilometres driven.

7.2 High efficiency of learning from simple events (encounters)

Applying the accident prediction models developed by Persaud and Mucsi (1995), the efficiency of learning with respect to avoiding head-on collisions resulting from encounters can be estimated. Figure 4 shows the results. A value of 1 indicates perfect learning, i.e. a hyperbolic risk function.

Figure 4 about here

It is seen that the efficiency of learning goes asymptotically to a value close to 1 as the number of encounters goes to infinity. This shows that an increased number of repetitions is associated with more reliable performance. Another mechanism likely to be operating here is the influence of traffic density on driver alertness. On roads with a dense traffic flow, the driver is constantly reminded of the presence of oncoming vehicles and pays attention to them more or less automatically.

7.3 Low efficiency of learning from complex events (arrivals in junctions)

Three-leg junctions and four-leg junctions differ greatly with respect to their potential for generating complex traffic situations. There are nine potential conflict points between the traffic movements in a three-leg junction; thirty-two potential conflict points between the traffic movements in a four-leg junction. All else equal, four-leg junctions will produce many more complex traffic situations than three-leg junctions.

To test whether the efficiency of learning from potential conflicts is greater in three-leg junctions than in four-leg junctions, a set of 732 junctions for which a number of accident prediction models have been developed was used (Elvik 2013). The best fitting model (i.e. the model with the smallest over-dispersion parameter) was selected. Based on the predictions of this model, empirical Bayes estimates of the long-term expected number of accidents were developed for each junction. The empirical Bayes estimates are a weighted average of the recorded number of accidents in each junction (which in the majority of junctions was zero) and the model-predicted number.

The potential number of conflicts in each junction was estimated by applying the closed-form expressions given in Elvik, Erke and Christensen (2009). The estimates developed by these formulas are only approximately correct, as they are based on an assumption that all approaches to a junction have the same traffic volume. Risk was estimated as the empirical Bayes estimate of the number of accidents divided by the potential number of conflicts. This estimator indicates how successful road users are in managing the conflicts so that they do not develop into accidents. The higher the risk, the less the success. Risk was, unsurprisingly, negatively related to the potential number of conflicts. The higher the potential number of conflicts, the lower the risk. In keeping with the definition of perfect learning, the risk associated with perfect learning was defined as the inverse value of the potential number of conflicts. The closer the actual risk function is to the hyperbolic curve, the higher the efficiency of learning.

The junctions were divided into groups based on the number of legs (3 or 4) and speed limit (50, 60, 70, 80 or 90 km/h). Three-leg junctions with a speed limit of 50 km/h were assumed to represent the easiest situation. There are few conflict points, and the low speed limit will give road users more time to understand and solve the conflicts than higher speed limits. At the other end, four-leg junctions with a speed limit of 80 km/h were assumed to represent a more demanding situation. There were too few junctions with a speed limit of 90 km/h to use in the analysis.

If complexity makes effective learning more difficult, one would expect the efficiency of learning to be lower in the high-speed four leg junctions than in the low-speed three-leg junctions. Figure 5 shows that this is indeed the case. The circles represent three-leg junctions with a speed limit of 50 km/h, the triangles represent four-leg junctions with a speed limit of 80 km/h. The greater efficiency of learning in the three-leg junctions is apparent from two facts:

1. The curve fitted to the data points is steeper than the curve fitted to the data points for four-leg junctions.
2. At a high potential number of conflicts, the data points are closer to perfect learning in three-leg junctions than in four-leg junctions.

Figure 5 about here

The complexity of traffic events is therefore one of the characteristics that influences how much, and how well, road users learn from the events.

7.4 Behavioural adaptation to winter conditions limit efficiency of learning

A well-known case of a negative relationship between exposure and accident rate is the relationship documented in Sweden between the amount of driving taking place on roads covered by snow or ice and the relative accident rate on such road surfaces. Figure 6 shows this relationship, based on information given by Niska (2006).

Figure 6 about here

There is evidence that driving more on snow- or ice-covered roads is associated with a reduced accident rate. It is reasonable to interpret this as an effect of learning. Note, however, that the exponent in the power function is only –0.46. The risk curve is therefore flatter than the one presented in Figure 3 for driver accidents rates, which had an exponent of –0.68. As mentioned earlier, this indicates that drivers do not fully adapt their behaviour to slippery roads, but make a trade-off by accepting a somewhat higher risk rather than add to travel time. It is worth noting that the degree of behavioural adaptation may vary between road users, as found by Morgan and Mannering (2011)

8 DISCUSSION

Traffic is the continuous movement of people and vehicles. It may therefore seem logical and natural to define exposure as a continuous variable. Vehicle kilometres is normally interpreted as a continuous variable, as opposed to a (discrete) count variable. The advantage of using vehicle kilometres as an estimator of exposure is that data are easily available and that the total number of vehicle kilometres produced in a traffic system can be interpreted as an indicator of the total volume of activity in that system. Vehicle kilometres is thus an activity-based estimator of exposure.

