THE SAFETY BENEFITS OF COLLISION WARNING APPLICATIONS – EVIDENCE FROM ON-ROAD DATA

O. MUSICANT[1,2] & A. BOTZER[1]
[1]Ariel University, Israel.
[2]Ran-Naor Institute for Road Safety Research, Israel.

ABSTRACT

A collision warning system (CWS) facilitates timely crash-avoidance behaviours by providing real-time warnings to drivers about imminent collisions. Despite its potential benefits in terms of both shorter response times and ability to maintain longer headways, its adoption has been slow. Smartphone-based collision warning applications (CWAs) may assist in stimulating wider adoption of collision warning technology, as they are much less expensive and are accessible in many types of smartphones. However, driver behaviour with CWAs has never been studied.

Aim: This study explored the behaviour of 26 drivers in the initial 2–3 weeks of using a CWA, with respect to (1) their responses (speed behaviour) to the warnings they received, and (2) the number of warnings they received over time.

Method: Drivers were asked to install a CWA on their smartphone and share their trip data in return for monetary rewards. The data logged by the CWA included instantaneous speed and the time-stamped warnings that were received during the trips. The analysis employed several linear and non-linear regression models.

Results: The CWA generated safer behaviours: drivers lowered their speed when warnings were issued and maintained safer headway distance over time. In view of the high penetration rate of smartphones, it is suggested that ways to further test and use CWAs be developed.

Keywords: collision warning systems, driver behaviour.

1 INTRODUCTION

Rear-end collisions account for more than 30 percent of accidents involving another vehicle [1]. The main causes of rear-end collisions are inattention and close following [2]. Collision warning systems (CWSs) have been developed as a means to mitigating these causes. A CWS feeds data from sensors as radar and camera into an on-board processing unit to compute time to collision (TTC). An auditory, visual, tactile or any combination [3] of warning modalities is issued when TTC is lower than a predefined safety threshold.

A body of naturalistic and simulator studies has demonstrated the safety potential of CWSs. For example, Lee *et al.* [4] showed that warnings assisted drivers (N = 120) on the releasing of the accelerator and reduced kinetic energy of simulated crashes. Mohebbi *et al.* [5] reported that driver (N = 18) response time to simulated impending collisions was shorter with warnings than without.

In an on-road study, headway warnings not only led drivers (N = 30) to maintain safer headways, but also taught them to assess headway distance more correctly: compared to the pre-use of the warning system, they kept safer headways even when warnings were no longer available [6]. In another study, 18 truck drivers used a CWS for 10 months. During that time,

This paper is part of the Proceedings of the 10th International Conference on Risk Analysis (RISK 2016))
www.witconferences.com

ISSN: 2041-9031 (paper format), ISSN: 2041-904X (online), http://www.witpress.com/journals
DOI: 10.2495/SAFE-V6-N2-362-371

drivers responded to the warnings and kept larger headways than before [7]. Faster responses to leading car decelerations in an on-road study were also reported by Dingus *et al.* [8]. Finally, an actuary analysis suggested that drivers with a CWS had fewer insurance claims than drivers without one [9].

In view of the safety benefits of using CWSs, the National Transportation Safety Board recommended making them standard on all vehicles [10]. Despite this, there is limited adaptation of CWSs mainly due to their cost [11].

A possible solution may reside in low-cost, smartphone-based collision warning applications (CWAs). CWAs only require a smartphone and phone cradle. They use image processing algorithms to identify vehicles in the phone-camera's video image and to estimate the timing of possible impending collisions [12]. The overwhelming market penetration of smartphones [13,14] along with experts' beliefs that CWAs will both promote safety behaviours and gain public support [15] provide the motivation for investigating their effects on driving behaviours. For instance, the frequency of false warnings by any of the currently available CWAs is unknown and therefore, the extent to which drivers would trust their warnings is unclear [16,17]. Previous studies demonstrated that when warnings came from a CWS that produced frequent false warnings, the frequency and intensity of collision avoidance behaviours have been attenuated [17,18]. The level of trust in a CWA compared to a CWS may also depend on the perceived quality of a smartphone-based, 'no warranty' CWA, versus the in-vehicle manufacturer version. These concerns suggest that results obtained with CWSs may not apply to CWAs, and driver responses to CWAs should therefore be tested.

In this study, we analysed on-road driver data to investigate (1) whether drivers reduced their speed in response to warnings and to what extent they reduced it in case they had; and (2) whether they maintained safer headways during the time they used the application.

