

Safety correlation and implications of an in-vehicle data recorder on driver behavior

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ABSTRACT

Understanding individual on-road behavior has been a key issue in traffic safety research. A deeper insight into the driving patterns has been so far restricted, due to limited availability of actual longitudinal data and exposure data. This paper presents an innovative approach in which actual driving data is obtained by means of an in-vehicle data recorder (IVDR). This data are used to evaluate drivers' behavior and safety. In particular, two major issues regarding the validity of such systems as safety promoters are analyzed. The first is the correlation between the accident risk indices calculated based on the IVDR data and drivers' records of car crash involvement. Once this correlation is established, the second issue is the ability of drivers to change their behavior in the desired direction, namely to become safer drivers. The results obtained, based on observations of 103 drivers in 18173 trips and more than 8400 driving hours indicate that the risk indices and classifications calculated based on the IVDR data are significantly correlated with past car crash involvement. Exposure to the feedback generated from the system has a potentially high impact on collision reduction with over 40% reduction in crash rates using before and after data. Finally, this behavioral change has been maintained for 9 months after the exposure to the IVDR feedback.

INTRODUCTION

Human behavior and driver errors are a cause in the overwhelming majority of road crashes [1]. Aside from a few general parameters such as age, gender, time of day and type of collision, good understanding of collision cause and individual drivers' risk levels are limited. Even when crashes are thoroughly analyzed – the analysis refers mostly to the circumstances of the collision itself and not to patterns of the behavior of the drivers involved. Most methods used to define drivers' skills and styles are based on stated preference tools, which could be biased and general. Otherwise, evaluations of driving behavior may only be performed on a limited scope and scale, for example in experiments involving a driving simulator [2]. Recently, with the advances in monitoring technologies, a new generation of data collection approaches is becoming available to evaluate actual driving behavior continuously, in much more detail and with large scale implementations. In-vehicle data recorders (IVDR), which are electronic monitoring devices installed in the vehicle, are one of several measures that enable to accurately measure drivers' behavioral patterns and to evaluate various strategies to influence drivers' behavior. This paper describes an evaluation of the potential of one such IVDR system to serve as a tool to evaluate and manage drivers' risk of crash involvement.

The rest of this paper is organized as follows: the next section reviews literature on IVDR systems and their potential uses and impacts. We then describe the IVDR system used in this study and report on results of experiments designed to validate its measurement and to evaluate its potential to impact drivers' behavior. The final section summarizes our findings and discusses potential future applications.

IN-VEHICLES DATA RECORDERS

In-vehicle data recorders (IVDR) are on-board devices that record information about the movement, control and performance of the vehicle [3]. IVDR technology is generally based on the collection of data on the vehicle performance and its immediate environment. This data is analyzed to detect patterns, which are then matched with decision rules that control activation of certain driver support functions [4]. A number of IVDR systems have been developed in recent years. While their details, capabilities and intended use vary, the information they commonly collect may be classified in several categories ([5], [6]):

1. Vehicle movement: i.e. longitudinal and lateral accelerations and the speed of the vehicle.
2. Driver control, which includes variables such as the engine throttle and brake application and wheel-angle.
3. Engine parameters, such as RPM.
4. State of the vehicle safety systems, such as air bags, seat belts, ABS and traction control.
5. Vehicle location, using GPS systems.
6. Time.
7. Visual documentation both inside and outside the vehicle.

Safety-related applications of IVDR systems can be broadly classified into two categories:

1. Short-term prevention, such as with speed adaptation, collision avoidance systems, weather information, vision enhancement and lane keeping assistance.
2. Analysis of collision events, such as within collisions investigations, emergency response and research and development of safety devices.

In addition to these applications, feedback and training based on the information collected by IVDR may also help reduce collision risk in the longer-term [7]. For example, Lehmann [8] reports several case studies in which the installation of IVDR systems in various fleets resulted in reductions of 20-30% in collisions rates, and even more significant reductions in the related costs. Similar reduction rates were reported in an experiment reported by Wouters and Bos [9]. Several on-going studies aim to develop and evaluate IVDR systems that will provide feedback to drivers. Some systems were intended for the insurance market (e.g. [10]), while others serve research needs ([11], [12]). NHTSA [13] has recently conducted an ambitious study in which 100 vehicles were instrumented with IVDR as well as video cameras, radar sensors, GPS and lane trackers for a period of 13 months. The data collected with these vehicles include a full documentation of 82 crashes, 762 near crashes and more than 42000 hours driven. Preliminary analysis of the huge data set collected in this study indicates great potential to enrich traffic safety research such as evaluation of risky driving behavior and collision risk, evaluation of relative risk of engaging in secondary tasks, and evaluation of driver response to lead vehicle brake lights. These results illustrate the capabilities of the technology to evaluate behavior and increase safe driving. In summary, IVDR hold a potential for significant improvements in traffic safety, however, further research is needed to validate these systems and to identify the data collection needs and feedback types that would best serve this goal.

