INDIVIDUAL DRIVER'S UNDESIRABLE DRIVING EVENTS - A TEMPORAL ANALYSIS

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ABSTRACT

The advantage of in-vehicle monitoring technology enables the collection of accurate and high resolution driving information. The availability of such large amount of information may open new possibilities to analyze behavior of small samples and even individual's driving behavior in order to evaluate change over time, strengths and weaknesses which can be used to create personalized interventions and feedback massages. In this paper, we demonstrate how information from technology can be used for analyzing a single driver's behavior. We analyzed individual driver's information received from a novel in-vehicle technology, which identifies the occurrences of undesirable driving events such as extreme braking and accelerating, sharp cornering and sudden lane changing. During the three years measurement period, information about more than 5704 trips, 2107 driving hours and 6878 undesired driving events was recorded. The maximum likelihood estimation was used to fit the Negative-Binomial model for the events rate. Then, several negative binomial regression models were used to analyze how trip duration, daytime, and day of the week are linked to the rate of undesirable driving events. A generalized additive model (GAM) with the P-spline method for smoothing was used to evaluate how driving behavior changes over time, and a "before" and "after" study was performed to test the effect of providing feedback about driving behavior. Insurers and safety officers in commercial fleets can use driving information collected by technology to analyze trends in behavior and to evaluate the usefulness of intervention plans – even for a single driver.

Keywords: Driver behavior, safety, advanced driver assistance systems (ADAS)

INTRODUCTION

Transportation researchers investigating driving behavior are commonly interested in questions such as: How can one choose useful measures for behavior? How can one evaluate improvements over time? How can one assess whether, and to what extent, an intervention plan was successful? These questions are usually raised in the context of evaluating the behavior of a group of drivers (e.g. large fleets or young drivers), and are rarely asked with regard to an individual driver.

Nowadays, cars are equipped with advanced driver assistance systems (ADAS) that include GPS and navigation systems, sensor suites, and control systems that help people drive safely. For example, Intelligent Speed Adaptation (ISA) provides alerts to drivers when they exceed the speed limit (Rook and Hogema, 2005), and in-vehicle collision avoidance warning systems (IVCAWS) provide headway, time-to-collision (TTC) and lane crossing warnings to help drivers avoid accidents. Other devices encourage safer behavior by providing feedback about the occurrence of undesirable driving events as hard braking, sharp turning, swift lane changes, and aggressive acceleration (Lee, 2007). While the main purpose of these systems is to provide real-time driving feedback, researchers have found the information logged by them useful to model driving behavior as it is statistically correlated to crash involvement (Toledo, Musicant and Lotan, 2008), as well as helpful in discovering new information about behavior. For example, the rate of undesirable driving events was found to be higher at the beginning and end of trips (Musicant, Bar-Gera and Schechtman, 2010). Parental behavior was linked to novice driver behavior, and parental involvement was linked to a reduction in the events rate (McGehee, et al., 2007; Prato, Lotan and Toledo, 2009).

The information from technology provides the researchers with new measures to analyze behavior, yet little attention has been paid to the issue of personalization. Personalization involves using technology to accommodate for differences between individuals. Once confined mainly to web applications (e.g. Facebook, LinkedIn, Google search), it is increasingly becoming a factor in education, health care , television, and other "business to business" and "business to consumer" settings. One example of "business to consumer" personalization in the context of traffic safety is "pay as you drive" insurance (Litman 2009). The main idea is to set the insurance policy according to the driver risk, as evaluated based on his or her behavior, rather than relying on demographic details (e.g. age, gender) only. In practice, “pay as you drive” premiums focus on the number of miles driven per year (Litman 2008), so they are actually “pay as much as you drive” policies, but personalization is introduced when the individual behavior index is fed into the policy scheme. The ability to analyze individual driving behavior and answer questions that are usually evaluated per large groups (e.g. was the intervention plan useful? What is the change in behavior over time?) is an important step toward providing drivers with feedback to encourage improvement. In this paper we demonstrate how information about behavior of an individual driver can be used to answer questions that are typically evaluated per large samples. The rest of the paper is organized as follows: Section 2 details the method and procedure for collection of data about the occurrence of undesirable driving events by the means of in-vehicle technology. Section 3 discuses the statistical methods suitable to analyze the information about undesirable driving events. Sections 4 and 5 discusses a temporal analysis of the events rate including the analysis of changes over time, the effect of intervention, time of day and day of the week on the events rate. Section 6 summarizes our main findings and discusses possible implementations.