2 METHOD

CWA: The CWA used in this study (IonRoad, Tel-Aviv, Israel) computes TTC by applying real-time algorithms to the smartphone's motion sensors, camera and GPS streams. It provides graded auditory and visual warnings according to two TTC thresholds: 2.5 s and 1.5 s. A series of short beeps is sounded and a yellow square with the word 'careful' appears when the 2.5 s threshold is breached. Louder lower-tone beeps are sounded and a red square with the word 'warning' appears when the 1.5 s threshold is breached. Therefore, hereon, we refer to the 2.5 s and 1.5 s breaches as yellow warning and red warning, respectively. Finally, the CWA also logs the time stamp of the warnings (in minutes), and vehicle speed and acceleration according to a 10 s resolution. This telematics is subsequently used to analyse drivers' behaviour and their responses to CWA warnings.

Participants: Thirty participants volunteered for the experiment. None of them had previous experience with collision avoidance technology. Four of the participants dropped out due to technical problems (e.g. unexpected shutdowns, trip data not saved). The remaining 26 participants (8 female; 18 male; age range 24–60 years; mean = 31.45; standard deviation = 12.37) were all licensed drivers with two or more years of driving experience. In return for their participation, they received the CWA they used in the experiment (priced US $4.99) and monetary rewards according to the number of trips they took with the application, but no greater than 50 Israeli Shekels (~ US $4.99).

Data: Overall, 372 trips were recorded across the 26 participants. The number of trips per participant ranged between 4 and 28 with an average of 14.31 trips (SD = 7.39). These trips accounted for a total driving time of 131.35 hours, ranging between 0.75 and 11.17 hours per participant (mean = 5.05, SD = 3.10).

Overall 399 warnings were logged. The number of warnings per participant ranged between 0 and 36 with an average of 15.34 (SD = 9.85). Rate of warnings per minute was ~0.05. There were 371 (93%) yellow warnings and 28 (7%) red warnings. For the purpose of statistical inference, there was not enough data to provide a separate analysis for the red warnings. Excluding red warnings, however, would also mean excluding important information about driver behaviour and we therefore decided to conduct our analysis on yellow and red warnings together.

Analysis: To investigate whether participants responded to warnings from a CWA, we studied, for all participants, the statistical linkage between the dependent variable 'speed' and two main independent variables 'warning' (yes or no) and 'trip index' (first trip, second trip, etc.). To study whether participants maintained safer headways during the time they used the CWA, we tested whether the dependent variable count of 'warnings per trip' (WPT) is linked to the independent variables 'trip index' and 'trip duration,' and speed (greater than 90 km/h (common posted speed for highways in Israel) and greater than 50 km/h (above common posted speed for urban roads).

3 RESULTS

3.1 Effect of warnings on speed

This section focuses on analysing driver speed when warnings were issued. Speed samples (km/h) were available every 10 seconds, while time stamps for warnings were available according to a one-minute resolution. Our database was therefore arranged according to a one-minute resolution so that the 7,881 rows in the database represented 7,881 minutes of driving. Database features included driver index, trip index, whether warning was present or not and the last speed sample recorded at the specific minute. In 7,528 (95%) minutes, there were no warnings at all. In 312 minutes (4%), there was one warning and in the remaining 41 minutes (1%) there were 2 or 3 warnings. Of the six samples of speed available in every minute, the last of the six was used in the analysis as an indication of the speed after warning.

According to the information provided in the introduction section, drivers typically respond to warnings by slowing down. Thus, speed should be low after warnings compared to before warnings. Yet, slowing down may also indicate that drivers have merely responded to the event that triggered the warning rather to the warning itself. To differentiate between the two cases, we tested whether drivers tended to slow down when warnings were present and also tested whether such tendency to slow down increased over time. We suggest that the increasing tendency to slow down is related to drivers gaining more trust in the system, responding more intensely to its warnings.

Our investigation of whether drivers responded to warnings was based on the gap between the speed recorded at the end of each driving minute (recall that our data is given in a resolution of minutes) and the driving speed recorded at the end of the preceding driving minute. This index is denoted hereon as SG (speed gap). A negative value of SG implies slowing down. It is difficult in field studies to control for factors such as congestion, road quality, weather and lighting that may impact driving behaviour. However, as the SG index compares speed in sequential minutes with similar driving conditions, the impact of such factors on behaviour is to some extent controlled.

