In-Vehicle Data Recorder for Evaluation of Driving Behavior and Safety

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This paper describes the overall framework and components of an in-vehicle data recorder (IVDR) called DriveDiagnostics and presents results from a study to validate its performance. This IVDR has been designed to monitor and analyze driver behavior not only in crash or precrash events but also in normal driving situations. It records the movement of the vehicle and uses this information to indicate overall trip safety. A validation study involved 33 drivers whose vehicles were instrumented with the IVDR. The experiment first included a blind profiling stage in which drivers did not receive any feedback from the system; that stage was followed by a feedback stage in which drivers had access to personal web pages with the information recorded by the system. Data collected in the blind profiling stage was used to investigate the connection between driver safety indices as captured by the system and historic crash data. The results show significant correlations between the two data sets, suggesting that the driving risk indices can be used as indicators of the risk of involvement in car crashes. This connection enabled investigation of the potential impact of the system on driving behavior and on safety. The results show that the initial exposure of drivers to the system has a significant positive impact on their behavior and on safety. Access to the feedback provided by the system has further impact on driver performance. However, if follow-up efforts are not made, neither of these positive impacts is sustained over time.

The human and cost implications of car crashes are staggering. Blincoe et al. (*1*) estimated the direct cost of a car crash at $14,000, of which $3,600 is the cost of damage to vehicles and other property. The total direct annual cost of car crashes in the United States in 2000 was estimated at $230.6 billion, and the total cost to society at $493.3 billion. Thus, it is clear that the implications of a potential reduction in the risk of involvement in car crashes are large. There has been an increased interest in recent years in technology-based solutions that can assist drivers in reducing their risk of involvement in car crashes. One class of solutions that have been proposed is the installation of in-vehicle data recorders (IVDRs), which monitor and provide feedback on driver behavior.

IVDRs are on-board devices that record information about the movement, control, and performance of the vehicle (*2*). A number of IVDR systems have been developed in recent years. While their details and capabilities vary, the information they commonly collect may be classified into several categories (*3*, *4*):

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1. Vehicle movement, which includes the longitudinal and lateral accelerations and the speed of the vehicle;
2. Driver control, which includes variables such as engine throttle and brake application and wheel-angle;
3. Engine parameters, such as revolutions per minute;
4. State of the vehicle safety systems, such as air bags, seat belts, antilock braking systems, and traction control;
5. Vehicle location using Global Positioning Systems (GPSs);
6. Time; and
7. Visual documentation both inside and outside the vehicle.

Most applications of these systems have centered on the car crash event itself (e.g., crash investigations, emergency response, research and development of safety devices). However, the IVDR data may also be used in other avenues, such as prevention and training. The IVDR system described in this paper is specifically designed to collect driving behavior data that may be used to monitor and provide feedback to drivers for purposes of education and training. This direction has been adopted in several ongoing recent studies, including the Drive Atlanta experiment (*5*) and the TripSense program (*6*), which used IVDR data to determine insurance rates for participating vehicles. NHTSA (*7*) 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 13 months. Preliminary analysis of the huge data set collected in this study indicates great potential to enrich traffic safety research.

The limited empirical evidence reported in the literature indicates that installation of IVDR systems and the fact that drivers know their behavior on the road is monitored and documented affect driver behavior and safety. For example, Lehmann (*8*) reports several case studies in which the installation of IVDR systems in various fleets resulted in reductions of 20% to 30% in crash rates and even more significant reductions in the related costs. Similar reduction rates were reported for an experiment by Wouters and Bos (*9*). While these results are promising, the authors are not aware of any study that explains the causes of the safety improvements and therefore how they can be reproduced. For example, it is not clear to what extent these benefits are transferable to private vehicles, where the monitoring itself may not be an important deterrent of unsafe behavior. It is also important to investigate whether the safety effects stem from changes in driver perceptions and attitudes that would affect driving behavior in the long run and carry over to trips driven in vehicles that are not equipped with IVDR systems.

This paper describes a specialized IVDR called DriveDiagnostics. This system has been designed to monitor and analyze driver behavior in both normal driving situations and crash events. The rest of the paper is organized as follows: first, it describes the overall framework and components of the IVDR system, the data it collects and analyzes, and the information provided to users. Next, it describes an experiment designed to evaluate (*a*) the relevance of the statistics calculated by the system to describe driver behavior and its impact on safety and (*b*) the potential impact of the installation of the system and of the feedback it provides to drivers on their behavior. Within this experiment, historic crash records are used to establish the connection between the data collected by the system and the actual involvement in car crashes at the level of the individual driver. Finally, the paper presents ongoing and potential applications of the IVDR data in research on driving behavior and safety.

DRIVEDIAGNOSTICS SYSTEM

The overall framework of the DriveDiagnostics system is shown in Figure 1. The system incorporates four layers of data collection and analysis: measurement, identification, analysis, and reporting.

