IN-VEHICLE DATA RECORDERS FOR MONITORING AND FEEDBACK ON DRIVERS' BEHAVIOR

Published in Transportation Research Part C 16(3), pp. 320-331, 2008

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Abstract

This paper describes the potential of in-vehicle data recorder (IVDR) systems to be used in various commercial and research applications as tools to monitor and provide feedback to drivers on their on-road behavior. The implementation of IVDR is demonstrated using the example of the DriveDiagnostics system. This system can identify various maneuver types that occur in the raw measurements, and use this information to calculate risk indices that indicate on the overall trip safety. Drivers receive feedback through various summary reports, real-time text messages or an in-vehicle display unit. Validation tests with the system demonstrate promising potential as a measurement tool to evaluate driving behavior. Reductions in crash rates and the risk indices are observed in the short-term.

Introduction

The human and cost implications of car crashes are staggering. For example, Blincoe et al. (2002) estimated the total direct annual cost of car crashes in the US in 2000 at $230.6 Billion, and the total cost to society at $493.3 Billion. The direct cost of a car crash was estimated at $14,000, out of which $3,600 is the cost of damage to vehicles and other property. For company vehicles, various studies (Fidderman 1993, Murray et al. 1996, Lynn and Lockwood 1999) estimated that 20-65% will be involved in car crashes each year. Lynn and Lockwood (1999) also found that even after controlling for the larger distances they drive company car drivers are 50% more likely to be involved in car crashes compared to other drivers. Thus, it is clear that the potential benefits of tools and methods that can reduce the rate of involvement in car crashes are huge, and that this potential is in particular substantial for vehicle fleets.

Driver behavior and errors are a cause in the overwhelming majority of car crashes (Evans 2004). Understanding and influencing drivers' behavior is therefore essential in order to improve road safety. An important obstacle to better understanding of drivers' behavior is data availability. Most tools used to define drivers' skills and styles are based on self-reported scales, which could be biased and general (see Podsakoff and Organ 1986 for a discussion). Otherwise, evaluations of driving behavior may only be performed on a limited scope and scale, for example in experiments involving driving simulators (Comte 2000).

Recently, In-Vehicle data recorders (IVDR) have emerged as new tools to collect data on driving behavior and to provide feedback to drivers continuously, in much more detail and with large scale implementations. IVDR are on-board devices that collect and record information on the movement, control and performance of the vehicle (NHTSA 2001, Chidester et al. 2001, Correia et al. 2001). The technology was first used in event data recorders (EDR), which store information on the states of the vehicle's systems for a short time (about 30 seconds) before, during and after crash events. This information is used to evaluate and improve safety equipment and to investigate crash causes and allocate fault (see NHTSA 2005 for a thorough review). Limited empirical evidence suggests that the installation of EDR may affect drivers' behavior. Lehmann (1996) and Lehmann and Cheale (1998) report reductions of 15-30% in crash rates, and even more significant reductions in the related costs, in several vehicle fleets that installed EDR. In all cases, drivers did not receive any feedback, but were aware of the EDR presence. Wouters and Bos (2000) report an overall reduction of 20% in crash rates in several truck, bus and taxi fleets that installed EDR. Drivers received feedback from the EDR after a crash has occurred. In contrast, Heinzmann and Schade (2003) found that EDR did not have any significant impact on the behavior or on crash rates of young males.

Several studies focused on development and evaluation of systems that monitor drivers' behavior continuously and not only in crash events. NHTSA (Neale et al. 2002, Dingus et al. 2006) conducted an ambitious study in which 100 vehicles were instrumented with IVDR that continuously measure the vehicle's position, speed and acceleration using GPS and accelerometers as well as video cameras showing the inside and outside of the

vehicle, radar sensors and lane trackers. The system also extracts information from the vehicle's on-board diagnostics system. The experiment was conducted over a 13 months and yielded a data set with over 43,000 hours and 2 million miles driven. This data has great potential for traffic safety research. However, instrumentation at this level is costly and so unlikely to be deployed in large scale in the near future.

Ogle (2005) used an IVDR system to collect data from 172 vehicles. The system incorporates a GPS receiver and is able to connect to the vehicle's on-board diagnostics system. It can collect the time and durations of trips, distance traveled, second-by-second position, speed and acceleration as well as various engine parameters and information on seat belt usage, emissions and brake and throttle positions. Trip level information was stored in the unit and transmitted to the application server once a week through a wireless network. The availability of location data allowed identification of geographic information, such as types of roads traveled and posted speed limits. The system does not provide any feedback to drivers. While the author points out a wide range of studies the data may be used for, the analysis she presents was limited to a model that predicts the maximum speeding level above the speed limit in individual trips as a function of the driver's socio-demographic characteristics, the type of road facility and trip characteristics (e.g. time of day, level of congestion). Within this model, there was no significant relation between speeding behavior and past crash records.

