Profiling Drivers' Risky Behaviour Towards All Road Users

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Abstract

Demographics, crash records and self-reported driving behaviour have typically been used as the basis for building driver profiles of crash risk. These capture the most serious of crashes but underreport other events such as less severe crashes and near-crashes. Improved technology has allowed for the collection of more disaggregate data on day-to-day driving. In turn, this has the potential for use in more comprehensive risk assessments. However, isolating the influence of the driver on behaviour from behaviour influenced by external factors including the road environment can pose a challenge. This paper presents a framework and methodology for profiling drivers along multiple dimensions of behaviour and risk to the driver and other road users using empirical data. Using 8 million second-by-second GPS data observations collected from 106 drivers in Sydney over several weeks, this paper examines the effectiveness of this approach. The results indicate that over 90 percent of drivers exhibit more variability in speeding, acceleration and braking behaviour between different road environments than within the same road environment. This analysis points to the potential for using more disaggregate data but also the necessity to control for temporal and spatial factors when studying driver behaviour. Building comprehensive driver profiles using the proposed framework has the potential to provide a different way of classifying drivers other than demographics or (rare) crashes.

Keywords

Risk Profiling, Speeding, GPS

Introduction

Crash statistics are typically reported using demographics of drivers. As a consequence, much of the road safety literature examines driving behaviour and risk to different demographic groups. Although crash records provide useful information on the aggregate differences in behaviour, injuries and fatalities, they only include the small number of crashes reported to police and therefore mask the variability in driver behaviour within and between drivers (Greaves and Ellison, 2011). Since understanding the characteristics of drivers is an important element in developing and targeting road safety strategies, developing more precise methods of describing drivers by their risky behaviour would be beneficial in improving road safety. Hutchinson and Wundersitz (2011) argue that assessment of road safety campaigns should be based on changes to frequent measurable behaviours that can be used as proxies for risk, such as speeding, although at present there is no 'best' proxy. This reflects the reality that crashes are very infrequent events and are therefore subject to random variability.

Driver risk profiling is a method of representing driver characteristics that can include multiple driver trait characteristics including demographics, personality and behaviour (de Winter and Happee, 2011). This provides a more comprehensive method of describing and categorising drivers than more limited methods that look only at one or two variables (typically age and gender). Some researchers have used driver risk profiling to categorise drivers on the basis of the risks to which they as drivers are exposed. However, there remains a gap in our understanding as we assume that each individual driver behaves similarly through time and across different situations. The advent of instrumented vehicles, equipped with a range of monitoring devices and sensors, has demonstrated that this is not an accurate assumption and that there exists a large degree of heterogeneity in an individual's driving behaviour. In addition, risk profiling has focused on identifying the risks to the driver of a crash, injury or fatality but has not decomposed the risk drivers impose on themselves, their passengers and other road users as well as the risks they are exposed to by others.

This paper presents a proposed framework and methodology for developing driver risk profiles that could be used to assess the risk of crashes, injury or fatalities for a number of different road users. Using second-by-second GPS data collected from 106 drivers in Sydney over five weeks, we examine the potential for this type of data using a sample of measures of risky behaviour as an illustration of how this would differ from traditional profiles.

In terms of prior research, there is a wealth of literature on types of driving behaviour and their influence on the risk of a casualty crash. These behaviours include speeding (Pedan et al., 2004; Cameron and Elvik, 2010), aggressive acceleration and braking (af Wåhlberg, 2006; Jun et al., 2007; Bagdadi and Várhelyi, 2011) and exposure to intersections (Campbell et al., 2004) among others. Most of this research makes use of self-reported data which is relatively inexpensive to collect and therefore permits large samples. However, this method is known to suffer from under reporting of illegal driving behaviour (Corbett, 2001; Hatfield et al., 2008) and is less able to monitor drivers across time. Studies using GPS devices to monitor behaviour are able to collect much more disaggregate data from drivers during day-to-day driving but the higher monetary costs results in smaller sample sizes. The most notable studies examining driver behaviour are Musicant et al. (2010), Jun et al. (2007) and Dingus et al. (2006). They examined the behaviour of drivers immediately before crashes and what were termed 'near-crashes' to explore the factors that turned 'near-crashes' into crashes.

Most studies looking at the risk profiles of drivers categorise risk groups by demographics (primarily age and gender but sometimes location) (Wundersitz and Hutchinson, 2008). This method is consistent with how crash statistics are reported (NSW Centre for Road Safety, 2009) and is useful for studying the differences between demographic groups that are over/under represented in crash statistics.