The first layer in the system is the measurement module, which collects 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 with GPS. This raw information is analyzed in two information processing layers. The first layer, detection and evaluation, incorporates pattern recognition algorithms to identify and classify more than 20 maneuver types in the raw measurements. Examples of these maneuvers include lane changes with and without acceleration, sudden braking, strong accelerations, and excessive speed. The quality of performance of the detected maneuvers is also evaluated. This evaluation is based on both the parameters of the detailed trajectory of the vehicle during the maneuver—such as its duration and smoothness and the extent of sudden changes in the vehicle movement—and the speed at which it is performed. Unlike with other similar systems, with this IVDR, the information transmission is done in real time, continuously throughout the trip, and not only when a crash event occurs. The various information elements are transmitted through wireless networks to an application server, which maintains a database with vehicle-specific and driver-specific trip history and other relevant information, such as crash records, maintenance, and fuel costs. The next layer, which resides in the application server, synthesizes the specific maneuvers that were identified to evaluate an overall driving risk index at the level of the individual trip and of the vehicle overall performance, to characterize and classify the driver's profile and estimate the associated costs. In the current implementation, drivers are classified in three categories—cautious, moderate, and aggressive—on the basis of the rate and the severity of maneuvers they generate and on their speed profile.

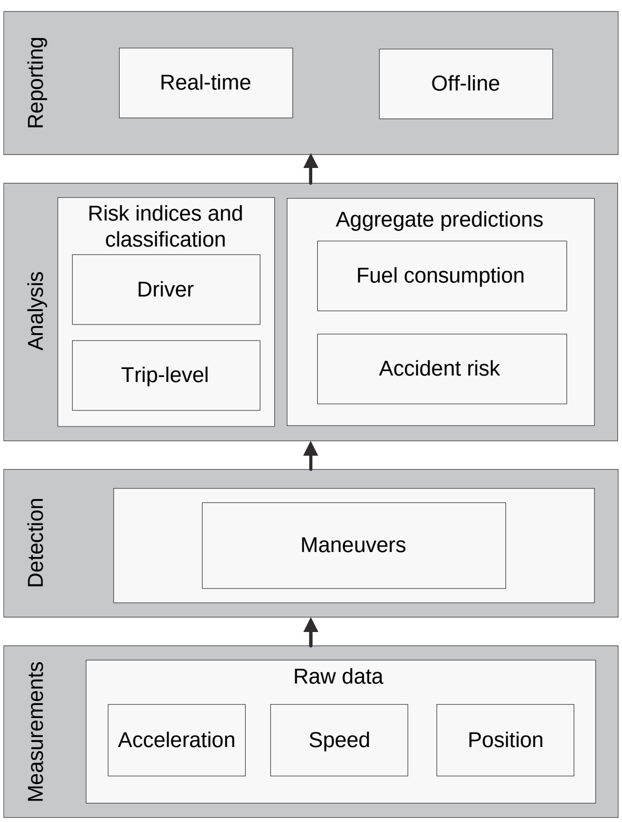

FIGURE 1 Overall framework of DriveDiagnostics system.

The final layer is a reporting layer that provides feedback on the basis of the information collected in the database. This feedback may be done both off-line and in real time. In an off-line application, various reports that summarize and compare information at the level of the driver, vehicle, or an entire fleet are produced and viewed as printed reports or through a dedicated website. An example of a monthly driver report is shown in Figure 2. Each square in the summary chart corresponds to a trip, from engine start to engine turnoff. 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, or red for trips in which driver behavior was classified as cautious, moderate, or aggressive, respectively. Real-time feedback, which typically includes warnings on aggressive behavior or on significant deviations from the normal driving patterns for the specific driver, can currently be provided in two ways: as a text message sent to the driver or to others (e.g., fleet managers or parents of a young driver) or to an in-vehicle display unit.

The dimensions of the sensor unit itself are about $11 \times 6 \times 3$ cm. The unit is typically installed under the plastic panel beneath the handbrake or in another hidden, flat location inside the vehicle. It requires a small amount of power (<250 mA) and so is wired to the car battery. The DriveDiagnostics system has so far been installed in almost 100 vehicles in a series of pilot studies validating its measurements and algorithms. About 15,000 trips have been analyzed. Preliminary results show promising potential for the technology to have a positive effect on the behavior of drivers.

VALIDATION STUDY

This section reports on the pilot study findings related to (*a*) system validation from the connection between the statistics collected and analyzed by the system and traffic safety and (*b*) the potential impact of the installation and the feedback from the system on driver behavior.