Commercial applications of IVDR have also emerged in recent years. The TripSense program (TripSense 2007) uses IVDR data to determine insurance rates for participating

vehicles. Installation of the system entitles drivers for a discount on their insurance premium. The discount level is determined by the vehicle utilization pattern (i.e. the hours and distance driven and their distribution over the day and the week) and the speed profile. Speeds are collected at 10 second resolution, but location information is not collected, and so speed limits are not known. The speed factor is therefore expressed by the fraction of time speed is over 75 mph. The system also collects, but does not use, information on the occurrence of sudden starts and stops. Results demonstrating the impact on drivers' behavior are not presented. ECMT (2006) report on the SAGA system developed in Iceland. This IVDR collects information on the vehicle utilization, speed and location using GPS. The location data allows comparison of travel speeds with posted speed limits. Weekly summary reports are sent to users by email. Installation of this system Iceland Post vehicles resulted in a 43% reduction in crash rates over a period of six months. The number of vehicles instrumented and the details of the feedback drivers received were not reported.

In this paper, we describe the details of a specific IVDR system and report several results that demonstrate its potential to measure and impact drivers' behavior: We find that risk indices that the system calculates are significantly correlated with past crash involvement. This result suggests that these indices may be used as indicators to the risk of crash involvement. We also find significant reductions in crash rates after the installation of the IVDR, and use the risk indices to study the temporal changes in the impact of the IVDR installation and feedback. Finally, we discuss potential applications of the technology, both commercial and academic.

The DriveDiagnostics system

The overall framework of the system, which is shown in Figure 1, comprises of four different tasks: measurement, detection, analysis, and feedback.

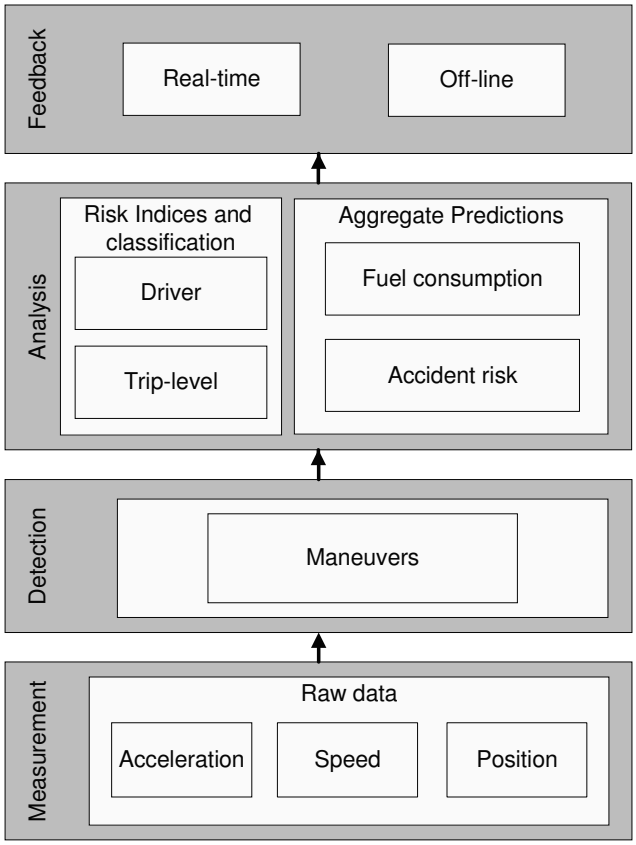

Figure 1 Overall framework of the IVDR system

Measurement

The IVDR collects the following information:

1. Vehicle and driver identification. Drivers are identified using magnetic keys, which are read by a special reader installed in the vehicle.
2. Trip start and end times.
3. The acceleration of the vehicle, both in the lateral and longitudinal directions. The acceleration is measured by accelerometers at a sampling rate of 40 measurements per second.
4. The vehicle speed, which is derived from the GPS receiver data or from the vehicle speed sensor (VSS).
5. The vehicle location measured by a GPS receiver.
6. The system may also connect to the vehicle on-board diagnostics system in order to obtain additional engine parameters.

The sensor unit with the accelerometers and the data recording and analysis unit are installed together, typically under the plastic panel underneath the handbrake. Their combined size is about 11x6x6 centimeters. They require a small amount of power (<250mA), and so are wired to the car battery.