While it makes perfect sense to view traffic as essentially continuous, in the sense that any partitioning of it into elementary units may be regarded as arbitrary, it is not meaningless to define specific traffic situations as countable events of a quite precise duration and spatial extension. The advantages of defining exposure as specific events are:

1. Most traffic events have a well-defined beginning and end and are therefore countable.

2. Traffic events represent a potential for an accident to occur. Without the events, there is no such potential. Events are thus estimators of the opportunities for accidents to occur.
3. There are many types of traffic events and some events can be logically linked to specific types of accidents. The type of exposure relevant for a specific type of accident can then be measured more precisely.
4. By providing a concise typology of events, it is possible to obtain a much more detailed description of exposure to risk than summary estimators of exposure afford.
5. Since events are opportunities for accidents to occur, any elementary event has two outcomes: accident, or no accident. This means that the probability of an accident can be defined simply as the proportion of events that have an accident as the outcome.

There are also disadvantages in using events as elementary units of exposure. In the first place, it may not be possible to establish clear links between all types of accident and specific events. Driving off the road on a straight road section, for example, is not clearly related to any of the events defined in this paper. In the second place, the definition of some events may be somewhat arbitrary, such as the event of negotiating a curve. One has to specify where the curve begins and ends and how sharp it must be to count as a curve. In the third place, some events may be a compound of two or more elementary events. An encounter in a horizontal curve with the car in front of you braking could fit three of the event types listed in this paper. The issue is whether such an event is of type A, type B, type C or some compound type, like AB. In the fourth place, events, at least as defined in this paper, are not very well suited to studying driver characteristics and individual differences between drivers with respect to their ability to learn from events. There are no doubt differences between drivers in this respect, but merely observing and counting events tells very little about such differences. In the fifth place, exposure to the risk of accidents is more than simply the occurrence of specific events. There is a risk even when driving on an empty freeway where, essentially, no traffic events occur. The risk may not be related to traffic events, but could be the result of, for example, driver fatigue, a car in poor condition or any other factor not manifesting itself in the form of an event as defined in this paper.

A sixth topic worth discussing is whether there are limits to learning, i.e. whether learning curves can become flat or even turn upwards, suggesting a decline in performance. Studies of learning curves (Howard 2014) suggest that this is definitely possible. Howard (2014) found that highly experienced chess players at the grand master level had learning curves that became flat and, for some players, even indicated declining performance. He suggests that the motivation to improve further may suffer when players have reached a high level at which competition is fierce and games highly complex. It is not difficult to think that similar mechanisms may operate in car drivers. Once drivers master common events at a satisfactory level, they may not be motivated to invest effort in further perfecting their skills. Forgetting skills that are rarely practised may also be a limit to learning.

This paper has only introduced the idea of defining exposure in terms of events. It is clear that considerably more research is needed to test the fruitfulness of this idea.

7 CONCLUSIONS

The main conclusions of the study presented in this paper can be summarised as follows:

1. It is proposed to define exposure as the occurrence of any event, limited in time and space, that has the potential of generating an accident by bringing road users close to each other in time or space or by requiring a road user to take action to avoid leaving the roadway.
2. Such events include: encounters (vehicles passing each other in opposite directions); simultaneous arrivals at points where road users enter from potential conflicting directions; turning movements in junctions; braking; lane changing; overtaking; negotiating curves.
3. Each of these types of events can be counted and the total number of events can be regarded as a sampling frame from which accidents are sampled. Each traffic event has two possible outcomes: accident or no accident.
4. The probability of accident occurrence is simply the number of accidents divided by the number of events having an accident as one of its potential outcomes.
5. The probability of an accident is likely to be negatively related to the number of events. The reason for this is that repeated experience of events can be regarded as a process of learning, in which road user performance becomes more and more reliable.
6. Examples are given of empirical studies showing a negative relationship between exposure and risk. These studies lend support to the basic

hypotheses proposed in the paper, but do not represent stringent tests of these hypotheses in terms of the new definitions proposed for exposure and risk.