There have been a number of attempts to categorise risk groups based on self-reported behaviour and risk preferences including Goldenbeld and van Schagen (2007) who categorised drivers based on low, average or high sensation seeking in addition to demographics, number of speeding fines and location of residence (rural/urban). Machin and Plint (2010) used a questionnaire of self-reported speeding, personality and perceptions to determine the factors that influence speeding behaviour of young drivers. The final model explained 50 percent of the variance in speeding behaviour identifying three risk perception variables, one personality variable and one coping strategy as statistically significant contributors to speeding behaviour. Arguably the more interesting conclusion is that at least five predictors were needed for the model and these predictors vary. In another study, hierarchical cluster analysis was performed to dynamically categorise drivers into four risk groups comprising a calculated risk taking group, an unintentional risk taking group, a continuous risk taking group and a reactive drivers group (Musselwhite, 2006). The development of risk profiles based on behaviour and risk preferences – and the assessment of risk itself – is complicated by the interdependencies of different risky behaviour (Musselwhite, 2006). This is confirmed by research on the reliability of seven different driving attitude scales, created using responses from a single survey, as predictors of speeding tickets and accidents. It found that the Speeding Attitude Scale (SAS) dominated other scales in tests of (weak but statistically significant) intercorrelations (Whissell and Bigelow, 2003). Another study using the Driver Behaviour Questionnaire showed that risk taking behaviours and attitudes were a more appropriate differentiator than demographics but this required a number of measures to be used together (Lucidi et al., 2010).

As identified by Schönfelder et al. (2002), much of the existing literature has not properly accounted for variability in driver behaviour and this has impaired the effectiveness of road safety policies. In the context of driver behaviour, variability reflects that drivers engage in a number of different behaviours associated with a low risk of a crash to a high risk – for the same driver across time and space – and for different drivers. This variability is confirmed by a study conducted in the United States using vehicles instrumented with Global Positioning System (GPS) and other sensors, which looked at various aspects of driving behaviour including driver inattention and fatigue. The study found that the frequency of occurrences of driver inattention was highly variable between drivers and the authors advised that this should be considered when interpreting the analyses (Dingus et al., 2006). This may (in part) be due to variability in people's risk choices which would be consistent with research on risk decision making (Ball et al., 2010) or reflect the influence of the road environment (such as school zone, road width, speed limit) or the temporal situation such as peak as opposed to off-peak driving. As the risks imposed and incurred by drivers are likely to vary based on the temporal and spatial environment, risk profiles should account for these variations.

Methods

As part of a broader study on driving behaviour (Greaves et al., 2010; Greaves and Fifer, 2011) demographic, personality and driving behaviour data was collected from 147 drivers in Sydney. To avoid any potential influence on answers to the survey or contamination of driving behaviour, drivers were only told the aim of the study was to track vehicle usage to help transport planning in Sydney. Initially participants completed a demographic survey which collected information on the driver, household and his/her vehicle. Following this a five section, fifty question personality survey was administered to collect information on each driver's personality, risk perception and perceived/self-reported behaviour (Greaves and Ellison, 2011). The surveys took 10 minutes to complete.

Following the completion of the demographic and personality surveys, *Mobile Devices Ingenierie* C4 GPS devices were installed by field-workers in participants' cars at their homes. Driving speeds, speed limits, location (latitude and longitude), date and time were monitored second-by-second for a minimum of five weeks for a total sample of 80 million observations. Although participants were not told that their speed was being monitored to avoid any possible influence on behaviour due to the installation of the GPS devices, nonetheless the first week of data were excluded from the analysis. Of the 147 drivers, 106 were selected for this analysis to ensure comparability of data between drivers. Drivers were excluded for a number of reasons including going on holiday during the study period, not completing all phases of the study, drop outs due to loss of interest and a small number with technical problems (Greaves and Fifer, 2011). For this analysis, 25 consecutive days of GPS data were used such that data for all drivers starts and ends on the same day of the week. The data is comprised of one GPS observation each second of driving, leading to 8 million observations and an average of 1062 km per driver. A summary of the distribution of driver demographics (age and gender) and vehicle characteristics (type and model year) for the 106 final drivers is shown in Table 1.