METHOD

This study used data gathered about a single driver. For convenience, we will refer to this driver as “David”. David worked as a technician in a large commercial fleet along with other technicians. The technicians' work involved driving to customer locations in order to install or repair communication equipment. They used company cars for this purpose. The fleet safety officer decided to equip all vehicles with an in-vehicle feedback and monitoring technology called "Green-Box".

The Green-Box is an advanced driver’s assistance system (ADAS) designed to provide drivers with feedback on their driving behavior. The Green-Box reports commonly used measures of speed, travel time, distance and location. Yet, its novelty lies in the real-time identification of undesirable driving events such as extreme breaking and accelerating, sharp turning and sudden lane changing. The identification procedure implements pattern recognitions algorithms over the speed and acceleration profiles and reports about the occurrence of these events in real time. A web application supplies aggregated information about the occurrences of these driving events to drivers and safety officers. The frequency of undesirable driving events can serve as a safety surrogate as it correlates to crash involvement records (Musicant, Lotan, amd Toledo, 2007; Lotan and Toledo, 2006; Toledo, Musicant, and Lotan, 2008). Further details about the Green-Box system can be found in Toledo, Musicant, and Lotan (2008).

The Green-Box was installed in this fleet in late 2006, but feedback from the system (including in-vehicle feedback and reports via the web application and email) was not available to the drivers or mangers until the beginning of 2007 in order to create a baseline for driver behavior. From 2007 until the end of the measurement period in 2009 feedback was available to drivers and safety officers. The safety officers could not see specific driver information because the data was aggregated.

The Green-Box was installed in David's vehicle for 1054 days from : from September 13, 2006 to August first, 2009, and collected his driving information throughout that period. During this period, he used the vehicle on 877 days, in which he accumulated 5704 trips, 126443.2 driving minutes, and 6878 undesirable driving events. David's rate was 0.054 events per minute of driving.

MODEL SELECTION

Our variable of interest is the count of events in a trip, thus a choice of Poisson or negative binomial as the underlying distribution seemed appropriate. Assuming a Poisson distribution implies that the mean and the variance of event count are equal. Yet, we found that for each given trip duration the variance was larger than the average count of events (Figure 1). Therefore, we chose the negative binomial distribution, which allows for different mean and variance.

In our previous study (Musicant, Bar-Gera and Schechtman, 2010) we demonstrate how a similar analysis performed for multiple drivers led to the selection of the negative-binomial as the underlying distribution for the count of events. A possible assumption was that differences between drivers were the cause for the over dispersion in the count data. From the analysis provided in Figure 1 we learn that the over dispersion phenomenon can be found even in the data of an individual driver.

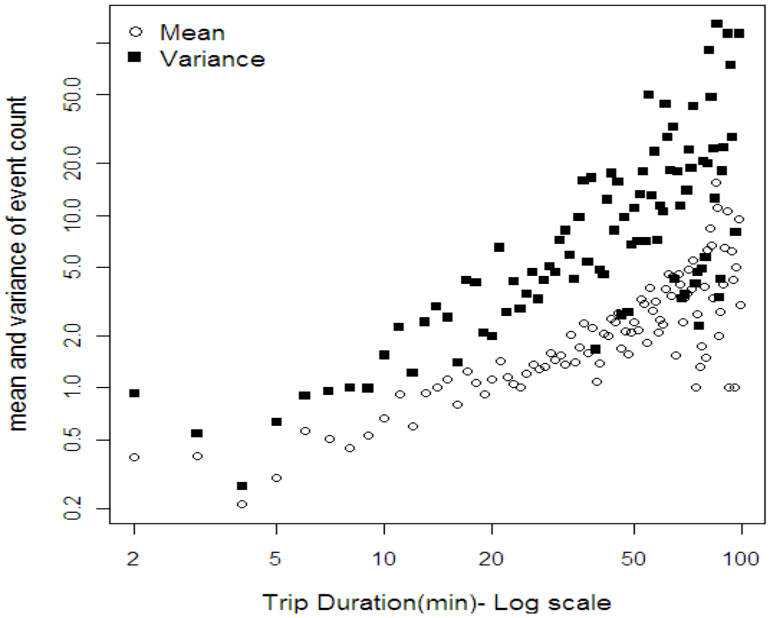

Figure 1: Mean and variance of event count by trip duration (minutes)