Experiment Setup

To evaluate the usefulness of the information provided by the system and its impact on driver behavior, an experiment involving 33 drivers was conducted. All drivers who participated in the experiment were

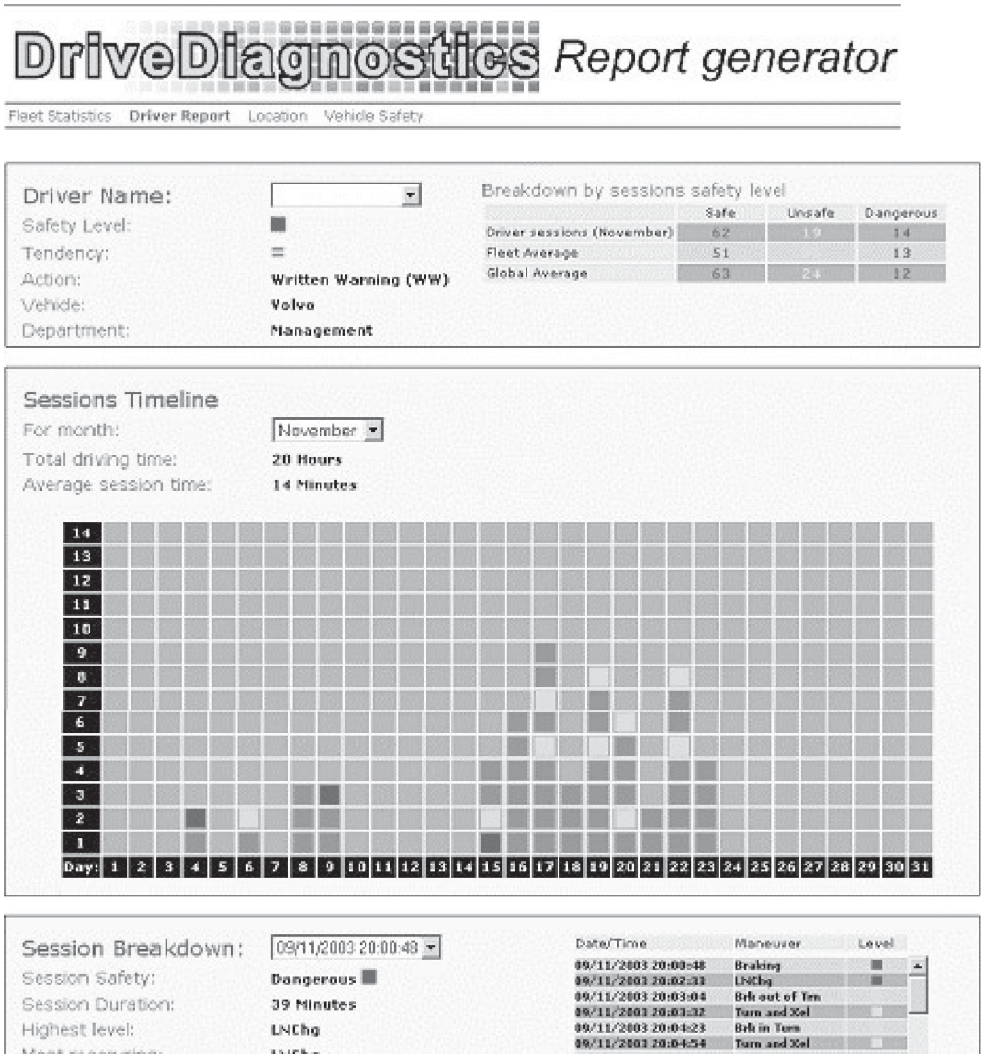

FIGURE 2 An example of monthly driver report.

employed by two companies that provide their employees with company-owned, midsize family cars as part of their employment benefits. This practice is quite common in Israel. The vehicles of these drivers were instrumented with the DriveDiagnostics system. The experiment included two major stages:

1. Blind-profiling stage. In this initial stage, the vehicles were instrumented. Privacy protection laws dictated that the drivers had to be informed about the installation of the systems. However, they received no explanation about the nature of these devices and their purpose or any feedback from them. It was therefore expected that, during this blind profiling period, the installation would have minimal effect on their behavior. This stage typically lasted for 1 or 2 months.

2. Feedback stage. At the end of the blind-profiling stage, the drivers were invited to a group meeting with their company's safety officer. In this meeting, they learned about the character of the system. In addition, personal meetings were held with each driver. In these meetings, information about their driving behavior was discussed. Following these meetings, the drivers received access codes to their personal web pages, which presented the recorded information relating to all the trips they had made (Figure 2). Drivers could access information only about their own trips but also received information about fleet averages, so they could put their own figures in context. These web pages were continuously updated in real time with new information as new trips were made.

In addition to the data collected by the DriveDiagnostics system, two additional items of information were collected:

- Historic crash data for the drivers that participated in the experiment. The data were obtained from the records of the two companies. The data included the number of crashes and crashes at fault and the associated repair costs for each driver for the last 5 years. The companies are responsible for all expenses related to maintenance and service of all vehicles that participated in the experiment. Drivers do not contribute toward these expenses, even in cases of crashes at fault. Thus, they have no incentive to avoid reporting car crashes.
- Records of all the log-ins made by all drivers to their personal web pages. These were collected from the server managing the driver web pages.

Next, these data were used (*a*) to establish the connection between the information obtained by the IVDR system and driver risk of involvement in car crashes and (*b*) to evaluate the potential of the installation of the system and the feedback it provides to affect driver behavior.