Table 1: Driver Demographics and Vehicle Characteristics (N=106)

Age	Gender	Vehicle Type	Vehicle Model Year
18-30 (26%)	Male (40%)	Sedan (44%)	<= 2000 (34%)
31-45 (35%)	Female (60%)	Hatchback (34%)	2001 to 2005 (35%)
46-65 (39%)		Other (22%)	2006 to 2010 (32%)

Driver risk profile

Driver behaviour and its impact on the risk of injury or fatality is composed of a number of different elements which are inter-dependent. For example, driver behaviour is influenced by the road environment but the road environment also affects the risks associated with a particular behaviour. Most conventional methods of analysing driver behaviour – and comparing risk between drivers – do not take this into account.

We illustrate how a driver profile built on behaviour can potentially be examined on the basis of drivers' contribution to the risks imposed on themselves and other road users. Individual risk factors apply for each perspective of risk for a number of different elements – for example behaviour, demographics, spatial environment and temporal environment – that together represent the risks imposed on society as whole. The following sources of data are used to represent these factors:

- An individual driver's observed driving behaviour, demographics, personality and perceptions;
- Spatial and temporal data to account for the known road environment such as speed limits, road types, school zones and intersections;
- Aggregate data from all the drivers to account for the unknown road environment such as recurrent congestion; and
- Relative risk factors for behaviours, demographic groups and personality profiles derived from the literature and (when available) from crash statistics.

These profiles are combined as shown in Figure 1 to form a composite risk score and risk margin which are placed on a risk index. The risk index is a normalised scale from 1 (low risk) to 100 (high risk). The risk score is a representation of how safe an individual driver is. The driver can therefore be described at the most aggregate level by the risk score and risk margin.

Risk indices and margins can be created at an aggregate level for each driver on the basis of a particular behaviour (or set of behaviours) that impose risks specifically on the driver, the risk to passengers, the risk to other road users (pedestrians, cyclists, motorcyclists) and the risks imposed on the driver by other road users. In this way, it is possible to recognise that a particular driver's behaviour imposes risk on their own safety as one would expect to see in a driver who regularly exceeds the speed limit on motorways but the same driver may exhibit relatively low risk to other road users if they rarely speed in urban areas with relatively higher numbers of vulnerable road users.

It is noted that there are a very large number of factors in addition to those used here that contribute to how a driver behaves and therefore the risk of an injury or fatality on the road. These include alcohol, fatigue, familiarity, distractions inside and outside the vehicle, emotions, road congestion and the behaviour of other drivers on the road among many others. This study does not have access to data for these factors but the framework has been designed to be scalable such that additional data sources can be added if they become available. In this paper, the temporal and spatial variables shown in Table 2 are used.

Table 2: Spatial and temporal variables

Spatial	**Temporal**
Active school zone	Time of day
Rain	Weekend
Signalised intersection	Primary driver
Non-signalised intersection	Trip purpose
Roundabout	Number of passengers
Speed limit	