Figure 1 presents the mean SG with corresponding error bars (±1 standard error) against trip index for minutes in which warnings were issued (in black) and for minutes without warnings (in grey). The colour-coded lines are statistical models that will be subsequently

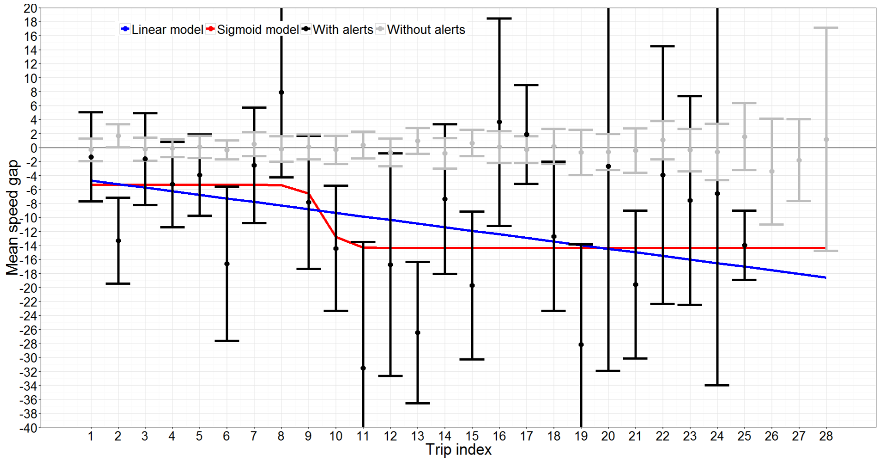

Figure 1: Mean speed gap according to trip index.

described. Several conclusions emerge. First, in the case where warnings were not issued (in grey), the mean SG is fairly around zero for all values of trip index. Second, when warnings were provided, the mean SG is, in most cases, below zero. The error bars are wider in these cases as there are much less minutes with than without warnings. Third, the statistical models suggest that mean SG indeed decreased with higher values of trip index. Thus, SG became more noticeable as drivers used the application more number of times. Two statistical models were calibrated to analyse the link between trip index and SG: a linear and a sigmoid model. In addition to the trip index, the SG may also depend on the speed before the warning was given. More specifically, the SG is potentially more pronounced (negative) when the initial speed before the warning is high. To control for this, we added the speed at the minute preceding the minute in which a warning was issued as an explanatory variable. The linear model is formally presented in eqn (1).

$$SG_{t,i,j} = \beta_0 + \beta_1 S_{t-1,i,j} + \beta_2 T_{i,j} + b_j + e_{tij} \quad (1)$$

Where $SG_{t,I,j}$ is the difference in speed between driving minute t and driving minute *t*-1, in trip i of driver j. $SG_{t-1,I,j}$ is the speed recorded at the end of minute *t*-1 in trip i of driver j minus mean speed of 62.18 km/h. This was done so the intercept value (β_0)will reflect the speed gap at average speed, rather than for the less relevant case of speed = 0.$T_{i,j}$ is the trip index of trip i of driver j. $\beta_0 - \beta_2$ are the fixed effect parameters in the linear model. To control for the repeated measures for each driver (multiple trips), a random effect parameter (b_j) was added to the model. We assume that $b_j \sim N(0, \sigma_b)$. The e_{tij} is the error term.

Although a linear relationship is the simplest (and perhaps common) modelling choice, a more careful visual investigation of the pattern in the black points (and error bars) suggests that, the effect of trip index weakens and even levels for larger values of the trips index possibly pointing to a ‘limit’ on how strongly drivers respond to warnings provided to them.

Based on this idea, we considered an S shape function (sometimes referred to as sigmoid or logistic function) to model the relationship between SG and trip index. Thus, our sigmoid model combines a linear form to control for the initial speed and an S shape function to control for the trip index. The sigmoid model is formally presented in eqn (2).

Table 1: Models for SG by trip index and speed.