THE DRIVEDIAGNOSTICS IVDR SYSTEM

The specific IVDR system evaluated in this paper was developed by DriveDiagnostics LTD. The overall system framework is described in Figure 1. The system performs a sequence of four data collection and analysis steps: measurement, identification, analysis, and reporting.

1. **Measurement.** In this module information on the movement of the vehicle is collected. This information includes the two-dimensional acceleration and speed of the vehicle at a sampling rate of 40 measurements per second. The system also records the position of the vehicle using GPS.
2. **Detection.** In this module pattern recognition algorithms are applied to the raw data in order to detect certain maneuvers that the vehicle performs. The system currently identifies over 20 different maneuver types, such as lane changes, sudden brakes, strong accelerations, excessive speed and so on. The identified maneuvers are also classified in terms of their severity based on parameters of the detailed trajectory of the vehicle during the maneuver, such as the maneuver duration, extent of sudden changes during the maneuver, the speed it is performed at and the magnitude of the forced applied on the vehicle.
3. **Analysis.** The information on the maneuvers detected by the system is stored in a database. The analysis module uses this information to build several driver-specific and vehicle-specific indices and statistics that can be used to characterize drivers' behavior and their personal risk of crash involvement. The following indices are used in the current implementation:
 - Overall risk index: this index is a numeric measure that aims to estimate the drivers' risk of involvement in car crashes. Values typically range between 0 and 500 with high values implying higher risk. The index depends on the types, numbers and severity of maneuvers that the driver has performed. The accumulated of driving time is used to normalize the amount of maneuvers.
 - Risk classification: based on the risk index, drivers are classified in three risk categories. One of the main purposes 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" (aggressive behavior).

- Trip-level risk index and classification: a risk index is also calculated for each individual trip. This index takes into account the maneuvers that occurred during the trip and their severity as well as other factors such as the trip duration. As with the overall index trips are also classified in three risk categories: Green, Yellow and Red.
 - Speed index: this numeric value reflects the driver's speed profile. While it is also taken into account in the overall risk indices, speed has been shown to be an important predictor of crash risk involvement in many studies.
 - Driving Patterns indices: In addition to the speed index, other indices that reflect drivers' performance in several specific categories are calculated using only the information on the relevant maneuvers. Examples include performance indices for corner handling, lane keeping and braking patterns.
 - Fuel consumption index: the information related to drivers' performance is combined with other information such as vehicle types to predict fuel consumption.
4. **Reporting.** The final module is concerned with providing feedback to drivers. Feedback may be provided in a variety of forms and through several media channels. Reports can be tailored to include various information at different levels of detail that may be of interest to fleet safety managers, insurance companies, vehicle owners, drivers and researchers. An example of a monthly driver report is shown in Figure 2. In the figure, each square corresponds to 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: green, yellow and red for trips in which the driver behavior was classified as moderate, intermediate and aggressive, respectively. Detailed information on each trip and on the driving pattern indices in the various subcategories is also provided. In addition, the report includes information on the total hours of driving during the month and comparison of the drivers' performance to previous months and to other drivers in the fleet. These reports may be delivered through an internet website, emails or as printed reports. In addition, real-time feedback on current trips may be provided through mobile phone text messages and warning lights on an in-vehicle display board.

In terms of the communications systems, the first two modules are performed in real-time within the unit installed in the vehicle. Only the detection outcomes are transmitted to the application server. This design significantly reduces the amount of communications required between the vehicle and the server. The information is transmitted in real-time, continuously throughout the trip, through wireless networks. The analysis and reporting modules are performed at the application server. The server also stores other relevant information, such as collision records, maintenance and fuel costs etc.