While the random variable in the basic negative binomial model is the count of events, in cases where different entities (i.e. trips) have different exposures (i.e. trip durations) it is more convenient to look at the event rate given by the count of events per driving minute. A naïve model may assume that a change in the level of exposure automatically accounts for using rates (events per minute) instead of counts. This assumption is correct only if the expected event count is directly proportional to exposure. To check this, the following negative binomial model was fitted:

(1) Model 1: $\ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(Duration)$

where $\boldsymbol{Y}$ is the random variable representing the count of events in a trip, assuming a negative binomial distribution; and $\boldsymbol{Duration}$ is the trip duration in minutes. Model 1 considers two parameters: $\boldsymbol{\beta_0}$ is the free parameter and $\boldsymbol{\beta_1}$ is the coefficient for the exposure term.

The estimated parameters for model 1 are: $\beta_0 = -2.426\,(\mathrm{SE} = 0.0611)$ and $\beta_1 = 0.852(\mathrm{SE} = 0.018)$, indicating that the 95% confidence interval for β_1 does not include the value of 1.Thus, the events count is not proportional to the trip duration. ($\beta_1 = 1$ implies that $\mathrm{y} = \mathrm{c} * \mathrm{duration}$ where $\mathrm{c} = \exp(\beta_0)$). The sample size used in this analysis is large (5704 trips), making the hypothesis that $\beta_1 = 1$ easy to reject by statistical tests. Thus, we also compared between model 1 and an alternative simpler model that assumes that the events count is directly proportional to the trip duration (model 2).

(2) Model 2: $\ln\big(\mathrm{E(Y)}\big) = \beta_0 + \ln(\mathrm{Duration})$

In model 2, β_1 is set to be equal to 1 so the trip duration is defined as the offset term. The only estimated parameter is β_0 ($\beta_0 = -2.869$, SE =0.0217).

Figure 2 shows the events rate (events per minute) against the trip duration. The black points represent the observed events rate. The expected events rate by model 1 and model 2 are shown by the solid black lines.