	Linear model estimate (S.E)	Sigmoid model estimate (S.E)
Intercept (β_0)	−4.19 (3.13)	−5.23 (2.68)*
Speed (β_1)	−0.576(0.05)***	−0.57 (0.05)***
Trip index (β_2)	−0.514 (0.300)+	NA
Lower asymptote (a)	NA	−9.06 (4.323)*
Inflection point (K)	NA	9.544 (1.394)***
scale (c)	NA	0.298 (0.789)
σ_b	7.007	0.338
Log likelihood	−1559.091	−1557.679

*p value < 0.05, ***p value < 0.001

$$\mathrm{SG}_{t,i,j} = \beta_0 + \beta_1 \mathrm{S}_{t-1,i,j} + \frac{a}{1+e^{\left(\frac{k-\mathrm{T}_i}{c}\right)}} + \mathrm{b}_j + \mathrm{e}_{tij} \tag{2}$$

Where the S shaped part of the sigmoid model is characterized by three parameters: when negative, a represents the lower asymptote, the change point in the curvature of the curve (also called the inflection point, k) and the scale of the curve (c) that is inertly related to the steepness of change in behaviour.

The parameters fitted for the linear and sigmoid models are described in Table 1. In the fitting process, only minutes in which warnings were issued were used. It is clear from the data in Fig. 1 that there is no change is speed when warnings are not issued (see grey points and error bars). The colour coded lines in Fig. 1 describe the estimated SG where $\mathrm{S}_{t-1,i,j} = 0$, that is, driving at the average speed.

Both models suggest a significant effect of the speed and of trip index on SG. However, according to the log likelihood index, the sigmoid model fits the data better. In addition, the smaller value of σ_b suggests that in the sigmoid model, drivers' individual trends deviate less from the pattern described by the fixed effect part of the model. We therefore focus on the results obtained by the sigmoid model: the fitted intercept (β_0) indicates that relative to the average driving speed, the SG is reduced by −5.25 km/h. In addition, as suggested by the speed coefficient (β_1), SG is further reduced according to the driving speed. For example, for drivers driving at 90 km/h, the speed reduction following warnings is estimated by −5.22 − 0.57 * (90 − 62.18) = −21.077 km/h. The results so far indicate that drivers responded either to the warnings they received or to the circumstances causing the warnings by lowering their driving speed.

Pertaining to the link between trip index and SG: the lower asymptote is estimated by −9.06 km/h; thus, for example, a driver driving at the average speed of 62.18 km/h is expected to reduce his speed by −5.23 km/h for lower values (<8) of trip index and by −5.23 − 9.06 = −14.29 km/h for higher values of trip index (>11). This change in behaviour occurs between 8 and 11 trips of using the system where the inflection point is estimated at trip index = of 9.544. This means that as drivers gain experience with the CWA, they are more likely to respond more strongly to the warnings and reduce their driving speed more than drivers with less experience with the CWA.

3.2 Effect of the CWA on headway distance

This section analyses whether drivers maintained safer headways as a result of using the system, in other words, whether there were fewer warnings in later than in earlier trips. The variable of interest in this analysis was the count of WPT, and thus Poisson and negative binomial (NB) distributions are natural candidates to describe it.

In a Poisson distribution, the mean and variance are equal. For 21 of the 26 drivers (81%), variance to mean ratio was greater than 1. Median ratio was 1.35, mean ratio was 1.76 and standard deviation was 1.04. This analysis led us to test the NB distribution for WPT. The main variable tested for its effect on WPT is trip index. In addition to trip index, we also considered several control variables: trip duration is minutes was added as an explanatory variable as longer trips provide more opportunities for triggering warnings. As noted in Section 2, we also considered the proportion of driving speeds that were greater than 90 km/h and the proportion of driving speeds that were greater than 50 km/h as additional explanatory variables for WPT. The NB model was formally defined as follows:

$$\ln(E(WPT_{ij})) \sim Ln(\beta_0) + \beta_1 \ln(D_{ij}) + \beta_2 T_{ij} + \beta_3 P^{50-90}{}_{ij} + \beta_4 P^{>90}{}_{ij} + b_j \quad (3)$$

Where WPT_{ij} is the count of WPT *i* of driver *j*. D_{ij} is the duration in minutes of the *i* th trip of driver *j* and T_{ij} is his or her trip index. $P^{>90}$ and P^{50-90} are the proportion of driving speeds between 50 and 90 km/h and above 90 km/h, respectively. β_0, $-\beta_4$ are the model fixed effect parameters. The b_j is the random effect term, representing a seperate parameter for each driver. In accordance with the convention in mixed-effect models, we assume that $b_j \sim N(0, \sigma_b)$.