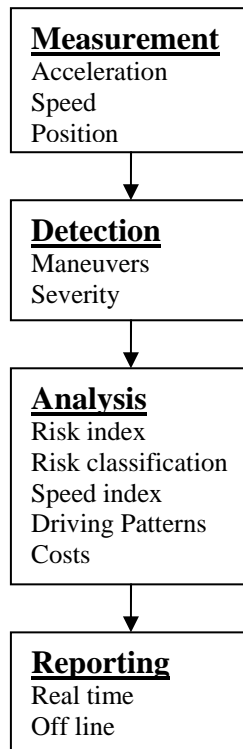


Figure 1 Overall framework of the DriveDiagnostics system

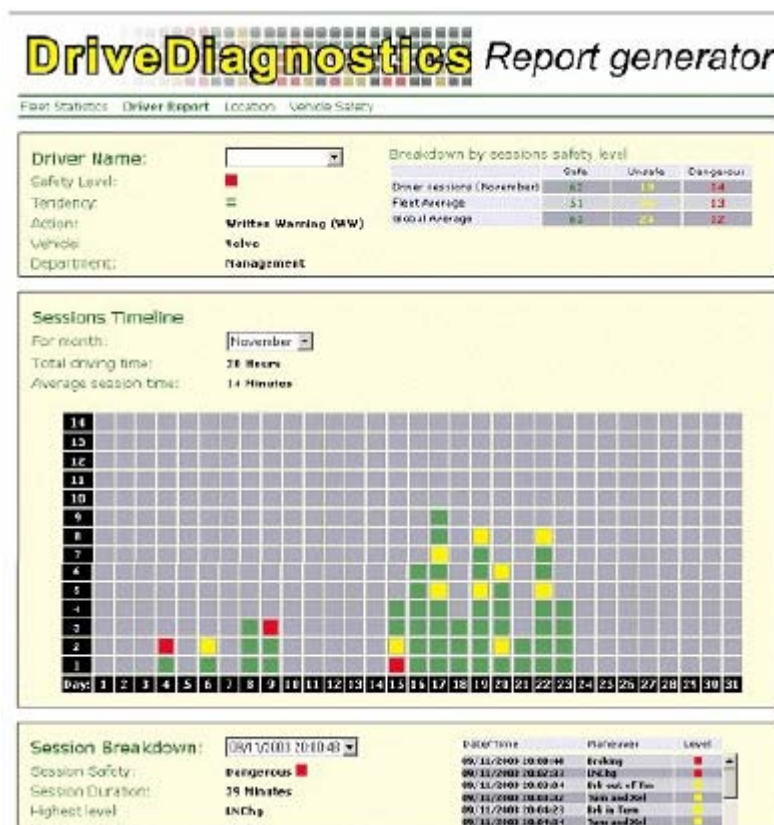


Figure 2 An example of a monthly driver report

OBJECTIVES AND METHODOLOGY

The main hypothesis underlying the application of the IVDR system is that the data collected and the risk indices calculated using these data are highly correlated with the actual risk of car crash involvement and therefore can be used as indicators to that (latent) risk. Preliminary results demonstrating the linkage between drivers' risk indices and their crash records were presented by Lotan and Toledo [14]. However their analysis was based on evaluation of only 29 drivers. In this study we conduct a new evaluation of the connection between risk indices and crash records using a larger and more diverse sample. After this connection is established we also evaluate the potential usefulness of the system, through the feedback it provides to drivers and other entities, to reduce crash rates and to sustain any reductions over time. We next describe the experiment procedure and results.

Sample selection

The drivers in the sample were chosen from the fleets of 6 different organizations in Israel that provide vehicles to their employees as part of their benefit programs. The drivers in the sample are between 24 and 65 years old, with an average of 41 years. These drivers have been using company vehicles for periods that ranged between 6 and 80 months, with an average of 39 months. These drivers, who are not professional drivers, may use these vehicles to commute, make other business trips and for any other personal trips. While the possibility to identify drivers with personal codes is available, it was not implemented in these commercial installations. Therefore, out of all the IVDR installed vehicles in these fleets, all vehicles that were only driven by a single driver were selected for the sample. Descriptive statistics of the resulting sample are summarized in Table 1.

	Drivers	Males	Females	Driving hours	Trips	Maneuvers detected
Sample statistics	103	80	23	8430	18173	35168

Table 1 Sample descriptive statistics

Procedures and measurements

The implementation of IVDR systems in all vehicles in the six organizations followed a similar process outlined in the following steps:

1. Initially, the systems are installed in the vehicles without providing a detailed explanation to drivers about the nature of the system or any feedback from it. Privacy protection laws dictate that the drivers consent to the installation, and so they were notified, but only received a general explanation that these are safety-related instruments that will be used in an experiment. The data collected in this initial period, which we refer to as the "blind profile" period, is useful to characterize the habitual behavior of these drivers prior to receipt of any feedback from the system.
2. About 8 weeks later, the participating drivers in each organization were invited to a meeting in which they learned about the IVDR system, its working and the feedback it provides. In this meeting they also received an initial feedback on their own driving and an access code to a secured web site where they could access their own data, as well as compare their performance to the fleet's averages. In all cases, it was determined that the IVDR records will not be used in any way against the drivers.