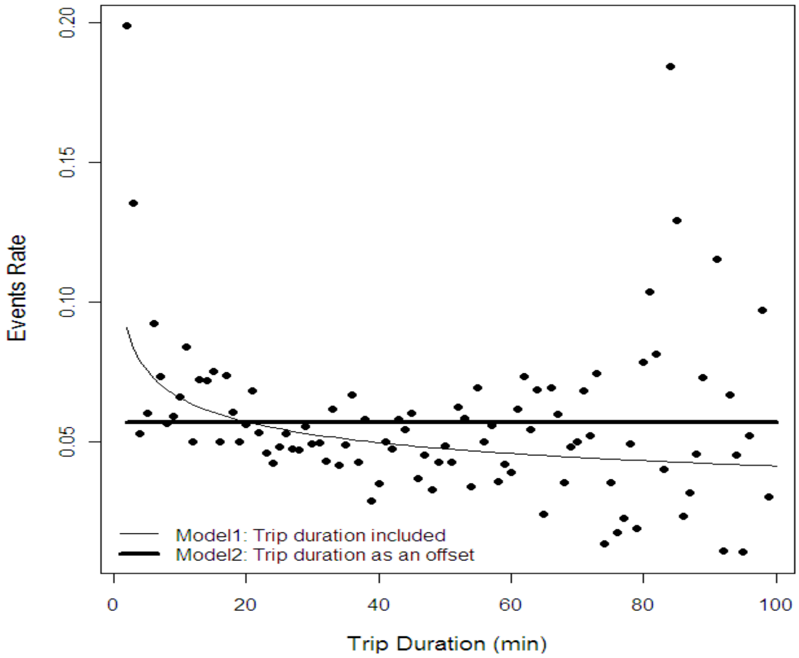

Figure 2: Event rate (events per minute) by trip duration

The AIC fit index of model 1 is 16180 while the AIC fit index for model 2 is 16220, which indicate that model 1 better fits to data. To better understand how the models fit the data, beyond the general AIC fit index, we used the cumulative residuals (CURE) method (Hauer & Bamfo, 1997). This method consists of plotting the cumulative residuals for each independent variable. To generate a cumulative residuals plot (Figure 3), trip durations are sorted in ascending order along the x-axis. For each trip duration, the residual (the predicted number of events minus the observed number of events) is computed. The residuals are added up, and a cumulative residual value is plotted for each value of the independent variable (trip duration). For a model that fits well, the cumulative residual should oscillate around zero. If the cumulative residual value steadily increases, this means that the model predicts more events than the number that was observed. Conversely, a decreasing cumulative residual line indicates that more events were observed than the number predicted by the model. A frequent departure of the cumulative residual line beyond 2 standard deviations of a random walk, given by the red lines, indicates the presence of outliers or signifies an ill-fitting model. The fit of model 1 is satisfactory because in most cases the cumulative residual is within the ±2 standard deviations of the random walk (red lines). Unlike model 1, model 2 drifts beyond the upper red line for shorter trips (<20 minutes), as it underestimates the number of events.

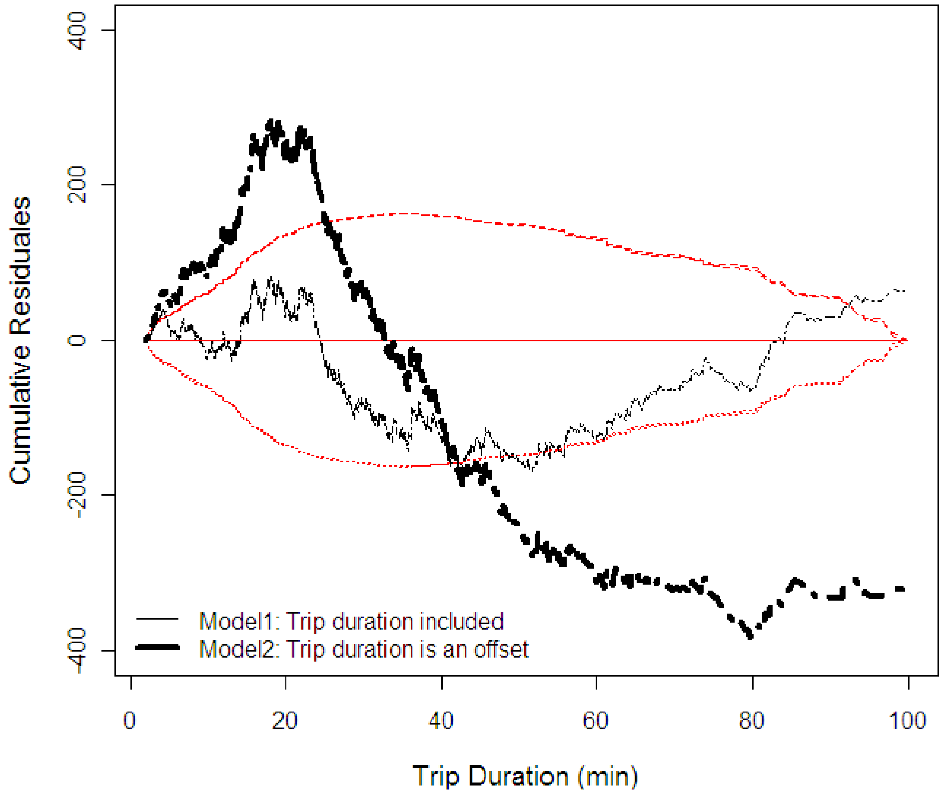

Figure 3: CURE plot for model fit evaluation

The results of the above analysis suggest using the negative binomial model with two parameters for modeling the event count in a trip for David's data.