Detection

In this task, pattern recognition algorithms are applied to the raw measurements in order to detect maneuvers that the vehicle performs. This step is necessary in order to reduce the large amount of raw information to meaningful observations, beyond speed and

acceleration distributions, that may be used to infer drivers' behavior. The system identifies over 20 maneuver types, such as lane changes and turns with and without acceleration, sudden brakes, strong accelerations, excess speeds and so on. These maneuvers are further classified by their relative direction (to the left or to the right) and in three levels of severity based on parameters of the detailed trajectory, such as the maneuver duration, extent of sudden changes in speed and acceleration and the speed it is performed at. Figure 2 shows characteristic acceleration patterns for a turn maneuver and a lane change. In both cases the longitudinal acceleration was close to zero, implying a roughly constant speed during the maneuver.

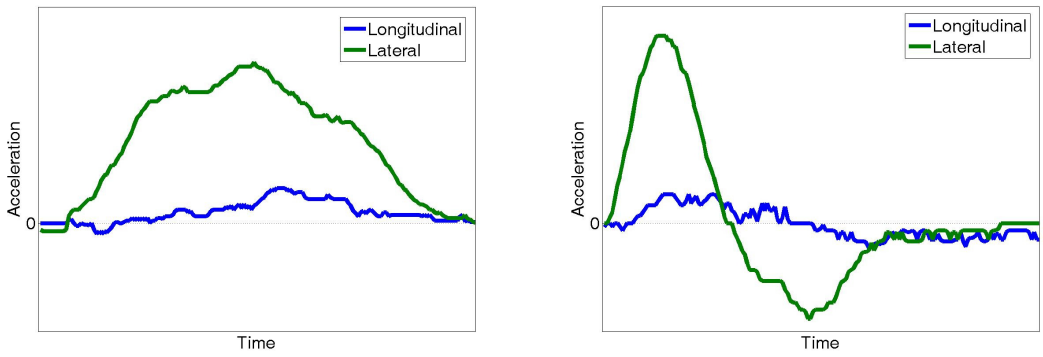

Figure 2 Characteristic turn maneuver (left) and lane change (right) patterns

Analysis

The detected maneuvers are used to calculate several driver-specific and vehicle-specific indices and statistics. The following indices are currently used:

- Individual risk index: this index is a numeric measure that aims to indicate the driver's risk of involvement in car crashes in a given period of time. It is calculated as a linear function of the numbers and severity of the various types of maneuvers that

the driver has performed. The driving time in this period is used to normalize the amount of maneuvers:

$$R_{it} = \frac{\sum_j \sum_s \beta_{js} N_{ijst}}{DT_{it}} \quad (1)$$

R_{it} is the risk index for individual *i* during period *t*. DT_{it} is the total driving time during this period. N_{ijst} is the number of maneuvers of type *j* and severity *s* the driver has performed. β_{js} are the weights of the various maneuvers.

The risk indices are then standardized to take values between 0 and 1, with high values implying higher crash risk.

- Risk classification: based on the risk index, drivers are classified in three categories. The main purpose of this classification is to provide a simpler system to report risk indices that will be understandable to layman drivers. For this reason the classes are also labeled as Green (moderate behavior), Yellow (Intermediate behavior) and Red (risky behavior).
- Trip-level risk index and classification: risk indices and classifications are also calculated for each individual trip.
- Speed index: this numeric value reflects the driver's speeding behavior. It depends on the extent and duration the driver exceeds pre-set speeds. While speeding is also taken into account in the overall risk indices, speed has been shown to be an important predictor of crash involvement and so a separate index is maintained.

- Fuel consumption index: the information related to drivers' performance is combined with other information such as vehicle types to predict fuel consumption.
- Exposure measure statistics, such as the distance and time traveled by the driver and their temporal (time of day, day of week) and spatial (urban, non-urban, off-road) distributions.

Feedback

Feedback may be provided both off-line and in real-time. In an off-line application, reports that summarize and compare information at the level of the driver, vehicle or an entire fleet may be produced. An example of part of a web-based monthly driver report is shown in Figure 3. The chart at the top of the figure shows the various trips the driver made in the month. Each square represents a trip. The X axis indicates the day of the month and the Y axis indicates the number of trips performed during each day. Trips are color-coded by their classification as described above: Green, Yellow and Red. Detailed information on each trip is presented as shown at the bottom of the figure. In addition, the report includes statistics of the total hours of driving during the month and comparison of the driver's performance to previous months and to other drivers in the fleet.