For each driver, all the data detected and analyzed by the IVDR system on all trips performed in the vehicle was collected. From these the indices and classifications that were described above were calculated. These are used as the independent variables on the analysis that follows. In addition, four other variables that represent drivers' past involvement in car crashes were collected from the records of the organizations that provide and maintain the vehicles. These variables, which are used as the dependent variables in our analysis, are defined as follows:

1. Collision rate, which is the number of crashes per year that the driver has been involved in. Crashes were counted from the date that the driver received an organization vehicle, but no more than 3 years before the date of IVDR installation.
2. Fault collisions rate, which is the number of crashes for which it was determined for insurance purposes that the driver was at fault.
3. Collision cost rate, as estimated for insurance purposes. The cost is the sum per year of the costs of all crashes that were recorded in New Israeli Sheqels (4.5 NIS \approx 1\$). This costs id the direct cost of the vehicle repair. No other costs were included.
4. Annual fault collision cost, which is the cost per year of fault collisions.

RESULTS

In this section we present results of analysis based on the data collected in the experiment described above.

Linkage of IVDR risk index and classification to crash history

As noted above, the risk index and classification computed by the IVDR systems may be useful, if it can be shown that they are highly correlated with the actual risk of car crash involvement. However, the risk cannot be directly measured and so we use past crash records as indicators to the risk. Crash records were collected for the 103 drivers in the sample. The IVDR risk indices used are the ones computed for the driving that these drivers undertook during the blind-profile period, which refers to the time between the device installation date and the first time the driver was exposed to the system data. Descriptive statistics of these data are presented in Table 2. The zero median values reflect the fact that over 50% of the drivers in the sample were not involved in car crashes in the 3 years prior to the installation of the IVDR.

	Risk index	Crash rate	Fault crash rate	Crash costs	Fault crash costs
Mean	40	0.38	0.20	986	826
Median	28	0.00	0.00	0	0
Std. Deviation	38	0.66	0.41	5188	5014
Minimum	2	0.00	0.00	0	0
Maximum	206	4.0	2.00	46958	46958

Table 2 Risk indices and crash data descriptive statistics

Table 3 shows the average and median values of the four safety indicators described above for drivers that were classified in each of the three risk categories: Green (moderate), Yellow (Intermediate) and Red (aggressive). In the sample, 39 drivers were classified as Green, 41 Yellow and 23 Red. With all crash indicators, the values are higher for the riskier classes: Red compared to Yellow and Yellow compared to Green. The differences are more significant for crash costs compared to numbers of crashes, which indicates that the crashes

that drivers in the riskier classes are involved in are also more severe. It should be noted that there were no significant differences ($p=0.582$) between the driving hours of drivers in the three categories.

	Green		Yellow		Red	
	Average	Median	Average	Median	Average	Median
Crash rate	0.18	0.00	0.34	0.00	0.79	0.33
Fault crash rate	0.09	0.00	0.14	0.00	0.49	0.16
Crash costs	270	0	515	0	3783	351
Fault crash costs	194	0	371	0	3219	0

Table 3 Collisions and Fault collisions by driver safety class

In order to test the statistical significance of the difference among the risk classes, a Kruskal-Wallis (K-W) test was conducted. This non-parametric test is designed to test the null hypothesis that the median crash rates in the three categories are equal. It does not assume normal distribution of the variables and therefore suitable for crash rate data [15]. The table reports the p-values for this analysis. The equality of medians can be rejected for crash rates and fault crash rates at 95% confidence and for crash costs at 90% confidence. The post hoc analysis is designed to identify homogeneous groups in the three categories. It was conducted through multiple applications of Wilcoxon Rank-Sum test. p-values were adjusted to the multiple categories using the Benjamin and Hochberg FDR rule. The analysis grouped together the Green and Yellow categories to one homogenous group that differs from the Red category for crash rates, fault crash rates and crash costs variables ($p \leq 0.05$). No significant differences were found among the categories with regard to the fault crash costs. These results imply that the driver classifications are indicative of crash risk and costs involvement. Table 4 summarizes the results of these tests.