Connection Between Driving Profiles and Crash Rates

The classification of trips and drivers as cautious, moderate, or aggressive on the basis of maneuvers they made and the way they made them may be intuitive, but it must be shown that the measurements and the algorithms applied in the analysis can indeed be used as indicators for the risk of involvement in car crashes at the level of the individual driver. The crash data were available for 30 of the drivers that participated in the experiment. The data included records of 57 crashes, with average repair costs of about 2,000 New Israeli Shekels (about \$450, 4.5 NIS ≈ US\$1) per crash.

The data collected during the blind profiling, the initial stage before drivers received any feedback from the system, were used to characterize the habitual driving behavior of these drivers and to study the connection with their crash records using regression analysis. The explanatory variable used in these regression models is the risk index the system calculates for each driver. This risk index is the basis for the classification of drivers as cautious, moderate, or aggressive. It depends on the quantities, types, and severity of the maneuvers the drivers perform. These indices are typically in the range of 0 to 10 (with 10 being the most aggressive). The average and standard deviation for the 30 drivers in this experiment were 3.03 and 2.41, respectively. Several functional forms were tested for the regression models. The functional form that best fit the data was as follows:

$$y_i = \beta_0 + \beta_1 e^{x_i} + \epsilon_i \tag{1}$$

where

y_i = the car crash statistic for driver i,
x_i = the risk index assigned to that driver,
β_0 and β_1 = parameters, and
ϵ_i = an error term.

Regression results showing the connection between the driving risk indices and the various car crash rates and costs are presented in Table 1. The fit of the various models, shown by the R^2 statistics, are reasonable. The correlations between driver risk indices and the crash involvement data, $r(e^{x_i}, y_i)$, are in the range of .632 to .873. Furthermore, in all cases, the *t*-statistics (shown in parentheses in the last two columns of Table 1) of all coefficients are highly significant. These data strengthen the conclusion that the driver risk indices computed by the DriveDiagnostics system can be used as indicators of the risk of involvement in car crashes. Which of the two companies employed a driver did not have a significant impact on the regression results.

Feedback Usage

IVDR systems can affect driver behavior in two ways. First, the instrumentation of the vehicles and the knowledge that their actions are being monitored can by themselves be moderating factors. Second, the feedback drivers receive about their behavior may enable them to improve their performance. In this experiment, the feedback drivers received included not only the records of their own behavior but also a comparison to the performance of the entire fleet. The information and feedback generated by the IVDR system was provided to drivers and to the two companies' safety officers only through the dedicated web server. Therefore, the number of times drivers accessed the feedback on the website was a useful indication to the level of interest in and usage of the information.

The average number of times drivers accessed the web page each month after they were first introduced to it is shown in Figure 3. In the 1st month, the system drew considerable attention, with an average of 14.78 log-ins per driver. However, in subsequent months, interest in the web page feedback steadily dropped, to a level of 2.33 log-ins in the 5th month. In the experiment, there were no follow-up activities beyond the initial meetings in which the system was introduced. The results suggest that it is not enough simply to provide the information and that routine follow-up activities may be necessary to maintain a high level of interest in the feedback.

Also examined was the question of whether the habitual driving profiles captured during the blind-profiling stage were useful in explaining the frequency of access to the feedback. However, the correlation between the blind-profiling driving-risk indices and the number of log-ins was low (.16 for the 1st month log-ins and even lower for subsequent months).

Impact of Feedback on Driver Behavior

The ultimate goal of the IVDR system is to have a positive effect on driving behavior. To evaluate the impact that the system has on driving behavior, it is useful to investigate how driver performance changes in the presence of the system. The results presented in this section are based on the records of 27 drivers for whom the data included records of at least 4 months of exposure to the feedback. Figure 4 shows the average driving risk indices for the months before and after drivers were informed about the system. The results indicate that the initial exposure of drivers to the system and the feedback it provides has a significant impact on driving behavior. The average driving risk indices dropped from 2.50 before the exposure to the system to 1.55 in the first month that feedback was provided. This

TABLE 1 Regression Results Linking Driving Risk Indices to Crash Rates and Costs

y_i	R^2	$r(e^{x_i}, y_i)$	β_0	β_1
Number of crashes per year	0.460	0.678	0.424 (4.7)	$1.551 \cdot 10^{-4}$ (4.9)
Number of crashes at fault per year	0.763	0.873	0.131 (3.1)	$1.401 \cdot 10^{-4}$ (9.5)
Cost of crashes per year (NIS)	0.524	0.724	531.0 (2.8)	0.368 (5.6)
Cost of crashes at fault per year (NIS)	0.400	0.632	297.0 (1.7)	0.268 (4.3)