Real-time feedback, which includes warnings on aggressive behavior or on significant deviations from the normal driving patterns for the specific driver, can be provided as a text message (SMS) or using an in-vehicle display unit. To reduce communications, the measurement and detection tasks are performed in real-time within the unit installed in the vehicle. The detection outcomes are automatically transmitted to the application

server using wireless networks. To date, the IVDR has been installed in over 800 vehicles. Over 400,000 driving hours in almost 930,000 trips have been monitored.

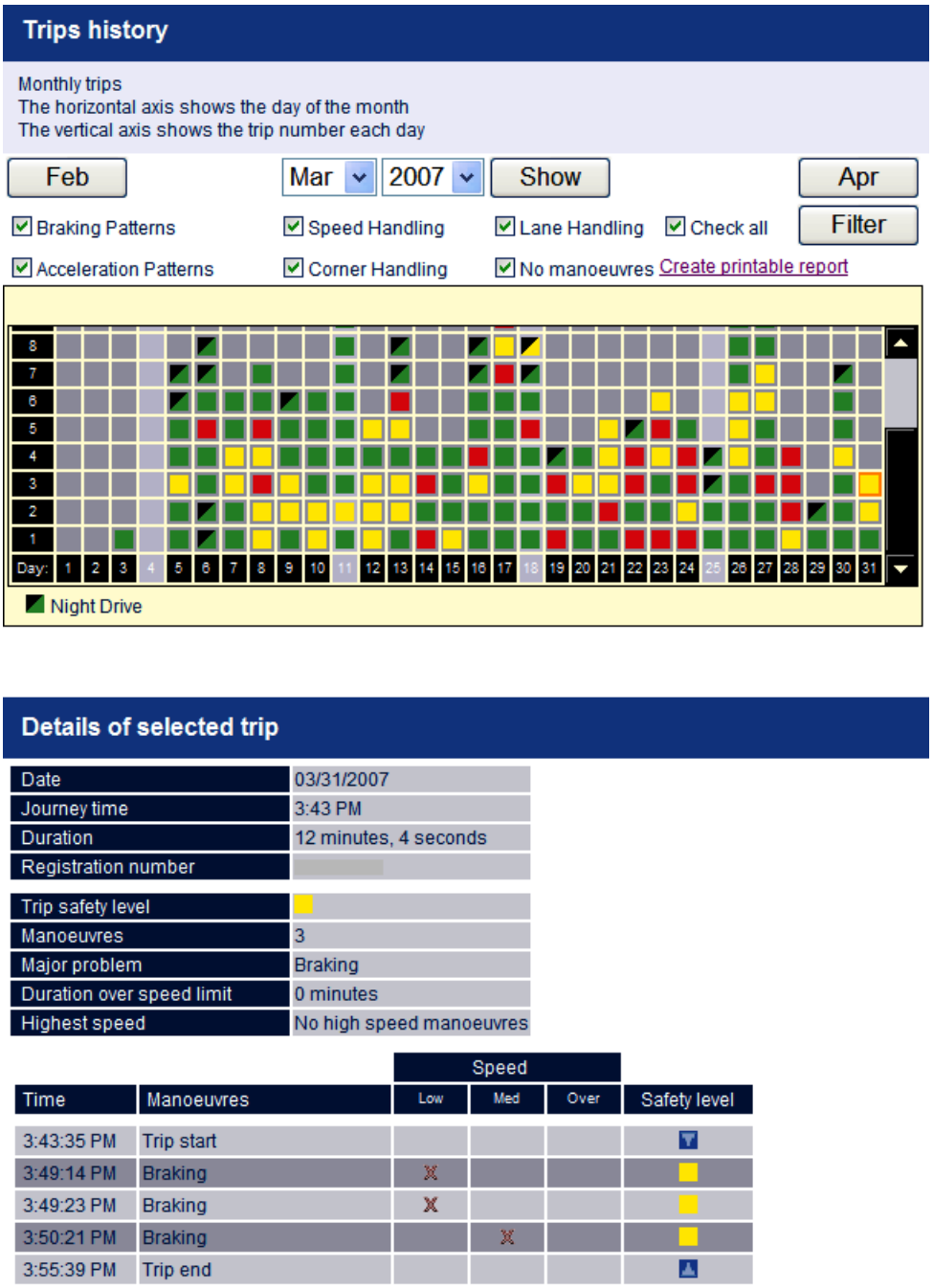

Figure 3 An example of a web-based driver report

Experiment

The results reported here are based on installations in 191 vehicles in a single company. The vehicles are all compact pickup trucks that are used only on the job, by technical employees that use them to travel between service locations. Each vehicle is assigned to a single driver, and vice versa. Although they drive significant mileage, the drivers (189 males, 2 females) are not professional drivers and are not employed as drivers. The implementation of IVDR systems in all these vehicles followed a similar process that includes two main stages:

1. **Blind-profiling stage**: This stage typically lasts about 8 weeks immediately after the IVDR installation. It is intended to measure the driver's baseline behavior. In all cases, drivers were informed about the installation of the IVDR, which is mandated by privacy protection laws. However drivers only received a general explanation that this is a safety-related system, and no feedback whatsoever. They were also informed that the information collected by the system will not be used by their managers. It is therefore expected that the installation had minimal effect on drivers' behavior during this period.
2. **Feedback stage**: at the end of the blind-profiling, the drivers were invited to a meeting in which they learned about the IVDR system and the feedback it provides. They also received initial feedback on their own driving and access codes to a web site that shows their own data, as well as comparisons to the fleet's averages. Real-time feedback was not available with these vehicles. In all cases, drivers are informed that the IVDR records will not be used in any way against them.

All the trips made in the vehicles were monitored. The system also maintains records of the log-ins made by all drivers to their personal driving reports. In addition, additional variables that represent drivers' past involvement in car crashes were collected from the company records:

1. All crashes – The number of crashes that the driver has been involved in using the company car.
2. Fault crashes – The number of crashes for which it was determined for insurance purposes that the driver was at fault.
3. Record period – The length of the period of time covered by the crash records. This period began from the date that the driver received a company vehicle, but no more than 3 years before the date of IVDR installation.

Results

Connection between IVDR risk indices and crash involvement

The risk indices computed by the IVDR may be useful, if they are correlated with the actual risk of involvement in car crashes. However, the "true" risk cannot be directly measured and so we use past crash records as indicators and test the hypothesis that they are correlated with IVDR risk indices. Crash records were collected for all 191 drivers whose vehicles were instrumented with the IVDR. These drivers are between 25 and 68 years old, with an average age of 41 years. The IVDR risk indices used in this analysis are the ones computed for the blind-profile period. Descriptive statistics of the risk indices and crash data are presented in Table 1. The zero median fault crash values reflect

the fact that 59% of the drivers in the sample were not involved in fault car crashes in the period prior to the installation of the IVDR. 39% were not involved in car crashes at all.

	Risk index	Crashes	Fault crashes	Months in record	Monthly driving hours
Mean	0.50	1.17	0.64	31.9	66.9
Median	0.50	1	0	32	67.2
Std. Deviation	0.28	1.37	0.97	4.2	24.6
Minimum	0.00	0	0	6	10.1
Maximum	1.00	7	5	35	149.2

Table 1 Summary statistics for risk indices and crash data

We used Poisson regressions to model the expected number of all and fault crashes for each driver and using the risk index as an explanatory variable:

$$\log\left[E\left(Y_i\right)\right] = \log M_i + \log T_i + \beta_0 + \beta_1 R_i \qquad (2)$$

Y_i is the number of crashes (all and fault only) recorded for driver i. R_i is the IVDR risk index for that driver. β_0 and β_1 are parameters. M_i and T_i are the number of months for which the driver's crash records were available (i.e. length of the available crash history), and the monthly number of hours driven during the blind-profile stage, respectively. These two variables are used as exposure measures that scale the number of crashes by an estimate of the total driving time.

Table 2 presents the estimation results of the two models, as well as goodness of fit measures. β_1 is positive and highly significant in both cases. Figure 4 illustrates the connection between the IVDR risk index and the expected crash rates. Note that not only the expected number of car crashes increases with higher risk indices, but also the fraction of these crashes that are at fault. This is a result of the larger estimated β_1 value for fault crashes compared to all crashes. However, the difference in the estimates of this parameter is not statistically significant (p=0.227 for the hypothesis that it is larger for fault crashes).