Although the analysis is adequate to the non-normal distribution of the crash rates and costs, it could be argued that the median does not characterize the safety categories as well as the mean because it does not capture the long tail affect. We therefore also conduct analysis on the mean values in the various categories. The sample averages and standard errors are present at Figure 3. To test the null hypothesis of equality of means one-way ANOVA and the Scheffe post hoc test were used. The results are also shown in Table 4. The equality of means can be rejected for crash rates and fault crash rates at 95% confidence and for crash costs and fault crash costs at 90% confidence. With all the indicators but the crash costs, the Scheffe test shows that the Green and Yellow class can be grouped together as being significantly different from Red drivers.

Statistic	K-W p-value	Post Hoc results	ANOVA p-value	Scheffe Test results
Crash rate	0.001	(green, yellow) (red)	0.001	(green, yellow) (red)
Fault crash rate	0.007	(green, yellow) (red)	0.000	(green, yellow) (red)
Crash costs	0.068	(green, yellow) (red)	0.068	-
Fault crash costs	0.236	-	0.091	(green, yellow) (red)

Table 4 Test results on the collisions and fault collisions by driver safety categories

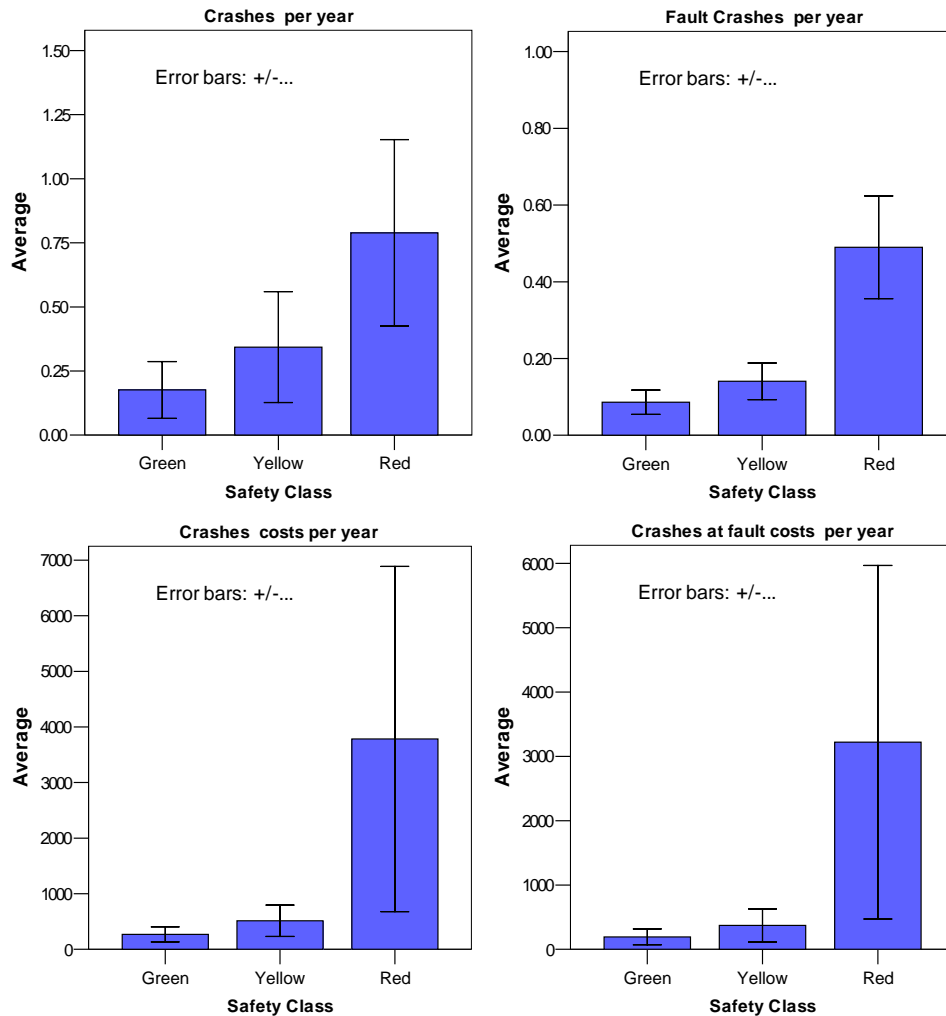


Figure 3 Average and standard deviation of the number of crashes and crashes costs per year by driver class

The risk index, which is continuous, is intended to provide a higher level of resolution on drivers' risk of crash involvement. To evaluate its compatibility with crash history linear regression analyses were conducted. Although the Poisson regression is more common for the analysis of crash rate data, linear regression was found more adequate since many of the drivers in the sample were not involved in any car crashes. The model also takes into account the existence of differences between the organizations in the approaches they use to record and investigate crashes. Organization-specific dummy variables were introduced in order to capture the organization effects. The resulting model is given by:

$$Y_i = \alpha_j D_{ij} + \beta X_i + \varepsilon_i \quad (1)$$

Y_i and X_i are the crash history variable and risk index for driver i , respectively. D_{ij} is a dummy variable, which takes the value 1 if driver i is with organization j , and 0 otherwise. α_j and β are parameters. ε_i is a random error term.