TEMPORAL ANALYSIS

To understand how David's behavior changed over time we plotted event rate over the measurement period time (Figure 4). The gray points are the event rate per trip. For visual clarity, the Y-scale is blocked up to 0.4 events per minute, where ~98% of the trips are represented. To assist the visual analysis of the data, the monthly average of the event rate is represented by the black lines. In addition, the red line presents a fitted generalized additive model (GAM) with the P-spline method for smoothing (see eq. 3 for model definition) as implemented in the R statistical software (R Development Core Team, 2010 , Hastie, 2010). Generalized additive models are extensions of generalized linear models (GLM), in which the linear predictor is given by a sum of smooth functions of the covariates plus a conventional parametric component of the linear predictor. In this case, the model was defined as follows:

$$(3)\quad \ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(\text{Duration}) + S(\text{Time})$$

where the addition of $\boldsymbol{S(Time)}$ to the conventional negative binomial (see eq. 1) indicates the P-spline method used for smoothing, based on the time in days from the beginning of the measurement period.

The solid red line in figure 4 is the estimated event rate given the average trip duration (22.19min), so the comparison between different points in time remains valid. The dashed red lines describe the confidence intervals for this estimation.

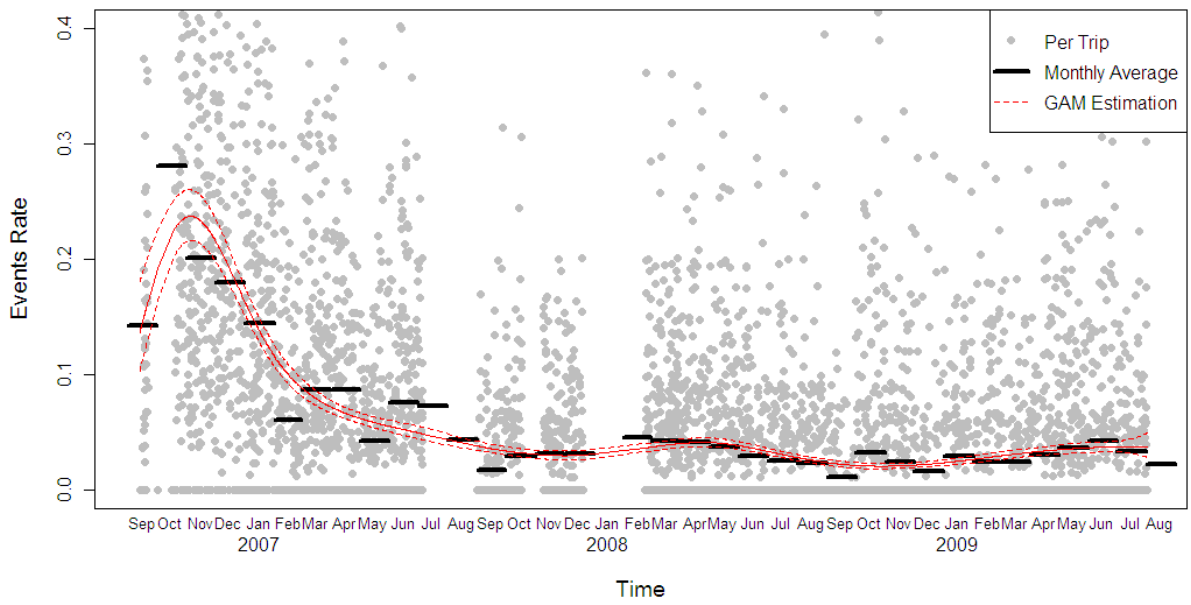

Figure 4: Event rate by time (observed and estimated by GAM)

David’s driving improved over time. At the beginning of 2007, the estimated log (events rate) by the GAM for the average trip duration was 1.293 (SE=0.043), while in the beginning of 2008 the estimation was -0.395 (SE=0.067). The difference between these parameters is significant (t statistic= 21.20) and suggests a reduction of ~82% in the events rate. The estimated log (events rate) for the average trip duration in the beginning of 2009 was -0.640 (SE= 0.058) log(events) fewer (t statistic=2.76) compared to the estimated parameter in 2008.