All crashes model			
Parameter	Value	Std. error	p-value
β_0	-8.036	0.153	<0.001
β_1	1.018	0.246	<0.001
$LL(\beta) = -287.23,\ \ Deviance(\beta) = 290.25,$ $LR(df = 1) = 17.24\ (p < 0.001),\ \ deviation\ R^2 = 0.056$			
Fault crashes model			
β_0	-8.816	0.215	<0.001
β_1	1.330	0.337	<0.001
$LL(\beta) = -205.47,\ \ Deviance(\beta) = 232.04,$ $LR(df = 1) = 15.96\ (p < 0.001),\ \ deviation\ R^2 = 0.064$			

Table 2 Results of regression of car crashes on IVDR risk indices

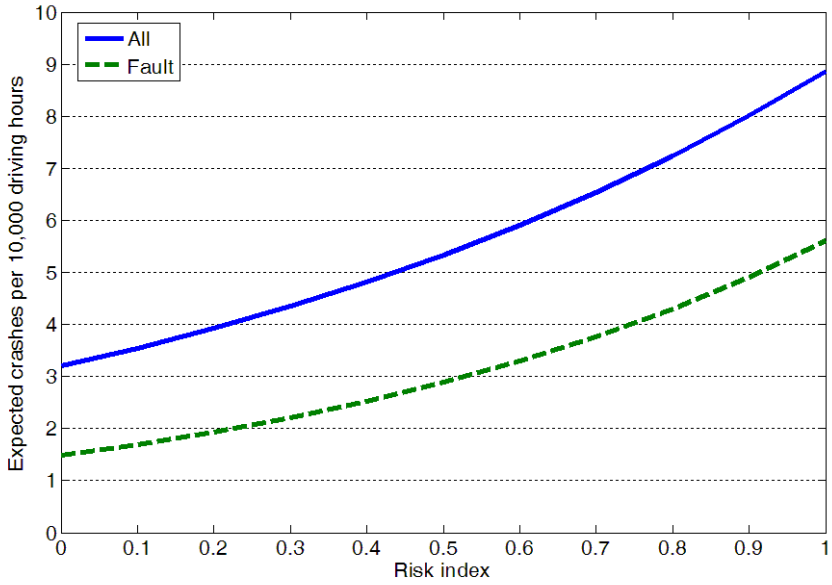

Figure 4 Connection between the IVDR risk index and expected crash rates

Impact of IVDR installation and feedback on crash rates

At the end of the blind-profiling stage, drivers are exposed to the information collected by the system and receive access to the website with the data and reports on their driving (shown in Figure 3). The IVDR information were not used by fleet managers in any way and so no further actions were taken in order to affect drivers' behavior. To evaluate the impact of the IVDR installation and feedback we analyze the crash rates in the periods before and after the exposure. Crash rates for the period before installation were calculated based on the available past crash records. For the period after installation these rates were calculated from the corresponding records for the feedback stage. The period after exposure includes feedback records for exactly 7 months for each driver. To make the data comparable, crash rates per 10,000 hours driven were calculated for all drivers. Summary statistics of the crash rates in the periods before and after the exposure to the

IVDR feedback are presented in Table 3. The results show a statistically significant reduction of 38% (p=0.018) in crash rates, but not in fault crash rates (5%, p=0.849). Some of the reduction in the overall crash rates may be attributed to a general decrease in crashes in the company fleet. The crash rate for the rest of the company fleet, about 1200 vehicles, has dropped by 19% from the period before the exposure to the period after it. It should be noted that the mix of vehicle types in this group differs from that of the experiment vehicles. Nevertheless, taking this trend as an approximate indication to the reductions in crash rates that would have been expected in the experiment vehicles without the installation and feedback, the reductions in crash rates reported here appear to be similar to those reported by Lehmann (1996). The small reduction in fault crash rates is surprising and contradicts with results reported in Musicant et al. (2007). It may be partially a result of the small number of fault crashes in the sample. Further study would be needed to understand the reasons underlying this result.

	All crashes		Fault crashes	
	Before	After	Before	After
Mean	6.30	3.91	3.26	3.10
Mean standard error	0.69	0.73	0.45	0.64
Median	0.16	0	0	0
Std. Deviation	9.60	9.94	6.27	8.79
Minimum	0	0	0	0
Maximum	78.59	52.55	56.14	49.06

Table 3 Crash rates per 10,000 driving hours before and after IVDR installation

Risk indices over time

While the results presented above indicate that the installation of the IVDR and the feedback they provide may an impact on safety, this impact may only be short-term. The number of crashes reported above is not large enough to fully evaluate this issue. However, an evaluation of the temporal effects could be conducted through a comparison over time of the risk indices, which have been correlated with the rate of crash involvement. For that purpose risk indices were calculated for the blind profiling period and for each one of the 7 months following the exposure to the feedback for all vehicles in the sample. Figure 5 shows the mean, median and 85th percentile of the risk indices distribution for the various months. The figure shows that the risk indices are lower after the initial exposure of drivers to the IVDR feedback. The reduction in the mean risk index from the blind profiling period to the first month after the exposure is 33% ($p<0.001$). The reductions in the median and 85th percentile risk indices are 47% and 12% respectively. The risk indices statistics remain at similar levels during the entire seven months after exposure. However, it should be noted that Musicant et al. (2007), who analyzed data over a longer period from other vehicle fleets, report an upward trend in risk indices statistics in the later months after installation.