The variance of the risk index values calculated based on the IVDR measurements decreases when more data is accumulated. Therefore, to account for this effect and maximize the efficiency of the parameter estimators, weighted least squares regression was used.

Weights were set according to the amount of driving each driver undertook during the blind profile period. The regression results are presented in Table 5. The slope β of the regression line captures the marginal effect of a change in the IVDR risk index on the predicted crash rates. This impact is, as expected, positive in all cases. It is significantly larger than zero at 95% confidence for all four cases. Figure 4 demonstrated the impact of the IVDR risk index on crash involvement as predicted by the regression model. The model predicts that a driver with a 150 points risk index is 42% more likely to be involved in a car crash and 46% more likely to be involved in own fault car crash compared to a driver with a 100 points risk index. The associated costs per year are likely to be 59% and 56% higher, respectively.

Dependent parameters	R ²	β (p-value)
crash rate	0.442	0.007 (.000)
fault crash rate	0.441	0.005 (.000)
crash costs	0.267	105.2 (.004)
fault crash costs	0.225	75.63 (.020)

Table 5 Results of regression of crash rates on IVDR risk indices

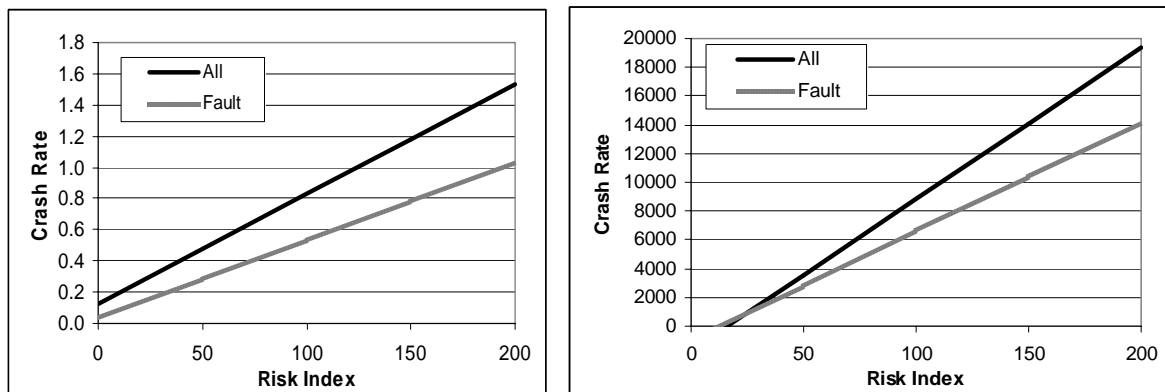


Figure 4 Impact of IVDR risk index on crash rates and crash costs

Impact of IVDR on collision reduction

After the blind profile period the drivers were exposed to the information collected by the system and were able to access the reports generated for them as shown in Figure 2 through a secured website. In all organizations, no other action was taken in order to affect drivers' behavior. Thus, it can be assumed that changes in crash rates can be attributed to the feedback received from the IVDR. To evaluate the impact of the IVDR a before and after study was conducted, in which the crash rates in the two periods were compared. The period before installation, refer to all the data that was available for the drivers in the past (from the time they received the organization vehicle). The period after installation, refer to all the data that was available for the drivers after they were exposed to the IVDR feedback. Data on the 70 drivers which used the IVDR system feedback for at least 5 months (and up to 14 months) was used in this analysis. To make the data comparable all data were normalized to annual rates and costs. In addition we found that there were no significant differences in the driving hours among the blind profile and each of the months after the exposure to the IVDR feedback, which indicate that drivers were not less exposed to risk. Figure 5 shows the average and standard errors of crash rates and costs in the periods before and after the exposure to the IVDR feedback. One-tailed t-tests were conducted in order to test the

statistical significance of the reductions in crash rates and costs that were observed. The test results are presented in Table 6. The results indicate reductions of 44% ($p=0.02$) in collisions rates and 38% ($p=0.097$) in fault collisions rate. The decreases in costs are even higher and statistically significant at the 95% confidence level. The reduction in crash rates reported here is more substantial compared to those between 20% and 30% reductions reported by Lehmann [8]. A possible explanation to some of the difference may be that Lehman's study included drivers of police vehicles and buses, which may not be as sensitive to the feedback as other drivers.