THE EFFECT OF INTERVENTION

The improvement in David’s behavior over time raises the question whether the feedback provided by the Green-Box contributed to this change. The feedback was disabled during 2006, while from the beginning of 2007 feedback was enabled both in real-time and in offline via web applications and automated reports. A common approach is to measure outcomes before the intervention and compare them with outcomes measured afterward. The question to be addressed is whether there is evidence for a prevailing “temporal trend”. It is likely that many forces act on outcomes, which themselves change over time, regardless of whether an intervention was applied. Thus, it is important to question whether an intervention is in fact responsible for a change in the outcomes. In general, it can be difficult to rigorously evaluate a safety intervention, and to untangle whether the observed change is the result of the intervention, because these interventions generally occur at a system level (i.e., throughout the fleet, the sub-organization) and it may not be practical to obtain suitable concurrent controls. In David’s case, no control group was available because all drivers in the fleet were exposed to feedback at the same time. Moreover, when analyzing field data, the researcher cannot be sure that drivers in the control group and in the experiment group differ only with regard to the studied variable. Considering these limitations, a before and after study was applied to evaluate whether David's exposure to driving feedback had an effect on his behavior.

When evaluating the effect of the intervention we must determine what the "before period" and the "after period" are. In general, the shorter the period is, the more certain we can be that no other unknown variable is "interfering" in our attempt to evaluate the effect of the feedback. On the other hand, more data enables us to develop more accurate models to evaluate this effect. In this case, the decision about the before period is not trivial as the events rate during 2006 were not stable. The events rate were increased in October compared to September and then events rate were reduced again during November and December 2006. Yet, except for the introduction of the feedback in January 2007, there was no other known factor for the instability of events rate during 2006. Bearing in mind that a reduction in events rate may start in October 2006, even before the availability of feedback,

a conservative approach for estimating the intervention effect would be to analyze the 2006 data starting from October 2006 while considering the trend over time in the statistical model. In addition, the slope of the graph became more leveled starting from March or April 2007, which means that the improvement trend in David's behavior had moderated. Thus, in this analysis the before and after periods included three months before providing the feedback and three months after.

To evaluate whether the availability of feedback accounted for reduction on the events counts beyond the general trend, we fitted several regression models described in equations 4 to 7. The 'Null model' assumes only log(trip duration) and time effect on the log of the expectation of event count E(Y). The effect of feedback was modeled using the segmented regression of interrupted time series approach (Wagner et al, 2002) to describe a change of level (eq. 5), a change of slope (eq. 6) and a change in level and slope (eq. 7):

(4) Null: $\ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(\text{Duration}) + \beta_2 \text{time}$

(5) Level change: $\ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(\text{Duration}) + \beta_2 \text{time} + \beta_3 \text{intervention}$

(6) Slope change: $\ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(\text{Duration}) + \beta_2 \text{time} + \beta_4 \text{time after intervention}$

(7) Level & Slope change: $\ln\big(E(Y)\big) = \beta_0 + \beta_1 \ln(\text{Duration}) + \beta_2 \text{time} + \beta_3 \text{intervention} + \beta_4 \text{time after intervention}$

where ***Duration*** is the trip duration in minutes, ***Time*** is the time in days from the beginning of the measurement period. ***Intervention*** is an indicator for time occurring before (intervention 0) or after (intervention 1); and ***Time after intervention*** is a continuous variable counting the time since the intervention, coded 0 before the intervention and (time – intervention time) after the intervention.

The fitted parameters for the four models are described in Table 1

Table 1: Time-dependent models for event count

	Null model	Level change	Slope change	Level & Slope change
$\beta_{0-\text{intercept}}$	-0.2407(0.142)	-0.2827(0.1558)	-0.2965(0.1776)	-0.4554(0.1902)*
$\beta_{1-\ln(\text{Duration})}$	0.7823(0.0406) ***	0.7824(0.0406) ***	0.7843(0.0407) ***	0.7852(0.0407) ***
$\beta_{2-\text{time}}$	-0.0089(0.0006) ***	-0.0076(0.0012) ***	-0.0077(0.0015) ***	-0.0056(0.002)**
$\beta_{3-\text{intervention}}$		-0.1483 (0.1186)		-0.1825(0.1205)
$\beta_{4-\text{time after intervention}}$			-0.0021(0.0025)	-0.003(0.0025)
AIC	3869.5	3869.9	3870.8	3870.5

* p<0.05, ** p<0.01, *** p<0.001

The fitted parameters β_3 and β_4 are not significantly different from zero in any of the models proposed here. In addition, the AIC statistic is smallest (best) for the Null model. These results suggest that there is no justification to assume that providing feedback affected David's behavior. However, a temporal change in behavior was observed, which indicates that the event rate decreased over time ($\beta_2 < 0, p\ value < 0.05$). The CURE plot for the Null model suggests that the model is fairly descriptive because the residuals follow a 'random walk' around the zero line and in most cases are within the control lines.