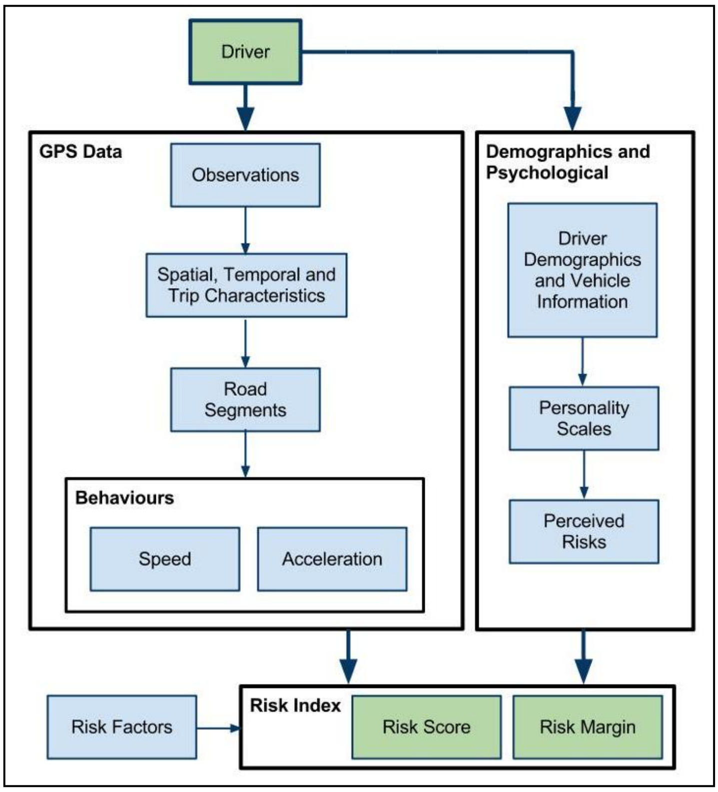

Figure 1: Risk index framework

The risk margin represents the range of behaviours of the same driver. A conceptually safe (low risk) driver has a low risk score and a small risk margin. The risk score may or may not be at the midpoint of the risk margin as shown in Figure 2. In effect, the risk margin reflects the range and variability of an individual's behaviour whilst the risk score reflects a driver's typical behaviour. For example, a driver with a low score and a wide margin is a driver who mostly drives safely but occasionally engages in dangerous driving. A driver with a high score and a wide margin is a driver who frequently engages in dangerous driving behaviour but in some circumstances drives safely (or safer).

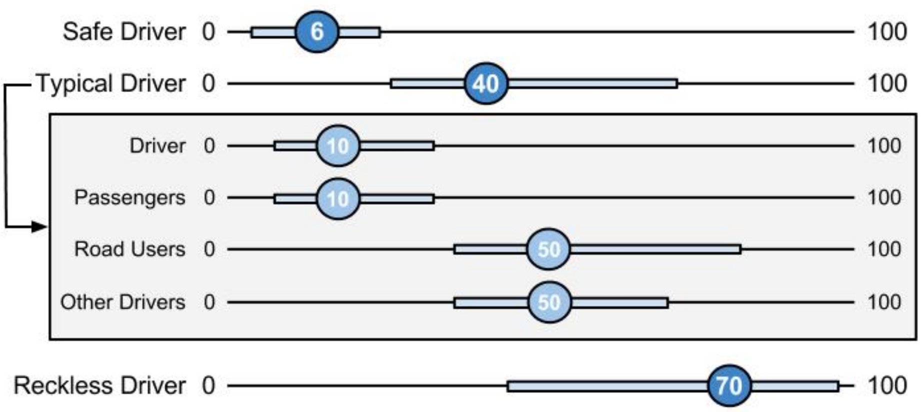

Figure 2: Illustration of risk index, risk score and risk margin using three conceptual drivers

Temporal and road environment

As the characteristics of the road environment are known to influence driver behaviour (Ewing and Dumbaugh, 2009; Rifaat et al., 2011), temporal and spatial characteristics were obtained for each GPS observation. The time and dates of travel are included as part of the GPS data. Additional variables such as the origin and destination were derived using the latitude and longitude for each point and reverse geocoding to obtain the closest street address for that location using the reverse geocoding functionality provided by the Google Maps Application Programming Interface (API).

During the monitoring period, a website was used to collect additional information from each trip that cannot be derived from the monitoring data. This included trip purpose, the name of the driver and the number of passengers. In the analysis presented in this paper, only trips where the participant was the driver are included. To help improve recall, each trip was presented on a map (Greaves et al., 2010).

For each observation characteristics of the road environment were retrieved using a Geographic Information System (GIS). These characteristics include proximity to signalised intersections, proximity to non-signalised intersections, presence of school zones and speed limit. In addition, using rainfall data collected by the Australian Bureau of Meteorology (BOM), a binary variable was used to indicate if it was raining (or not).

These temporal and spatial characteristics were combined into a single Temporal and Spatial Identifier (TSI). The final dataset at the most disaggregate level contains 8 million observations from 106 drivers representing 70,000 km of driving. On average, average driving distance was 678 km for each driver in 25 days, with a standard deviation of 453 km.

Observed driving behaviour

GPS devices provide information on a vehicle's location and speed[1]. For the purposes of testing the methodology, this analysis focused on two forms of driver behaviour which the literature confirms result in higher risks of injuries and fatalities to road users:

[1] There are a number of ways to calculate speed using GPS. In this case, the observed speed is the speed calculated by the GPS device using Doppler shift which has a claimed accuracy of ±0.1 m/s (Greaves et al., 2009).

1) Speed (and speed deviance from the speed limit) and;
2) Acceleration (positive and negative).