4.5 NIS ≈ \$1

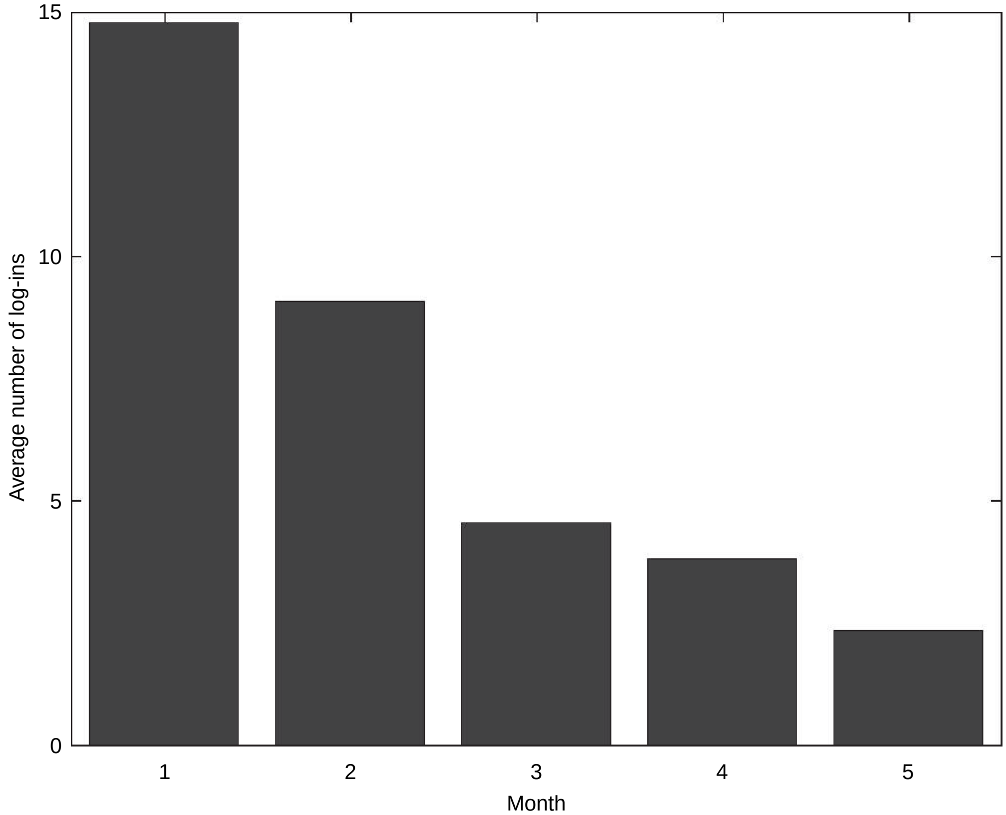

FIGURE 3 Average number of log-ins as function of time.

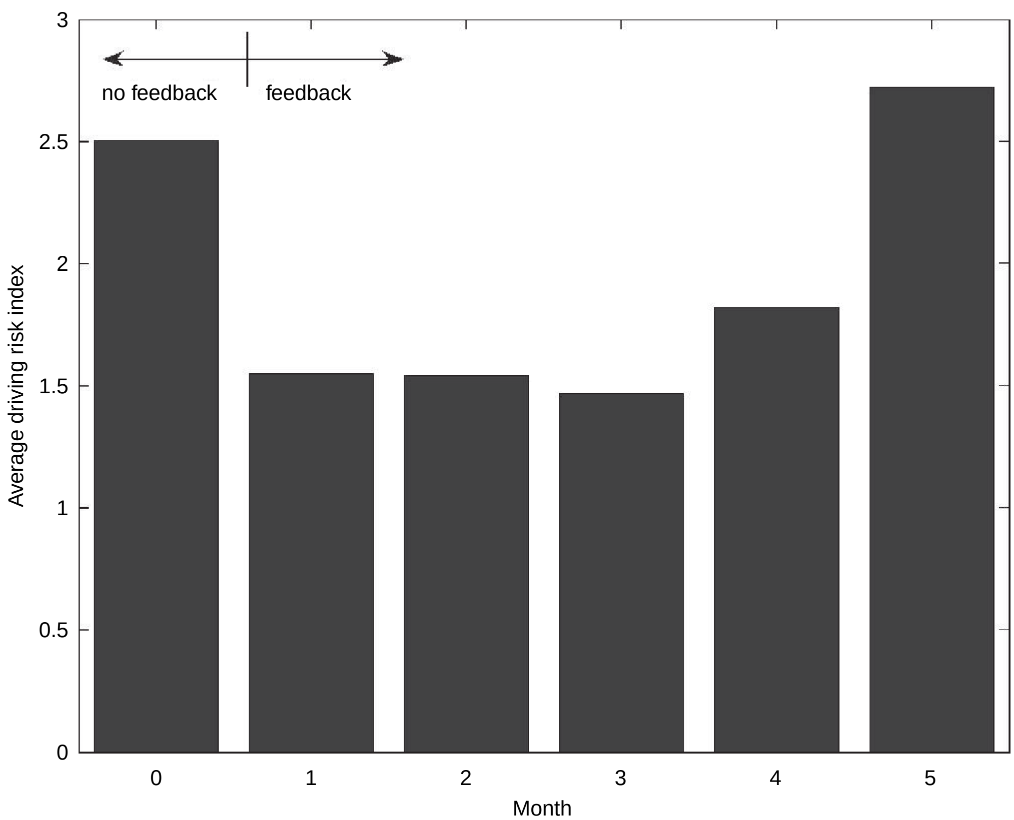

FIGURE 4 Average driving risk indices as function of time.

moderating effect remained roughly constant for 3 months. However, similarly to the situation with access to the feedback, the impact of the system on driving risk indices diminished in the next months. By the 5th month, driving risk indices were back to the initial values and even slightly higher (average of 2.72). This result again suggests that, while the initial impact of the system can be significant, it decreases over time without routine follow-up or maintenance efforts.