	t-statistic	p-value
Average crash rate	2.086	0.020
Average fault crash rate	1.309	0.097
Average crash costs	2.411	0.010
Average fault crash costs	1.864	0.034

Table 6 Collisions and Fault collisions before and after IVDR installation

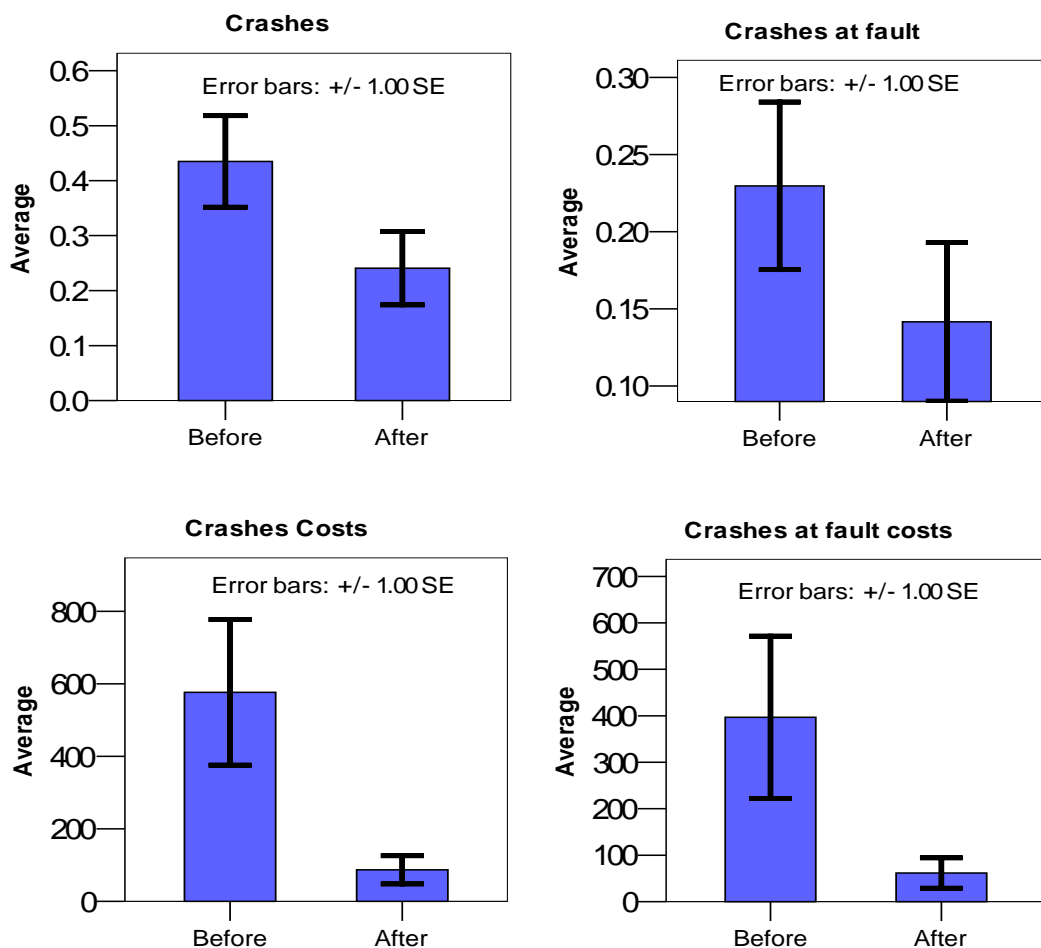


Figure 5 collisions rate and costs before and after exposure to IVDR feedback

Sustainability of the IVDR impact

While the results indicating that the feedback from the IVDR system can have a substantial impact on safety are important, it may only be a short-term impact. At present there is not enough longitudinal crash data 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 risk of crash involvement. For that purpose the risk indices were calculated for the blind profiling period and for each one of the 10 months following the exposure to the system. Figure 6 shows the average and 85th percentile of the risk indices distribution as well as the average speed index for the various months. The reduction in the average risk index from the blind profile to the first month after the exposure is 27%. Furthermore, there is a reduction of 30% in the 85th percentile risk index, which implies that the moderating effect is obtained not only on average but also for the drivers with highest risk indices in the sample. A similar reduction (32%) is also observed when considering only the speed component of the risk indices. The differences between the blind profile period and each one of the 9 months that follow in the average risk index are statistically significant at the 90% confidence level. The 10th month average risk index is not significantly lower than that of the blind profile period.