Table 2 presents the values of the estimates of the model. Results show that β_1 is significantly higher, indicating that longer trips are expected to have more warnings compared to shorter trips. As β_1 is also smaller than 1 (Z. test = 2.05, p value < 0.01), the contribution for every additional driving minute to the count of warnings in a trip diminishes as trip duration becomes longer. The effect of trip index (β_2) was not significant at the .05 level. The reduction in WPT from one trip to the next is approximately 1 percent ($1\text{-}e^{-0.010} = 0.99$). Thus, after 10 trips, the reduction in WPT is estimated to be around 10 percent and around 20 percent after 20 trips. The effect of speed was far from significance.

To test the fit of the NB model to the WPT data, a graphical analysis was used. The analysis method proposed by Hauer and Bamfo [19] consists of examining the cumulative residuals (CURE) against the explanatory variables (e.g. trip index or duration), using the

Table 2: NB model for WPT by trip duration and trip index.

	Estimate (S.E)
Intercept (in (β_0))	−2.093 (0.423)***
Ln (Trip Duration) (β_1)	0.754 (0.117)***
Trip Index (β_2)	−0.010 (0.010)
Proportion of speed between 50 and 90 km/h	0.107 (0.416)
Proportion of speed above 90 km/h	−0.460 (0.314)
σ_b	0.78

***p value < 0.001

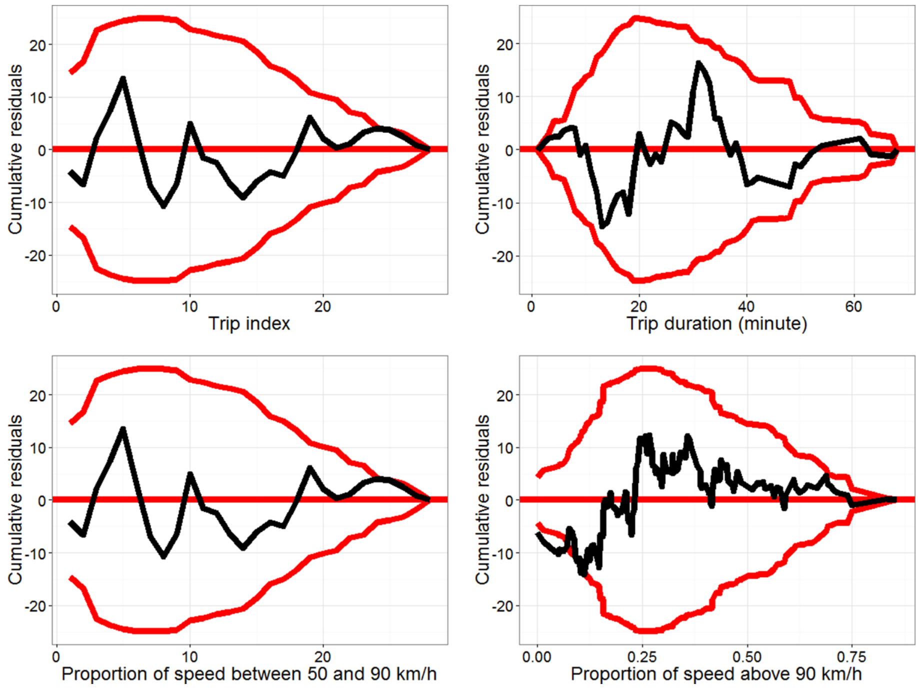

Figure 2: CURE plot for trip index (left) and trip duration (right).

CURE plot. The analysis is provided in Fig. 2. To generate a CURE plot, trips are ordered by the explanatory variable in an ascending order. For each unique value of the explanatory variable, a residual (predicted minus observed number of events) is computed. The residuals are added up, and a CURE value (vertical axis) is plotted against the explanatory variable (horizontal axis). In a perfect-fit model, all residuals and hence all CURE would be zero. With random residuals, the cumulative line should oscillate around zero in a random-walk manner. In addition to the CURE lines (in solid black), the red lines in Fig. 2 depict approximate ±2 standard deviations bands, under the random-walk assumption (see the derivations in Hauer and Bamfo [19]). If the CURE value increases steadily in a certain range of trip-duration values, this means that the model predicts more warnings than the number observed in this range. Conversely, a decreasing CURE line indicates that more warnings were observed than the number predicted by the model. Frequent departure of the CURE line beyond the random-walk band (red lines) may be due to either outliers or an ill-fitting model. As can be noted in Fig. 2, the CURE line (in black) plotted against all four explanatory variables presents no trend but a random walk around the zero line and in most cases does not deviate from the red band. It is therefore assumed that the NB model fits the data well.

4 DISCUSSION

This study explored two main aspects of driver behaviour with CWA: driver speed when warnings were presented, and driver maintenance of headway distance over time.