The potential of the system to change driver behavior in the long term is through the feedback it provides. Next, a model is developed to examine the impact of the initial exposure of drivers to the system and the extent of their usage of the feedback they receive (as measured by the number of times they access the web page). The data used for estimation included 123 observations of the 27 drivers who had used the system for 4 or 5 months after the initial blind-profiling stage. The data include one observation for each driver for every month. To account for the correlations among the observations of the same driver due to the drivers' unobserved characteristics, a fixed-effects specification was used; see, for example, Pindyck and Rubinfeld (*10*). This specification is given by the following equation:

$$y_{it} = \beta X_{it} + \gamma_i W_i + \epsilon_{it} \qquad (2)$$

where

y_{it} = risk index for driver i in month t;
X_{it} = vectors of explanatory variables;
β = corresponding parameters;
ϵ_{it} = generic error term;
γ_i = parameters for individual-specific effects, W_i; and
W_i = 1 (for driver i) or 0 (otherwise).

Estimation results for this model are presented in Table 2. The table does not show the values of the coefficients of the individual-specific effects (25 coefficients) and the model constant. These values are omitted because they depend on the alternative that is chosen as the base. The variable risk_index (0), which captures driver risk indices in the blind-profiling stage, also depends on this choice. However, it is presented to provide the full specification of the model. The term Δrisk_index (0, t − 1) is the difference between the initial risk index for the driver and the risk index in the previous month for each observation. The variable log ins is the number of times the driver accessed the feedback in the month. The fixed-effects model was superior to a pooled model that ignores the panel nature of the data. The F-statistics for the test of the null hypothesis that all individual-specific effects are jointly equal to zero is 1.67 with 25 and 92 df. Thus, the hypothesis is rejected at the 5% level.

The initial risk indices that were recorded for the various drivers represent their habitual driving. These variables have a significant positive impact on the risk indices in subsequent months. Coupled with the individual-specific constants, these variables capture differences in the behavior of different drivers due to differences in personal characteristics. The coefficient of this variable is roughly a unit, which indicates these risk indices can be viewed as a basis that risk indices in subsequent months deviate from. The variable Δrisk_index (0, t − 1) captures the deviation of the risk index in the previous month from the habitual driving profile. Positive values of this variable are obtained when the risk index in the previous month was lower compared with the initial risk index. The results show that lower-than-habitual risk indices in a given month indicate lower risk indices in the next month as well, suggesting that the risk indices of a given driver are correlated over time.

The results show that the temporal variability in the risk indices of a given driver over time can be explained by the access to the feedback from the system, as measured by the number of log-ins to the web site. Higher levels of access to the feedback are related to lower driver risk indices, which imply safer driving. This result suggests that the feedback the system provides can be useful in moderating driving behavior. Figures 5 and 6 further illustrate the connection between access to the feedback and driving risk indices. Figure 5 shows the marginal impact of the access to the feedback on risk indices. This impact is negative, which implies that risk indices decrease with every additional access to the feedback. This negative impact occurs at a diminishing rate; that is, the marginal impact on driving risk indices of additional log-ins to the website is lower for drivers who access the feedback more frequently compared with drivers who make infrequent visits to the website. Figure 6 shows the log-ins' elasticity of risk indices predicted by the model for a base risk index of 2.5. The elasticity captures the ratio of the rate of change in driving risk indices to the rate of change in the number of log-ins. It is negative, which again reflects the negative correlation between the number of log-ins and the driving risk indices. The value of the elasticity increases in absolute value as the number of log-ins increases but at a diminishing rate because of the diminishing marginal impact of log-ins.

TABLE 2 Regression Results for Monthly Driving Risk Indices

x	β	t-Statistic
risk_index(0)	1.156	2.8
Δrisk_index(0, t − 1)	−0.317	−3.2
logins	−0.069	−4.1
(logins)^2	0.00062	2.6

CONCLUSION

This paper described the overall framework and the components of an IVDR system called DriveDiagnostics and presented results from a study to validate its performance and algorithms. This system had been designed to monitor and analyze driver behavior not only crash or precrash events but also in normal driving situations. The system records the movement of the vehicle and uses this information to identify and classify over 20 maneuver types. These maneuvers are then used to calculate an overall driving risk index at the level of a single trip and for individual drivers.