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LIST OF FIGURES AND TABLES

Table 1:

Task description	Error probability	5th and 95th percentile bounds
Totally unfamiliar, performed at speed with no idea of likely consequence	0.55	0.35 – 0.97
Shift or restore system to a new or original state on a single attempt without supervision or procedures	0.26	0.14 – 0.42
Complex task requiring high level of comprehension and skill	0.16	0.12 – 0.28
Fairly simple task performed rapidly or given scant attention	0.09	0.06 – 0.13
Routine, highly practised, rapid task involving relatively low level of skill	0.02	0.007 – 0.045
Restore or shift system to original or new state, following procedures with some checking	0.003	0.0008 – 0.0070
Completely familiar, well designed, highly practised routine task, oft-repeated and performed by well motivated, highly trained individual with time to correct failures but without significant job aids	0.0004	0.00008 – 0.00900
Respond correctly to system when there is an augmented or automated supervisory system providing accurate interpretation of system state	0.0002	0.000006 – 0.000090

Figure 1:

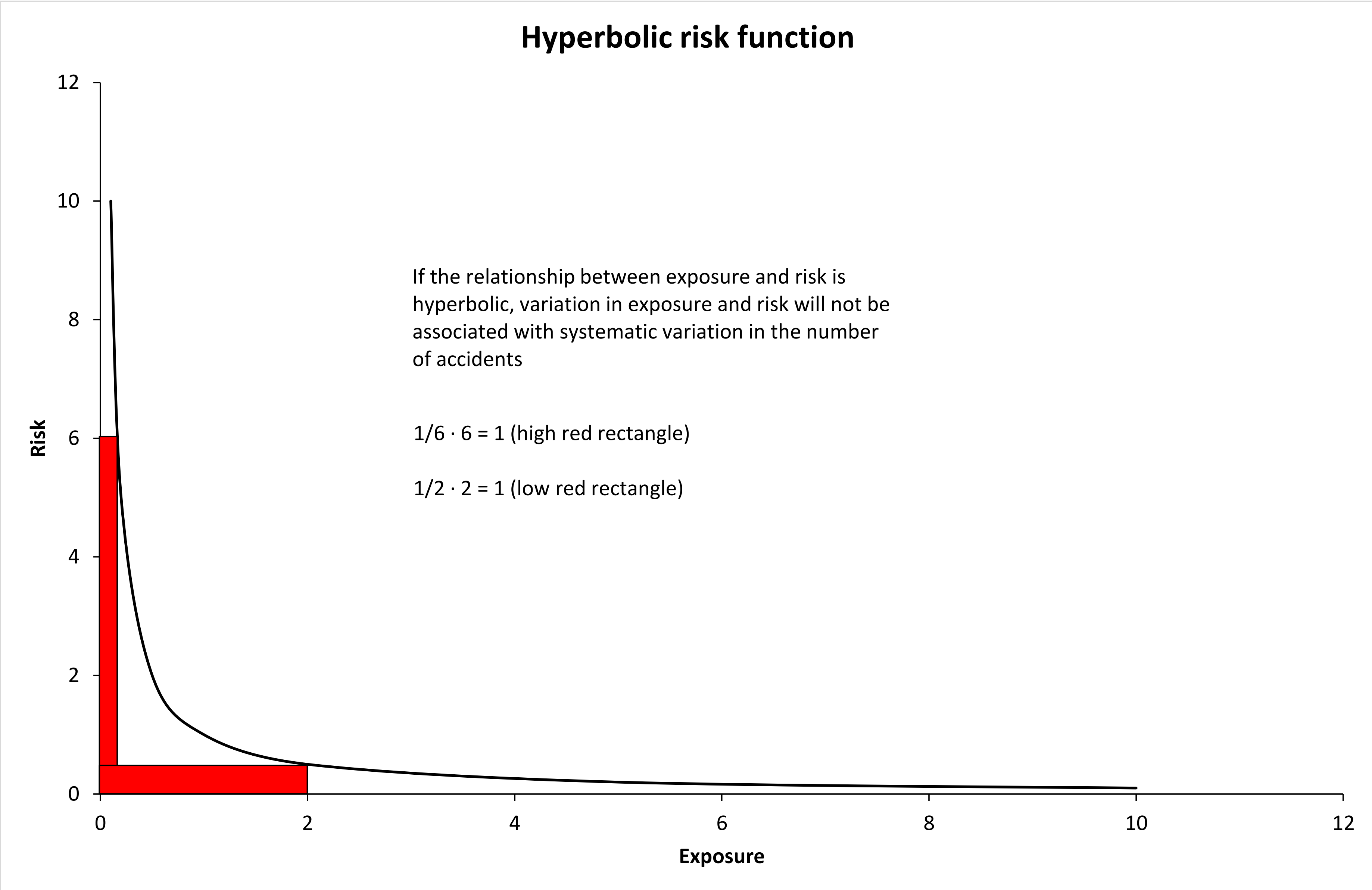

Hyperbolic risk function
12
10
8
6
4
2
0
Risk
If the relationship between exposure and risk is hyperbolic, variation in exposure and risk will not be associated with systematic variation in the number of accidents
1/6 · 6 = 1 (high red rectangle)
1/2 · 2 = 1 (low red rectangle)
0
2
4
6
8
10
12
Exposure

Figure 2:

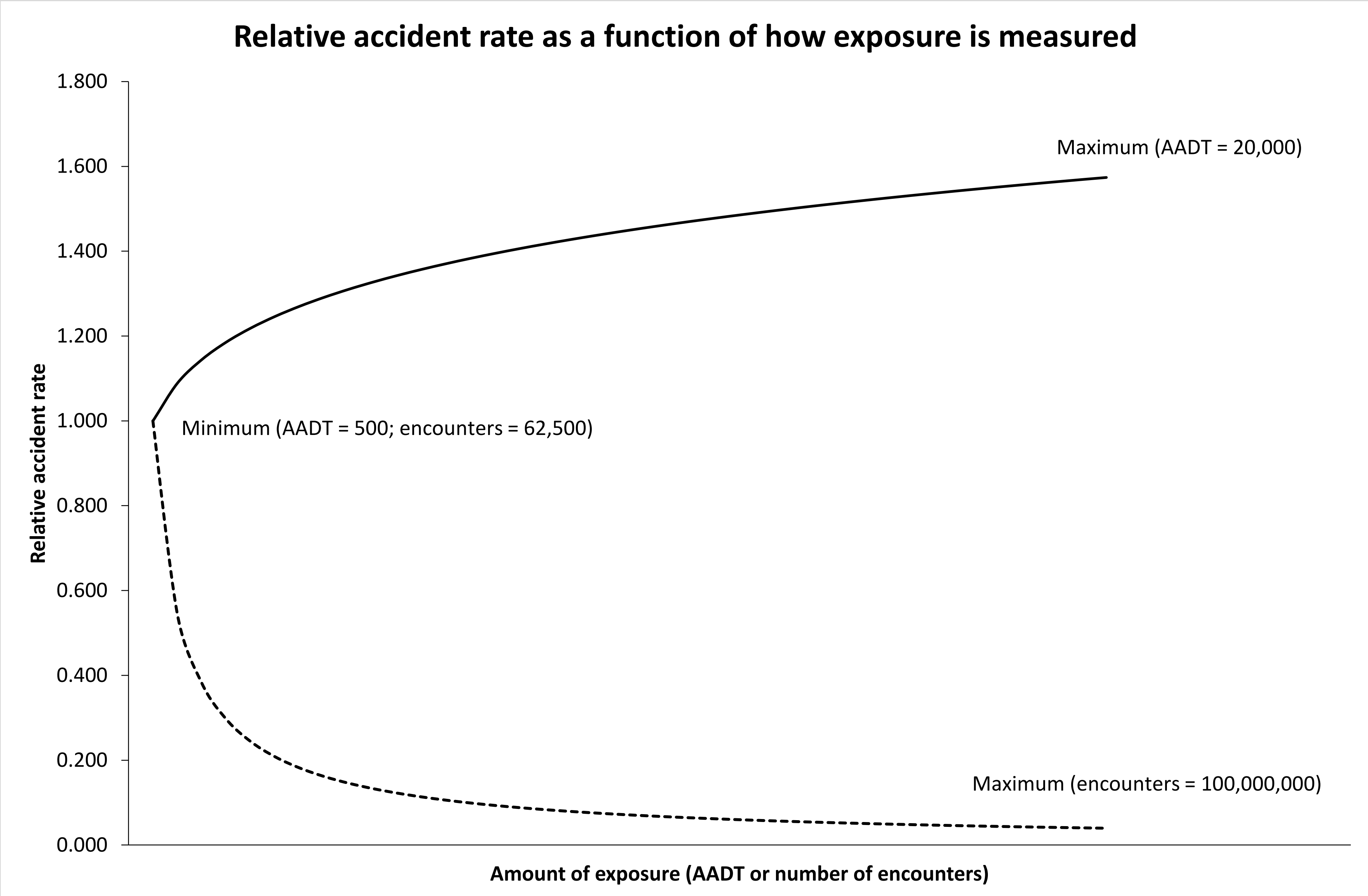
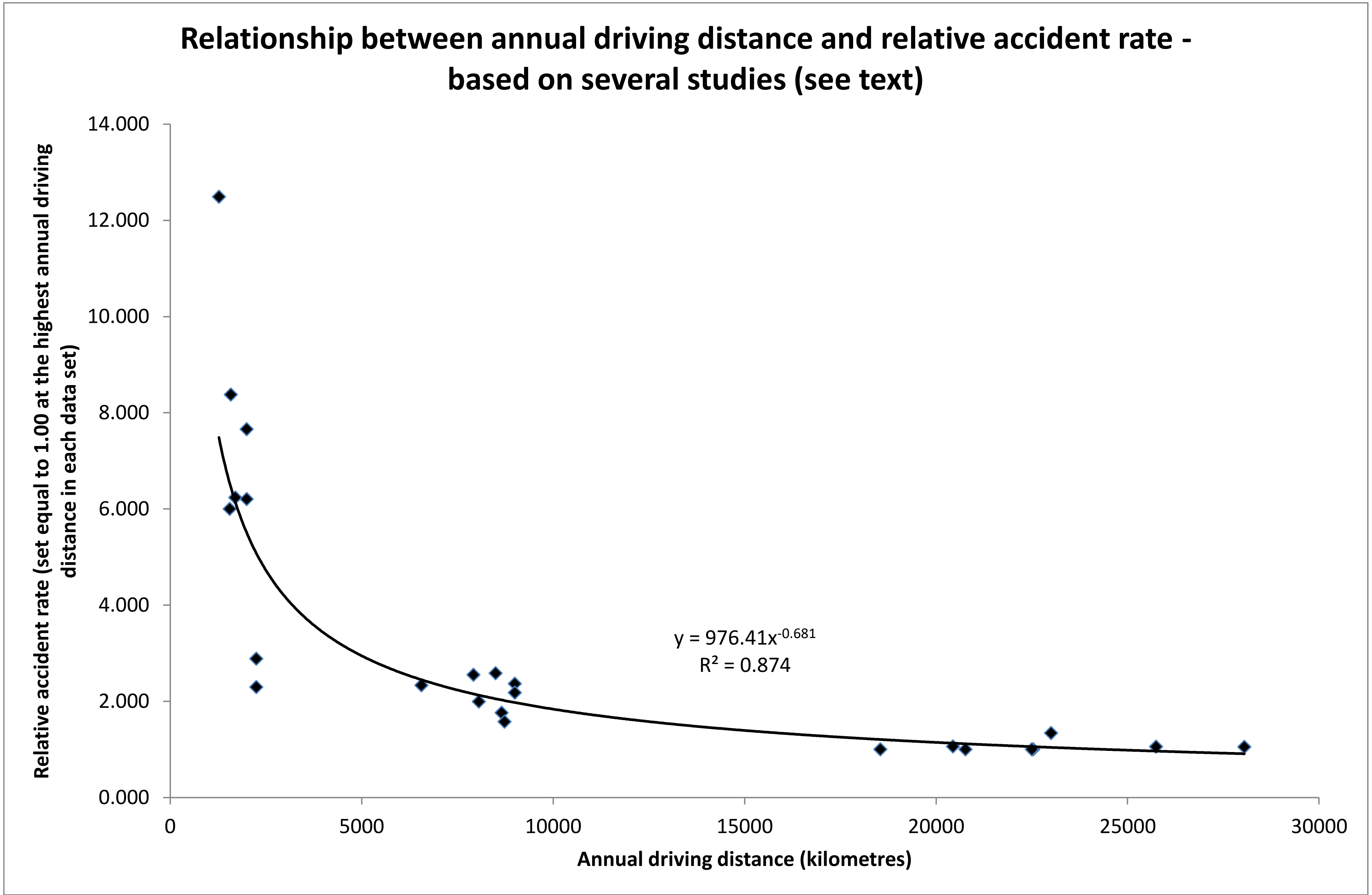

Relative accident rate as a function of how exposure is measured
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
Relative accident rate
Maximum (AADT = 20,000)
Minimum (AADT = 500; encounters = 62,500)
Maximum (encounters = 100,000,000)
Amount of exposure (AADT or number of encounters)

Figure 3:



Relationship between annual driving distance and relative accident rate - based on several studies (see text)
Relative accident rate (set equal to 1.00 at the highest annual driving distance in each data set)
14.000
12.000
10.000
8.000
6.000
4.000
2.000
0.000
0
5000
10000
15000
20000
25000
30000
Annual driving distance (kilometres)
$y = 976.41x^{-0.681}$
$R^2 = 0.874$

Figure 4:

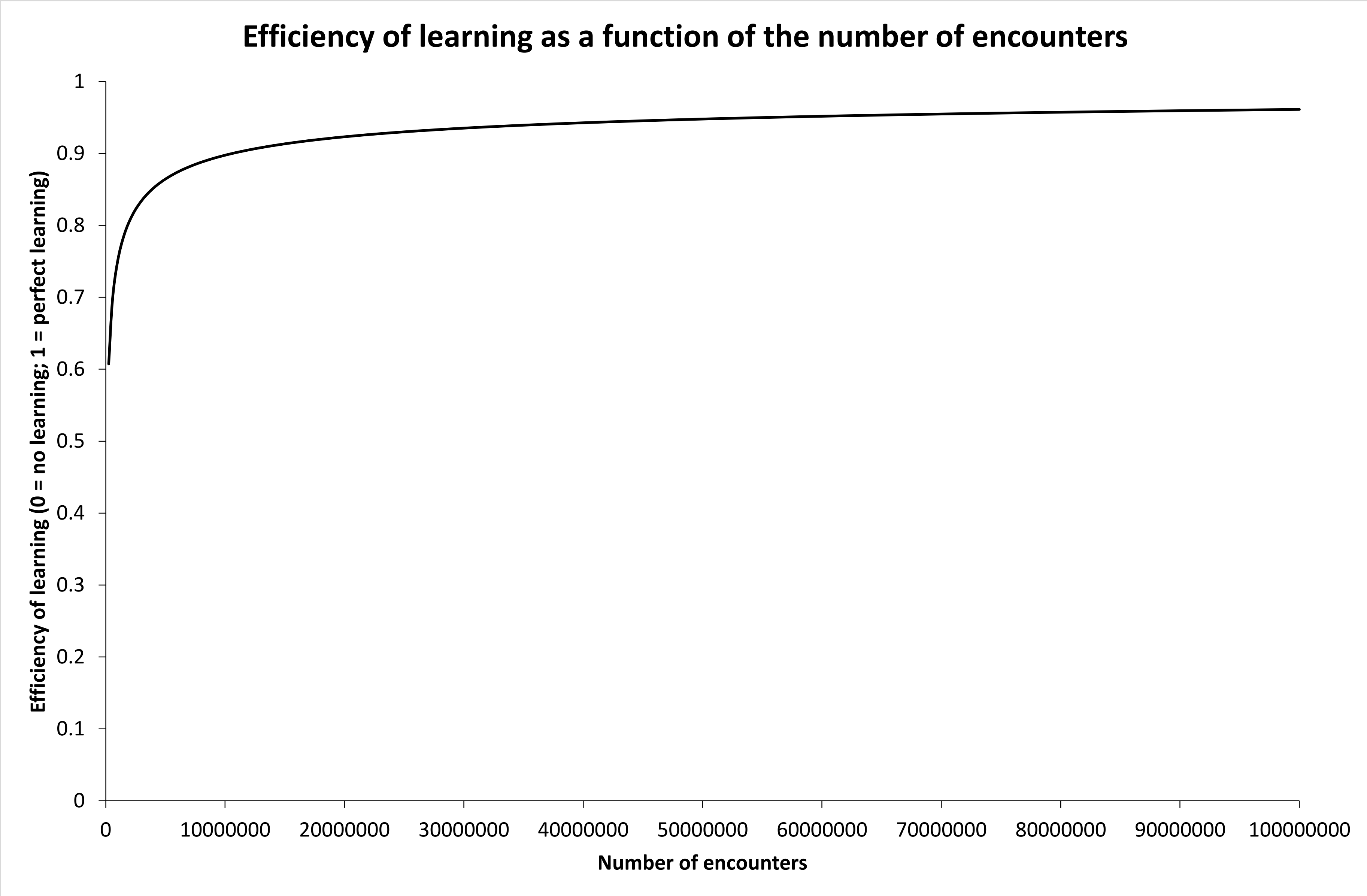

Efficiency of learning as a function of the number of encounters
Efficiency of learning (0 = no learning; 1 = perfect learning)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10000000
20000000
30000000
40000000
50000000
60000000
70000000
80000000
90000000
100000000
Number of encounters