Speeding is considered on the basis of distance and magnitude in three non-exclusive categories of 1 km/h or more over the speed limit, 10 km/h or more and 20 km/h or more in each individual observation. In terms of acceleration, there is an interest in the variation and the magnitude. It is known that typical every day driving exhibits negative (braking) acceleration of -3.1 m/s^2. Conflict situations exhibit negative accelerations of between -4.0 and -7.7 m/s^2. Although a safe driver would be expected to be involved in some conflict situations due to the behaviour of other drivers, we consider a driver with a particularly variable incidence of these events to be aggressive. We set a similar threshold for acceleration (4 m/s^2).

A road segment was created for each set of sequential observations with the same driver and Temporal and Spatial Identifier. This created a dataset with over 650,000 records and over 5,000 unique T&S identifiers (across all drivers). Since one objective of this analysis was to examine the variability within and between T&S identifier contexts, only T&S identifiers that appeared at least 20 times for any single driver were retained leaving 480,169 records. Across all drivers in the final dataset, the average T&S identifier has 271 associated road segments and a VKT of 28 km. A number of aggregate measures were then generated for each road segment as shown in Table 3.

Table 3: Summary of behavioural measures

Speed	**Acceleration**[2]	**Negative Acceleration**[3]
Maximum	Maximum	Maximum
Average[4]	Average	Average
Minimum	Standard deviation	Standard deviation
Standard deviation	Number of events where acceleration is >= 4 m/s^2	Number of events where negative acceleration is <= -4 m/s^2
Distance at 75% of speed limit	Number of events where acceleration is <= 1, <= 2, <= 3, <= 4, <= 5, <= 6, <= 7, <= 8, <= 9 and > 9 m/s^2	Number of events where negative acceleration is >= -1, >= -2, >= -3, >= -4, >= -5, >= -6, >= -7, >= -8, >= -9 and < -9 m/s^2
Distance at >= 1 km/h over speed limit, >= 5 km/h, >= 10 km/h, >= 15 km/h and >= 20 km/h		

These measures are weighted by the total distance driven in each T&S identifier for each driver. Using these (weighted) measures it is possible to determine the variability within and between T&S identifiers and therefore compare an individual driver's behaviour across several spatial and temporal contexts.

A key component of the paper is the use of spatial and temporal identifiers to attempt to disaggregate the effects of factors inherent in the individual from the spatial and temporal environment that may change during a trip, day, week or the data collection phase. If the spatial and temporal identifiers do genuinely affect drivers' behaviour, one would expect that the range of behaviours for a single driver conducted on road segments with the same spatial and temporal characteristics would be more alike than the same driver's behaviour across all

[2] No minimum acceleration is recorded because when the speed (velocity) remains the same, acceleration is zero.
[3] Negative acceleration and braking are equivalent.
[4] Each observation is weighted by distance travelled (VKT) to ensure that observations at lower speeds are not overrepresented.

spatial and temporal contexts. To test this we look at the variance of the difference between the mean behaviour within and between road segments with different T&S identifiers (but the same driver) as compared to the mean of all segments together looking at each driver individually. Specifically we look at seven measures of speeding and acceleration behaviour, namely:

1. Speeding by 1 km/h or more over the speed limit;
2. Speeding by 10 km/h or more over the speed limit[5];
3. Speeding by 20 km/h or more over the speed limit;
4. Proportion of events with an acceleration of 4 m/s^2 or more;
5. Proportion of events with a negative acceleration of -4 m/s^2 or more;
6. Average number of segments with any acceleration events of 4 m/s^2 or more; and
7. Average number of segments with any negative acceleration events of 4 m/s^2 or more.

In these results, a small variance for a behavioural measure would indicate that there is not much difference in behaviour between road segments with different T&S identifiers. A larger variance would indicate that the heterogeneity and variability that is seen frequently in driver behaviour is driven (at least partly) by temporal and spatial characteristics. In effect the variance measures indicate to what extent a driver's behaviour varies across temporal and spatial contexts and therefore whether tailoring road safety messages should include specific contexts in which the behaviour(s) of interest are most likely to occur. These results are presented for each driver as a whole but different risk factors are associated with different road users in different spatial contexts. The purpose of examining variability in this way is to determine if controlling for temporal and spatial differences in this way would isolate drivers' inherent behaviour.