For the validation, the study used data collected by the system in the blind-profiling stage, before drivers were exposed to the system, to investigate the connection between driver profiles as captured by the system and historic crash data. The results show significant correlations between the two data sets and thereby suggest that the driving risk indices calculated by the system can be used as indicators of the risk of involvement in car crashes at the level of the individual driver. The connection between driving risk indices and crash rates and costs allowed investigation of the potential impact of the system on driving behavior and on safety. The results show that the initial exposure of drivers to the system has a significant positive impact on their behavior and on safety. Furthermore, access to the feedback provided by the system can further affect driver performance in the desired direction. However, if drivers do not make follow-up efforts, neither of these positive impacts is sustained over

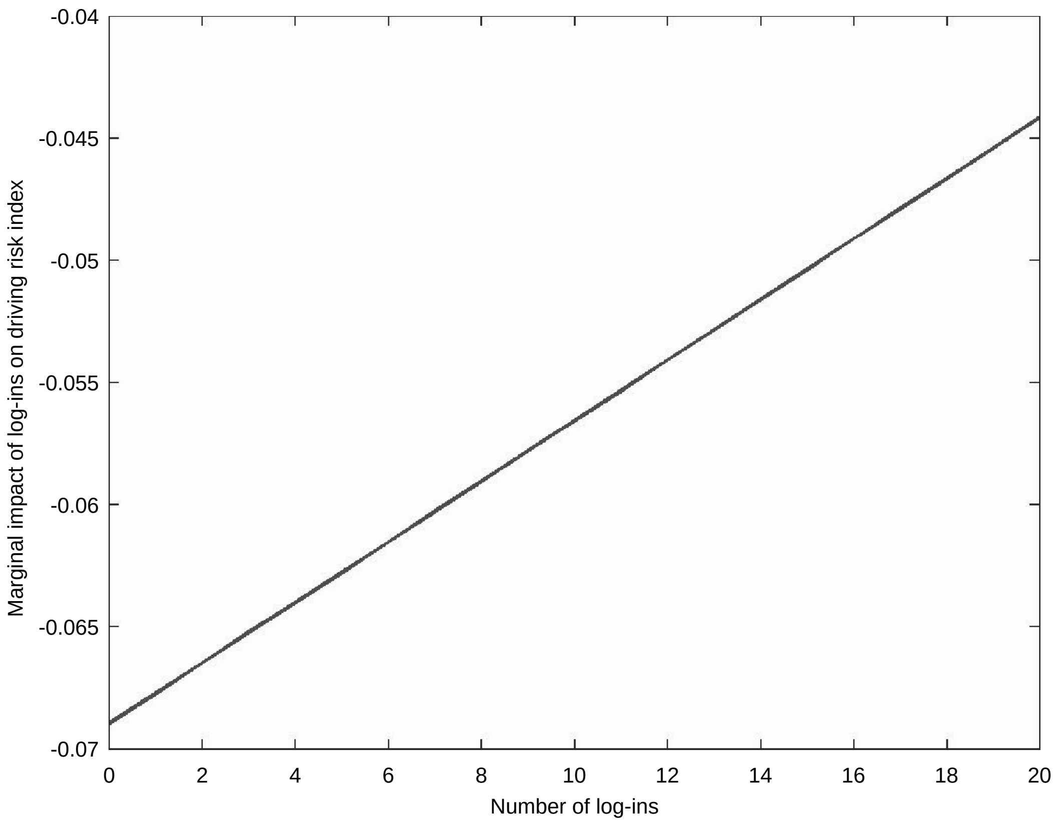

FIGURE 5 Marginal impact of log-ins on driving risk index.