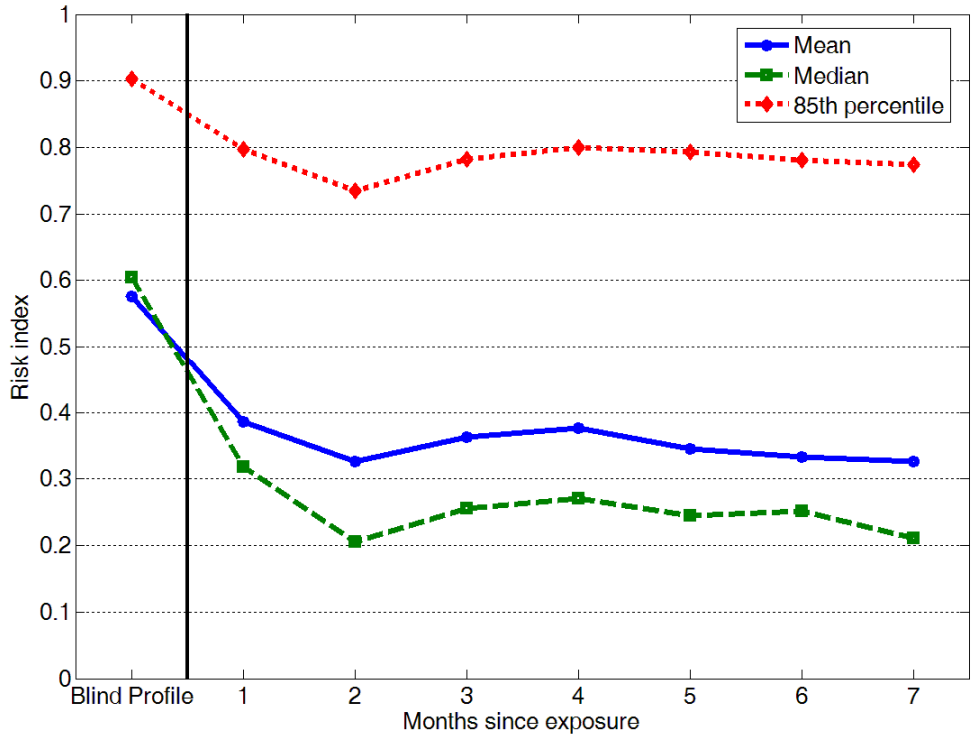

Figure 5 Monthly mean, median and 85th percentile driving risk indices

We next develop a model to examine the temporal changes in the risk indices and the impact of the initial exposure and access to the feedback drivers receive on these indices. The data used for estimation includes records of the risk indices and related variables for each driver for every month since the IVDR installation. The dependent variable in the model is the change in risk indices between consecutive months, $\Delta R_{it} = R_{it} - R_{it-1}$. The model specification is given by:

$$\Delta R_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \qquad (3)$$

X_{it} is a vector of explanatory variables for driver *i* in month *t*. β is the corresponding vector of parameter. α is a constant. ε_{it} is an error term.

The model was estimated using the weighted least squares method, with weights proportional to the monthly driving hours. Estimation results are presented in Table 4. All coefficients in the model are significant at 95% confidence level. The variable R_0 represents drivers' habitual behavior, which is measured by the risk indices in the blind profiling period. It captures differences in driving characteristics between the various drivers. The coefficient of this variable is negative, which implies that the potential of feedback to reduce risk indices increases with this initial value. $\Delta R_{0,t-1}$ measures the deviance of risk indices in the previous month from the habitual ones, which captures the change that has accumulated so far. The coefficient of this variable is positive, which creates a tendency back towards the initial value (i.e., if the risk index in the previous month was lower than the initial risk index, it will induce an increase in the risk index in the current month). The variables *Exposure_dummy* and *Access_dummy* capture the impact of the feedback on risk indices. *Exposure_dummy* is a dummy variable with value 1 if the driver was first exposed to the IVDR feedback in the current month, and 0 otherwise. The coefficient of this variable expresses the marginal impact of the exposure on risk indices. It is negative, which implies a reduction in risk indices following the exposure. *Access_dummy* is a dummy variable with value 1 if the driver access the feedback (through the website) in the current month, and 0 otherwise. It has a negative coefficient in the model, which indicates that accessing the feedback contributes to lowering the risk index.