Figure 5:

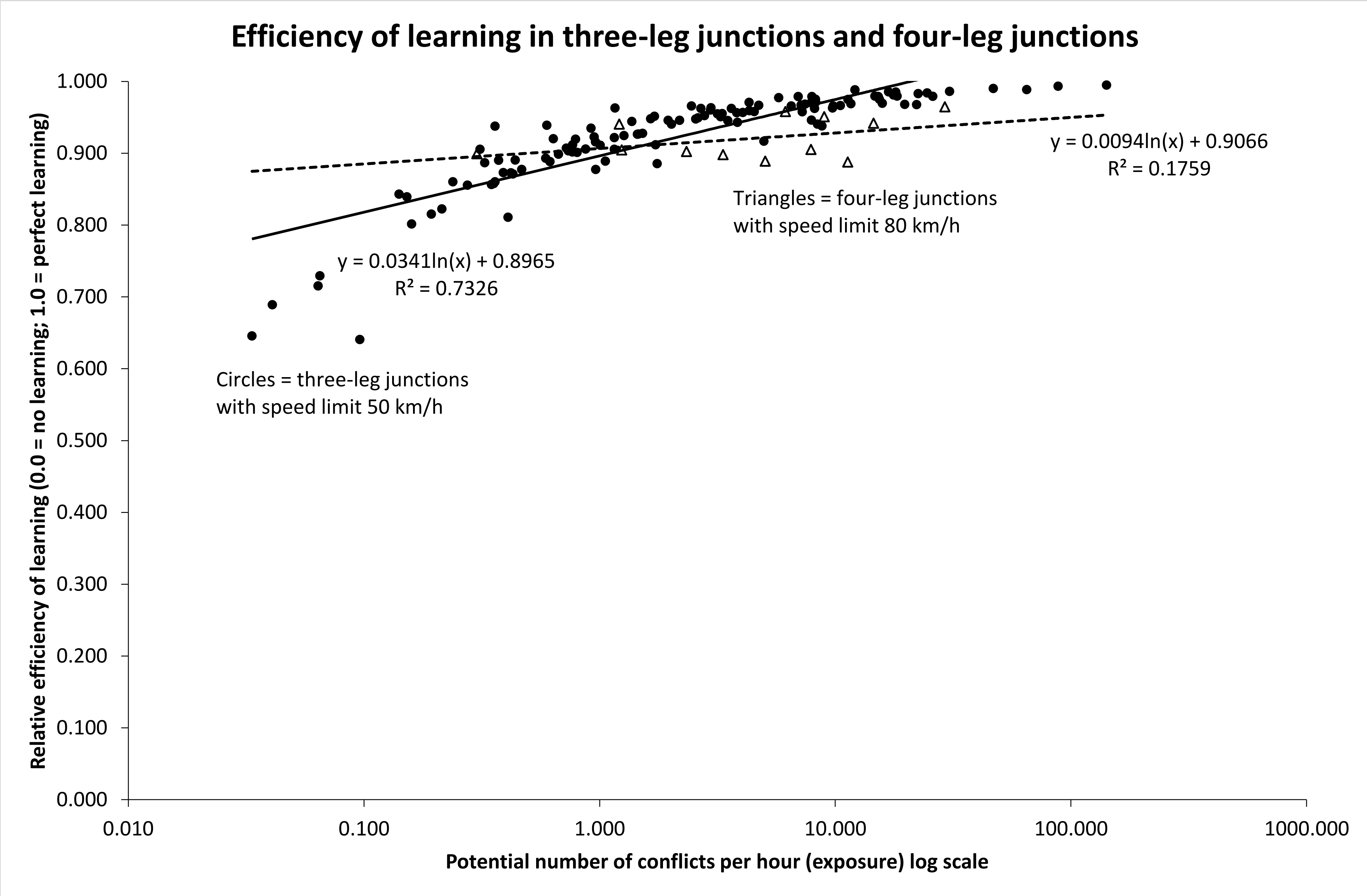
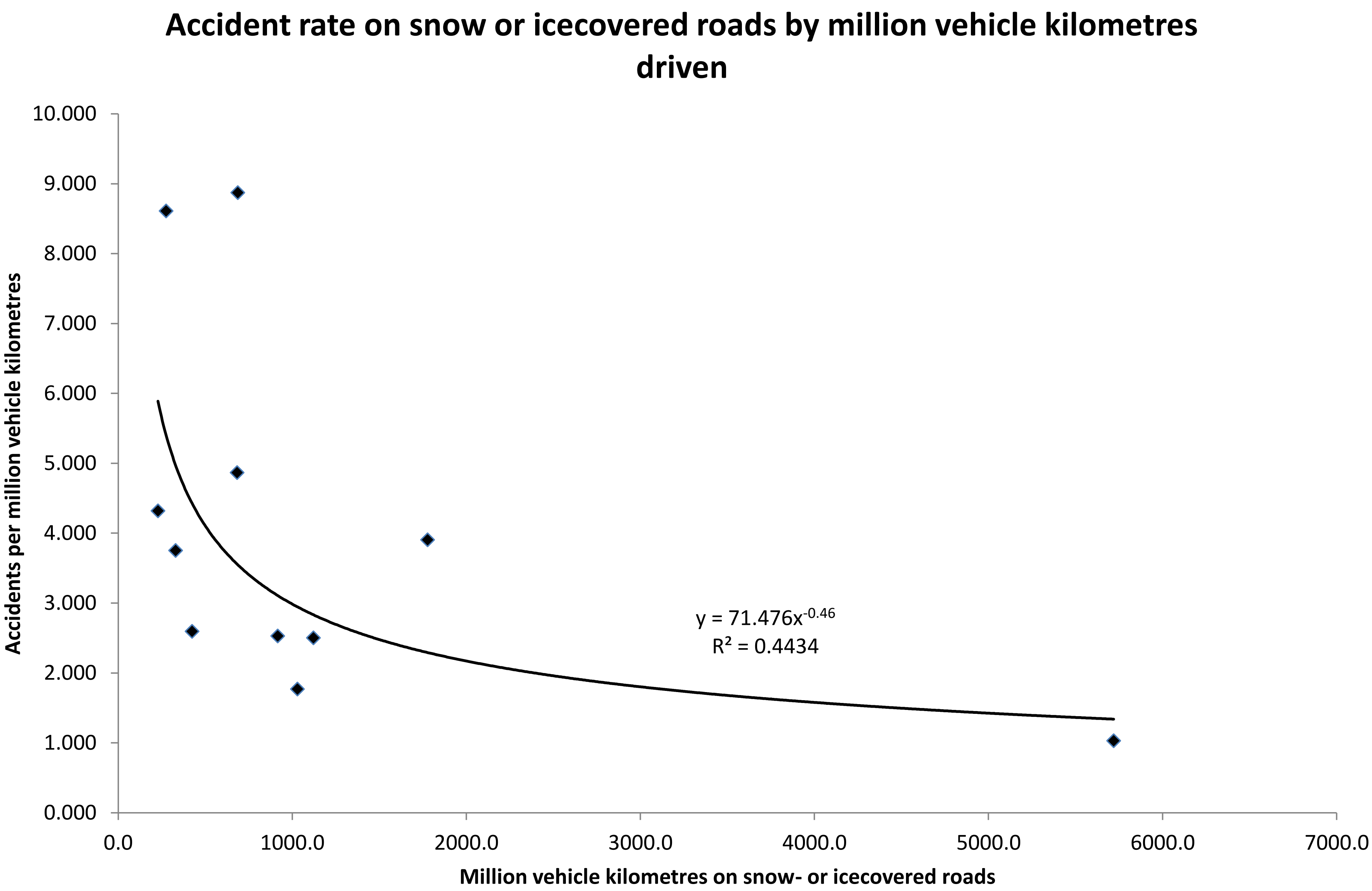

Efficiency of learning in three-leg junctions and four-leg junctions
1.000
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
Relative efficiency of learning (0.0 = no learning; 1.0 = perfect learning)
0.010
0.100
1.000
10.000
100.000
1000.000
Potential number of conflicts per hour (exposure) log scale
y = 0.0094ln(x) + 0.9066
R² = 0.1759
Triangles = four-leg junctions
with speed limit 80 km/h
y = 0.0341ln(x) + 0.8965
R² = 0.7326
Circles = three-leg junctions
with speed limit 50 km/h

Figure 6:



Accident rate on snow or icecovered roads by million vehicle kilometres driven
10.000
9.000
8.000
7.000
6.000
5.000
4.000
3.000
2.000
1.000
0.000
Accidents per million vehicle kilometres
0.0
1000.0
2000.0
3000.0
4000.0
5000.0
6000.0
7000.0
Million vehicle kilometres on snow- or icecovered roads
y = 71.476x-0.46
R² = 0.4434