Results

Looking first at the measures of speeding in Figure 3, there is a large variance in speeding behaviour between different spatial and temporal identifiers at 1 km/h or more over the speed limit and to a lesser extent at 10 km/h or more. Each observation shown on the plot represents the variation in a single driver's speeding in the three over-the-speed-limit categories. The small variance exhibited at speeds of 20 km/h or more over the limit is likely due to the small proportion of driving (less than two percent of distance travelled) at these speeds. Overall, 95 percent of the drivers in the study exhibited less variation in speeding behaviour within the same temporal and spatial environment than between different temporal and spatial environments. The figures for positive and negative acceleration are similar at 95 and 90 percent respectively. Despite a fairly small proportion of driving at these speeds, this behaviour is particularly prone to road crashes and casualties (Kloeden et al., 1997). It also represents behaviour that cannot conceivably be considered inadvertent due to inattention as lower magnitudes of speeding may be (Aberg and Warner, 2008). This indicates (unsurprisingly) that a large degree of the variation in speeding behaviour is influenced in some way by the temporal and spatial characteristics. It is therefore essential that when analysing a driver's behaviour, both through the proposed framework and using other methods, that observations are disaggregated by the spatial and temporal characteristics associated with each point. The more detailed and heterogeneous the data, the more important this is.

[5] The three speeding measures are inclusive of each other. Speeding by 1 km/h or more includes all speeding by 10 km/h or more and all speeding by 20 km/h or more.

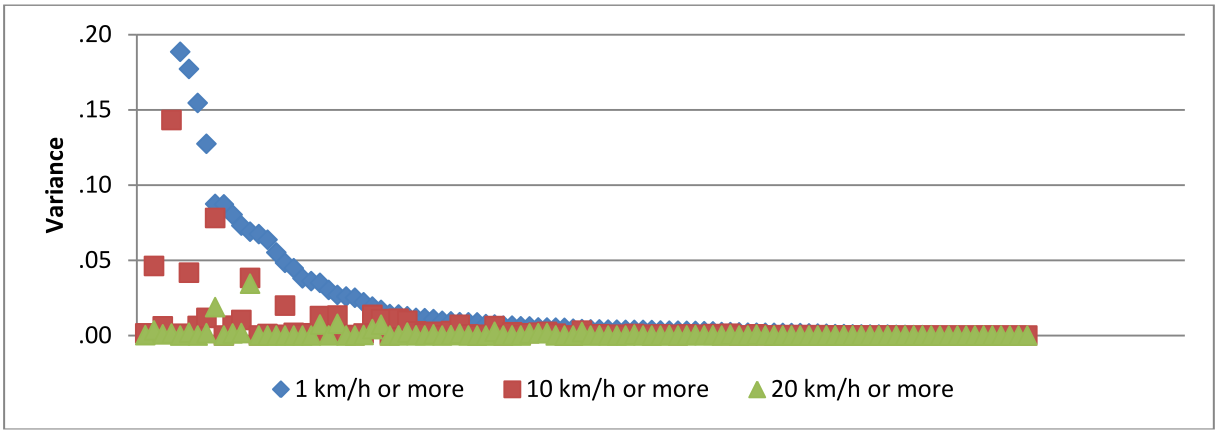

Figure 3: Variance in speeding behaviour between spatial and temporal identifiers by driver (n=106 drivers)

A similar effect is seen when looking at what can be termed "extreme" acceleration and braking events. These are events which are not associated with typical driving (af Wåhlberg, 2006) and which should only occur when required by the behaviour of other road users. If this is the case there would be very few observations in the high variance range.