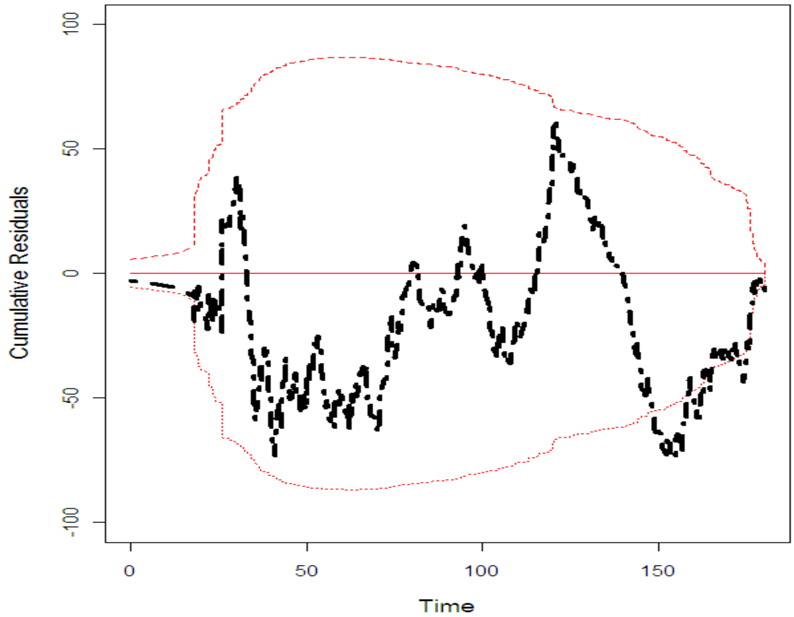

Figure 5: CURE plot for the "Null model"

The change in behavior cannot be explained by the feedback provided. Yet, other possible explanations can be considered. As we demonstrate in Figure 2, the trip duration is inversely linked to the event rate. Thus, the change in events rate may be a result of the fact that the trip durations became longer across time. Yet, this was not the case with David's trips' durations (Figure 6).

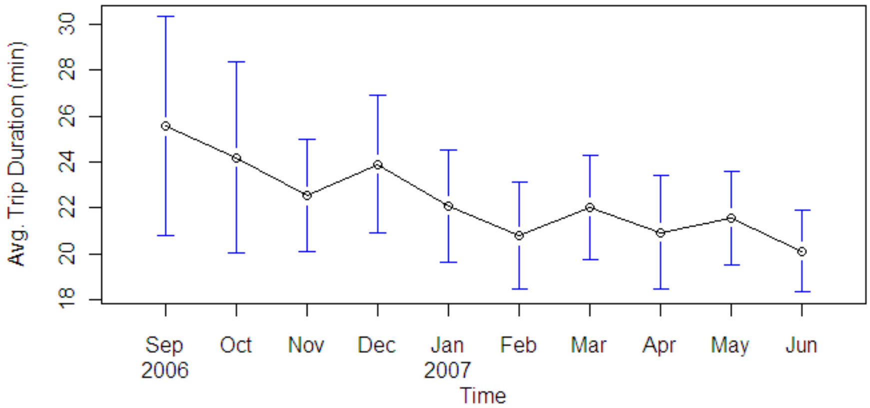

Figure 6: Average trip duration by month

It is likely that experienced drivers such as David are familiar with safe driving practices and can choose to use them if they wish, whether or not feedback from technology is available. The significant trend in the event rate indicates that the choice to engage in safe driving practices became more common in David's behavior. This choice may prevail over other driving purposes such as "finishing work quickly", or "passing slow traffic". David was aware of the monitoring technology in his car and may have tried to avoid being classified as an unsafe driver.