Explanatory variable	β	Std. error	p-value
Constant	-0.0258	0.0120	0.032
R_0	-0.0848	0.0172	<0.001
$\Delta R_{0,t-1} = R_0 - R_{t-1}$	0.215	0.023	<0.001
Exposure_dummy	-0.0981	0.0139	<0.001
Access_dummy	-0.0650	0.00994	<0.001
num observations = 1003, $R^2 = 0.224$, *adjusted* $R^2 = 0.221$			

Table 4 Regression results for monthly driving risk indices

Conclusion

The results presented above demonstrate the potential usefulness of IVDR systems, which may be important both in commercial applications and in research. In this section we list several current and potential applications of the technology. In these applications, the IVDR has two roles: Firstly, it is a tool to objectively measure and evaluate driving behaviors. Secondly, it can be used to impact drivers' behaviors through monitoring and provision of feedback.

IVDR have important advantages in both these roles that stem from the use of technology to collect the data, evaluate the behavior and generate the feedback. IVDR provide relatively cheap and continuous measurement of on-road driving behavior and vehicle

usage, which is otherwise difficult to observe. Furthermore, IVDR data may be significantly more accurate compared to responses to self-reported questionnaires. For example, Lotan and Toledo (2007), who used IVDR to evaluate the vehicle usage patterns of novice drivers at the various stages within a graduated driving license program, found significant differences between the self-reported amount of driving drivers undertook and the IVDR measurements of the same. The accuracy and objectivity of the IVDR measurements is also important in influencing drivers' behavior. Roetting et al. (2003) found that drivers are more willing to accept and act upon technology-based feedback compared to other forms. The continuous monitoring of vehicles during all the trips made creates a large database, which is valuable to several entities who are interested in monitoring drivers, and identifying and treating behaviors such as speeding, vehicle abuse and aggressive driving:

1. In research, IVDR data is a reliable source of driving behavior and vehicle usage data, which can be used to study driving behavior, the factors that affect it, and their safety and other implications. For example, Lotan and Toledo (2007) used IVDR to study the amount and temporal distribution of driving novice drivers undertake at the various stages of a Graduated Driving License (GDL) program. It may also be used to evaluate the impact of various treatments aimed to modify driving behavior and safety (e.g. safety management strategies, provision of information and feedback and various in-vehicle technologies).
2. Fleet safety managers, who need to evaluate company drivers. Beyond the direct value to the fleet in terms of reduced crash and operations costs, these activities also

help fleets comply with their legal safety responsibilities and lower the risk of prosecution under corporate liability laws.

3. Licensing authorities and parents of young drivers, who wish to monitor the behavior of novice drivers and to use the information in providing training and guidance.
4. Insurance companies, which are interested in differentiating between drivers based on their risk of being involved in car crashes. Programs such as TripSense (2007), which was described earlier in this paper, are already operating.
5. Road authorities may be able use the data that accumulates from a large number of IVDR-equipped vehicles to identify potential safety problem locations in the road network through analysis of the locations and types of maneuvers in the dataset. In addition, speed profiles, with a fine resolution both in space and time, may be generated from the speed and position measurements.

The system described in this paper records the movement of the vehicle and uses this information to identify and classify various maneuvers the vehicle performs. These maneuvers are then used to calculate various driving risk indices. The results presented in this paper show that these indices are correlated with drivers' crash records. This result suggests that risk indices may be used as indicators to drivers' rate of involvement in car crashes. A study of crash rates in the period before the installation and after drivers were exposed to the feedback from the IVDR shows large and statistically significant reductions in the crash rates. It should be noted that these results are based on a relatively short period of time after the exposure to the system and therefore need to be further

evaluated. An evaluation of the temporal changes in the IVDR risk indices showed that the initial exposure to the IVDR feedback causes a substantial reduction in risk indices, which can be further enhanced if drivers continue to access the IVDR feedback. Even without additional feedback the initial impact is sustained for several months. A similar analysis (Musicant et al. 2007) using data from other vehicle fleets showed that this impact diminishes over time. Therefore, further research is needed to better understand the temporal and the long term impact of the installation and to develop feedback management schemes to maintain drivers' interest in the feedback and maximize its impact. Finally, we note that while our analysis demonstrates that IVDR may be useful to impact drivers' behavior, we did not study the psychological and social mechanisms that underlie this change. Understanding these mechanisms is critically important in making effective use of IVDR systems.

Acknowledgement

The authors wish to thank three anonymous referees for their many helpful comments and suggestions.

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