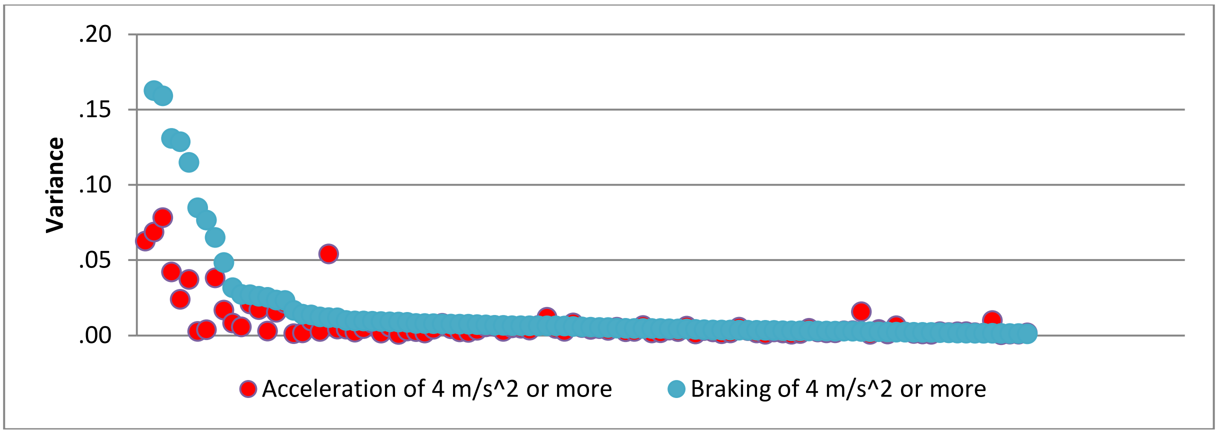

Figure 4: Variance in acceleration and braking behaviour of ±4 m/s^2 or more by driver (n=106 drivers)

The results are shown in Figure 4 with each driver represented by two points (one red for acceleration and one blue for braking) which, albeit preliminary, indicate that a subset of the drivers in this study exhibited large variations in the number of acceleration and braking events in excess of ± 4 m/s^2. These drivers exhibit fluctuations in acceleration and braking behaviour in different contexts. This points to the fact that although many have a relatively consistent (but not necessarily safe) driving style in different contexts, a significant minority are prone to behave very differently in terms of aggression in certain situations. In designing campaigns and interventions and subsequently assessing their effectiveness, this variability should be considered.

Discussion, limitations and conclusions

This proposed methodology can be applied in a number of ways. First, using a driver's observed behaviour (potentially) supplemented by demographics, personality and vehicle characteristics it is possible to define the risks imposed and received and identify the temporal and spatial characteristics which contribute to that risk. Second, the effectiveness of a road safety campaign or intervention can be assessed by comparing the risk scores and margins in a before and after study. This would be more conclusive than examining changes in crash rates although external factors would still need to be controlled for. Third, using simulated behavioural data, which represents desired behaviour using computer-generated GPS observations, there is potential to simulate how *potential* changes in behaviour would impact on individual and societal risks. In addition, since the data is stored in a relational database it allows for the calculation of a single risk index and any number of spatially and temporally specific risk indices to be created. This allows for comparisons to be made between different drivers and for the same driver in different situations.

This paper presents a proposed framework and methodology for describing drivers by risky behaviour using a composite driver risk profile. However, due to limitations on the availability of data on behaviours such as distraction, fatigue and drink driving, the behavioural elements are reliant on vehicle speed over the speed limit and acceleration as measures of risky behaviour. Future research would benefit from the addition of some of these additional behaviours. It is also acknowledged that many of the variables can be considered individual, temporal, spatial or environmental in nature and may change at different frequencies. The analysis in this paper is limited to examining the necessity of controlling for temporal and spatial factors when using disaggregate GPS data to profile drivers on the basis of their behaviour. Nonetheless, these preliminary results have a number of interesting and useful conclusions. They confirm that behaviour variability between temporal and spatial contexts is high among many drivers and, in general, more so than within the same spatial and temporal context. It also alludes to the presence of a segment of drivers who appear to be particularly prone to extremes in risky behaviour.

The driver risk profiles described in this paper have important implications for the targeting of road safety campaigns and messages. They allow a shift from targeting demographics to targeting drivers who more frequently engage in a particular risky behaviour. By examining the profiles of drivers who engage in the behaviour(s) of interest, it is possible to more accurately develop effective road safety messages. Furthermore, the ability to examine profiles in specific spatial or temporal contexts provides a mechanism for understanding behaviour in areas of particular policy interest such as school zones, urban centres and night time driving. Of particular importance is the understanding that although a driver's personal characteristics may be important in understanding driving behaviour, an individual's actual driving behaviour is very much an interaction with more changeable factors such as the road environment and the characteristics (purpose, passengers, etc.) of the trip. Arguably, it is easier to change behaviour through changes in these temporal and spatial factors than it is to change a driver's personality, risk preferences and attitudes. This is particularly true in areas where 'hard' traffic calming measures (speed humps, fencing, etc.) can safely be implemented. The framework and methodology presented in this paper can be used to assess, pre and post implementation, the effectiveness of road safety campaigns and strategies.

Ongoing research using this dataset is focused on refining the risk profiling algorithm to combine this with a driver's personality, vehicle and risk preferences data. More work is also underway on analysing driver profiles within spatial and temporal contexts and for different road user groups.

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