TIME OF DAY AND DAY OF THE WEEK

This section focuses on temporal variables (time of day and day of week) that may be useful for explaining behavior. For this analysis all available data collected between 2006 and 2009 were used. Because David is a company car driver, it was interesting to compare his behavior during and outside of working hours. Two categorical variables were defined for this purpose: "weekend" (No for Monday to Friday and Yes otherwise) and "leisure time" (No for 07:00 till 18:00 and Yes otherwise). David's formal working hours are 08:00 to 17:00. However, since driving to and from work can be counted as "working time", an additional hour was added to the beginning and end of the formal working time. The following figure presents the observed event rate according to working hours and working days.

Table 2: Observed events rate by weekend (yes/no) and leisure time (yes/no)

Weekday and Day time categories	Events	Driving minutes	Trips	Events rate (SE)
Mon-Fri & 07:00-17:59	4753	79940.35	3684	0.0595(0.00013)
Mon-Fri & 18:00-06:59	709	15062.67	737	0.0471(0.00058)
Sat-Sun & 07:00-17:59	1147	25264.48	991	0.0454(0.00047)
Sat-Sun & 18:00-06:59	275	6283.80	285	0.0438(0.00185)

A negative binomial model was calibrated to evaluate whether the differences in event counts presented in Table 2 are statistically significant while considering the driving minutes. The model included a free parameter (β_0 =-2.228, SE=0.097, p<0.001), an exposure parameter for duration (β_1 =0.824, SE=0.031,p<0.001) and additional parameters for leisure time (β_2 =0.341, SE=0.067, p<0.001), weekend (β_3 =-0.307, SE=0.058, p<0.001) and for the interaction between them (β_4 =0.214, SE=0.133, p=0.108), which was the only insignificant parameter. The results suggest that David's event rate was lower on weekends by ~26% and in leisure time by ~29%. The reason for this may be environmental (e.g. increased traffic during work hours), or organizational (e.g. time pressure, many driving tasks). However, David's moderate driving events during weekends and leisure time may indicate his ability to improve his driving.

CONCLUSIONS

Personalization is already a part of our daily lives, and was introduced into driving safety via new "pay as you drive" insurance schemes that currently focus on integrating limited exposure indices rather than actual behaviors. The evaluation of behavior indices over time for individuals' driving behaviors has not received much attention in research studies because researchers typically look for large samples to achieve results that can then be generalized to support large-scale decision-making. However, analyzing individuals' data may assist drivers, insurance agents, safety officers, or driving instructors who wish to understand how individuals' behaviors can change over time and what variables explain this change.
Advanced driver assistance systems now enable the collection of time series indicators for behaviors in high resolution (per trip).To date there has not been a published analysis that

assesses the feasibility of focusing on an individual's data in order to answer the types of questions that are typically asked in relation to large samples.

In this study, we demonstrate how information from technology can be used to analyze the behavior of an individual driver. The advanced driver assistance system used in this study identified occurrences of undesirable driving events such as extreme braking and accelerating, sharp cornering, and sudden lane changing. Information about 5704 trips, 2107 driving hours and 6878 undesirable driving events was recorded during a three-year measurement period. As commonly done with count data, the negative binomial model was used to develop regression models. Several regression models were used to analyze how driving behavior changed over time and how trip duration and other temporal variables, such as time of day and day of week, are linked to the rate of undesirable driving events. We found that David's event rate was lower during weekends by ~26% and during leisure time by ~29%. The reason for this may be environmental (e.g. increased traffic during work hours), or organizational (e.g. time pressure, many driving tasks). However, David’s safer driving during weekends and leisure time may indicate that he can further improve his driving. In addition, the trend in behavior over time suggested that David's driving safety improved. These results can provide David with positive feedback and can set an example for other drivers in the same fleet.

Considering the presented data, it is quite reasonable to assume that at least part of the reduction in events rate during the monitored period is due to the availability of feedback from the technology, although there seem to be other factors influencing events rate as well. A future study can look at other drivers in the same fleet to conclude whether this trend is common and thus probably relates to organizational or environmental factors. Otherwise, individual factors as temporal work pressure or a change of David’s driving tasks can be considered.

David's individual behavior cannot be generalized to claim that drivers improve over time or behave differently during working versus non-working times, but the analysis methods are useful for practitioners (e.g. safety officers, trainers) looking to provide feedback and analyze intervention programs for drivers.

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