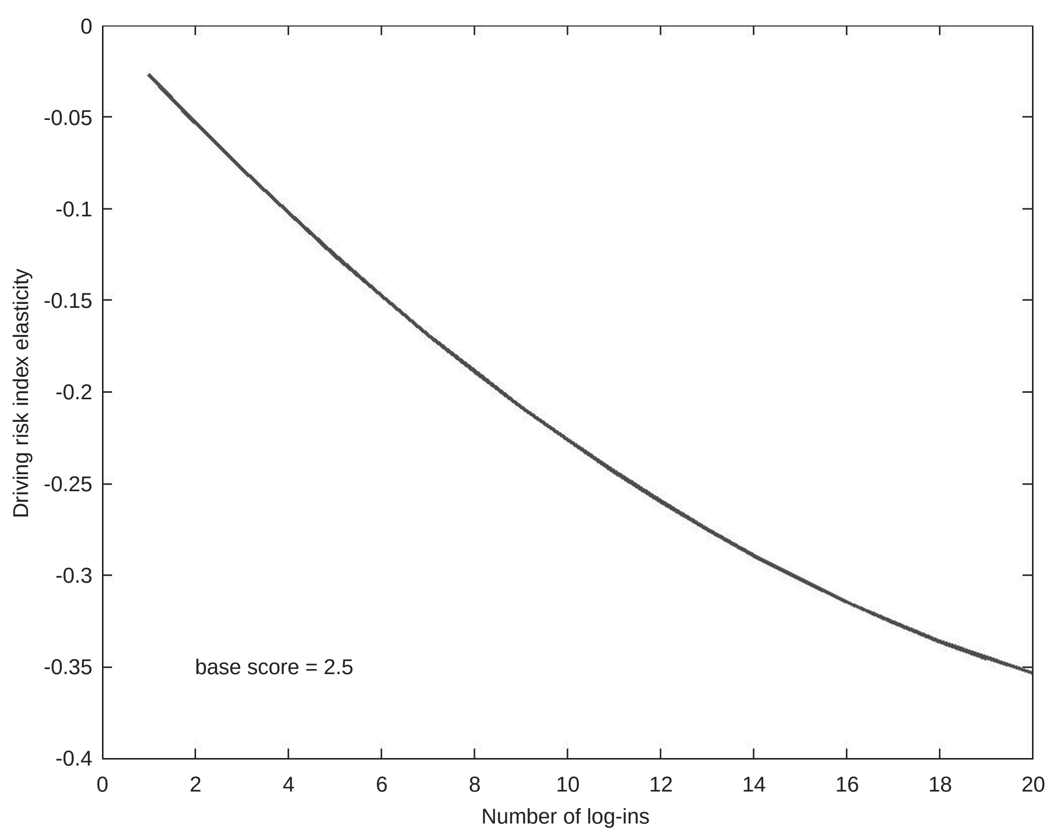

FIGURE 6 Driving risk index–log-ins elasticity.

time. In this experiment, the initial positive impact of the system diminished with time and disappeared within 5 months. Similarly, drivers initially made extensive use of the feedback from the system, but they accessed it less and less frequently as time passed.

An IVDR system that can monitor driver behavior and produce statistics that indicate safety performance may be a useful tool in many studies related to driving behavior and safety. The Drive-Diagnostics system is currently used in several research studies, and plans call for it to be used in others. Examples of these studies include the following:

1. A study of the driving behavior of novice young drivers and their families during the period of accompanied driving, which is mandated for young drivers in Israel immediately after licensure. This study aims to evaluate the effectiveness of a program designed to increase awareness and promote the accompanied-driving practice. The study looks at the impact of the extent of accompanied driving on the performance of young drivers and other members of the family as well as at issues of intergeneration transfer of behaviors. This study is described in further detail by Lotan and Toledo (*11*).
2. A study of differences between the behaviors of professional and nonprofessional drivers. The purpose of this study is to identify problem areas and training needs for these groups so that better programs can be designed.
3. A comparison of the behaviors of drivers from several fleets to investigate the impact of the safety policies and practices of the various companies on their performance.
4. A study of drivers who use multiple vehicles, the purpose of which is to learn about the impact of vehicle type and of circumstances of the various trips on driver behaviors.

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REFERENCES

1. Blincoe, L., A. Seay, E. Zaloshnja, T. Miller, E. Romano, S. Lutcher, and R. Spicer. *Economic Cost of Motor Vehicle Crashes 2000.* Technical Report DOT-HS-809-446. NHTSA, U.S. Department of Transportation, Washington, D.C., 2002.
2. Correia, J. T., K. A. Iliadis, E. S. McCarron, and M. A. Smolej. Utilizing Data from Automotive Event Data Recorders. *Proc., Canadian Multidisciplinary Road Safety Conference XII,* London, Ontario, Canada, 2001.
3. *Event Data Recorders: Summary of Findings by the NHTSA EDR Working Group.* Report NHTSA-99-5218. NHTSA, U.S. Department of Transportation, 2001.
4. Chidester, A. C. D., J. Hinch, and T. A. Roston. Real World Experiences with Event Data Recorders. *Proc., 17th International Technical Conference on the Enhanced Safety of Vehicles,* Paper 247, Amsterdam, Netherlands, June 4–7, 2001.
5. Drive Atlanta: Study Will Monitor Driver Behavior to Determine Role of Speed in Highway Crashes. *Georgia Tech Research News,* Georgia Institute of Technology, 2002. www.gtresearchnews.gatech.edu/newsrelease/DRIVEATL.htm. Accessed Aug. 1, 2005.
6. TripSense. tripsense.progressive.com/home.aspx. Accessed Aug. 1, 2005.
7. Neale, V. L., S. G. Klauer, R. R. Knipling, T. A. Dingus, G. T. Holbrook, and A. Petersen. *The 100-Car Naturalistic Driving Study Phase I: Experimental Design.* Report DOT-HS-808-536. U.S. Department of Transportation, 2002.
8. Lehmann, G. The Features of the Accident Data Recorder and Its Contribution to Road Safety. *Proc., 15th International Technical Conference on Enhanced Safety of Vehicles,* Vol. 2, pp. 1565–1568, 1996.
9. Wouters, P. I. J., and J. M. J. Bos. The Impact of Driving Monitoring with Vehicle Data Recorders on Accident Occurrence: Methodology and Results of a Field Trial in Belgium and the Netherlands. Report R-97-8. SWOV, Institute for Road Safety Research, Leidschendam, Netherlands, 1997.
10. Pindyck, R. S., and D. L. Rubinfeld. *Econometric Models and Economic Forecasts,* 4th ed. Irwin McGraw-Hill, Boston, Mass., 1997.
11. Lotan, T., and T. Toledo. Evaluating the Safety Implications and Benefits of an In-Vehicle Data Recorder to Young Drivers. *Proc., 3rd International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design,* Rockport, Maine, pp. 440–447, 2005.

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