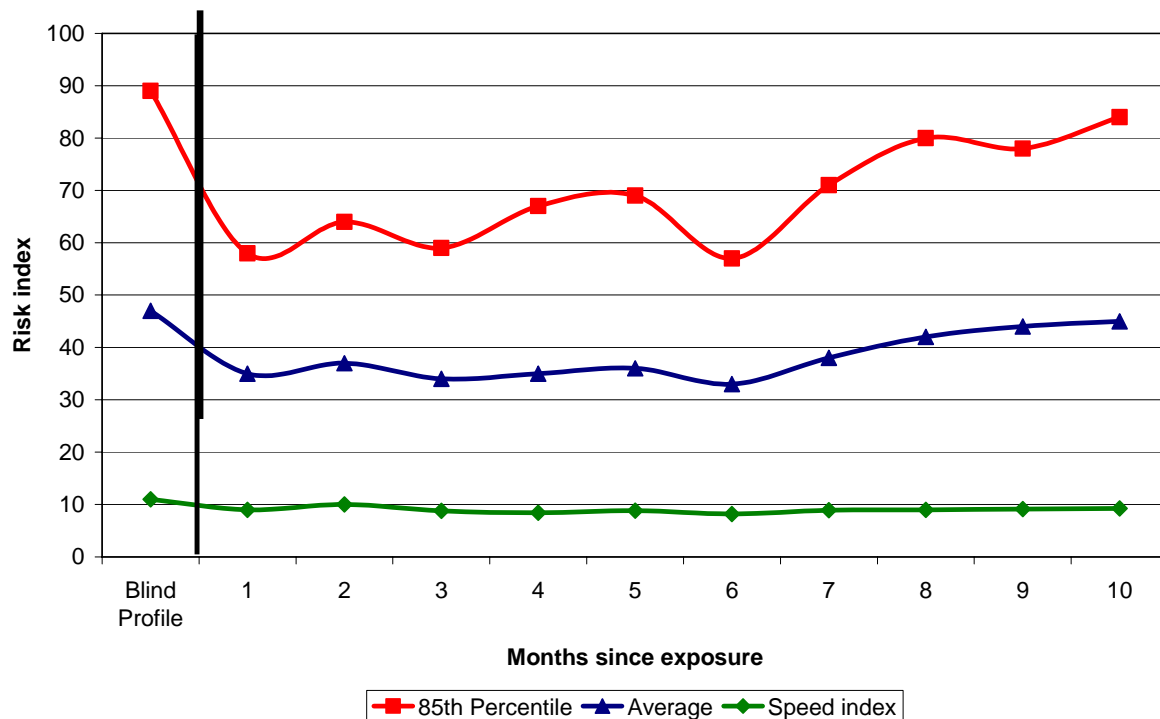


Figure 6 Temporal changes in risk indices statistics

DISCUSSION

This paper describes the overall framework and the components of an IVDR system called DriveDiagnostics, and presents results from a study to evaluate its diagnostic validity and impact on a driver's behavior. The system records the movement of the vehicle and uses this information to detect and classify over 20 different maneuver types. These maneuvers are then used to build a driver profile by calculating several risk indices and classifications. Three of those indices; overall driving risk index and classification and the speed index were used in this paper to investigate several aspects of the IVDR performance. Firstly, a

significant link between the IVDR indices to drivers' past crash records history was established. This result suggests that the driving risk indices calculated by the system can be used as indicators to the risk of involvement in car crashes at the level of the individual driver. A study of crash rates in the period before and after drivers' were exposed to the feedback from the IVDR system shows statistically significant reductions of over 40% in the crash rates. The cost reduction was also prominent, but not as statistically significant. 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. Finally, an evaluation of the temporal changes in the IVDR risk indices showed that the decrease in the average and 85th percentile of the risk indices distribution and in the average speed index are sustained over the first 9 months after the exposure to the IVDR feedback. In summary, the results presented in this paper demonstrate that the IVDR data are significantly correlated with the risk of crash involvement and that the feedback provided based on these data is useful in reducing this risk. The results thus suggest that an IVDR system that can monitor drivers' behavior and produce statistics that indicates on their safety performance may be a useful in several applications and research studies related to driving behavior and safety. Further research is still required to provide deeper the understanding of the IVDRs long term affect and the its potential application with specific groups of drivers (e.g. young drivers, professional drivers).

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