Our analysis of driver speed with and without warnings demonstrated that they responded to the warnings and that their trust in the CWA increased over time. It also suggested that trust may eventually be set around a certain level. This was evident from the analysis of the sigmoid model eqn (2). These findings demonstrate that a smartphone CWA may generate similar responses to warnings as those from an in-vehicle CWS and also have larger implications for the study and usage of collision avoidance technology. More specifically, according to the sigmoid model, while controlling for driving speed before the warning is given, we estimate that the effect of receiving warnings is manifested in reduction of 5.23 km/h and in additional 9.06 km/h after experience (and trust) with the CWA is gained. This reduction in driving speed may have meaningful effects on both the probability of accidents and their severity [20]. Thus, a CWA may not only generate similar responses as an in-vehicle CWS (e.g. braking) – but the responses they generate seem to be strong enough to offer considerable contribution to driver safety.

We also tested whether drivers maintained safer headways over time [7] regardless of their driving speed. We found that the frequency of warnings indeed decreased as drivers used the application more number of times. When considering the estimates derived from the mixed-effect NB model, an expected reduction of 20 percent in the count of warnings after 20 trips may have more than just a marginal effect on safety. This effect, however, was not statistically significant. It is possible that due to statistical power (372 trips per 26 drivers = 14.31 trips per driver), the mixed-effect model did not capture a true effect of the trip index. The effect of trip index may mean that CWA can serve as a training tool for safer driving, rather than just being a warning device. In other words, drivers received fewer warnings because they kept safer headways on different speeds and not because they attempted to avoid warnings by driving slower. The effect of such training can be estimated from the statistical model we presented (10% reduction after 10 trips and 20% after 20 trips).

To conclude, our findings suggest that a CWA may generate similar safety benefits as a CWS. Specifically, we found that drivers responded to warnings from the CWA and seemed to maintain safer headway distance over time when using it. We suggest that CWAs have great potential for improving public safety due to the high penetration rate of smartphones [13,14], the much lower price of such applications compared to an in-vehicle CWS, and due to their potential for generating safer driving behaviours.

ACKNOWLEDGEMENTS

We would like to thank research assistants Elad Lazar and Aviad Ohayon for their contribution to this study.

REFERENCES

[1] National Highway Traffic Safety Administration, Traffic safety facts 2006: A compilation of motor vehicle crash data from the fatality analysis reporting system and the general estimates system (NHTSA Publication No. DOT- HS-810-818). Washington, DC: U.S. Department of Transportation, 2006.

[2] Dingus, T.A., Jahns, S.K., Horowitz, A.D. & Knipling, R., Human factors design issues for crash avoidance systems. In *Human Factors in Intelligent Transportation Systems*, eds. W. Barfield & T.A. Dingus, Erlbaum: Mahwah, NJ, pp. 55–94, 1998.

[3] Lee, J.D., Hoffman, J.D. & Hayes, E., Collision warning design to mitigate driver distraction. *Proceedings of the ACM Conference on Human Factors in Computing Systems*, ACM: New York, pp. 65–72, 2004. http://dx.doi.org/10.1145/985692.985701

[4] Lee, J.D., McGehee, D.V., Brown, T.L. & Reyes, M.L., Collision warning timing, driver distraction, and driver response to imminent rear-end collisions in a high fidelity driving simulator. *Human Factors*, **44**, pp. 314–334, 2002.
http://dx.doi.org/10.1518/0018720024497844

[5] Mohebbi, R., Gray, R. & Tan, H.Z., Driver reaction time to tactile and auditory rear end collision warnings while talking on a cell phone. *Human Factors*, **51**(1), pp. 102–110, 2009.
http://dx.doi.org/10.1177/0018720809333517

[6] Ben-Yaacov, A., Maltz, M. & Shinar, D., Effects of an in-vehicle collision avoidance warning system on short- and long-term driving performance. *Human Factors*, **44**, pp. 335–342, 2002.
http://dx.doi.org/10.1518/0018720024497925

[7] Bao, S., LeBlanc, D.J., Sayer, J.R. & Flannagan, C., Heavy-truck drivers' following behavior with intervention of an integrated, in-vehicle crash warning system: A field evaluation. *Human Factors*, **54**, pp. 687–697, 2012.
http://dx.doi.org/10.1177/0018720812439412

[8] Dingus, T.A., McGehee, D.V., Mankkal, N., Jahns, S.K., Carney, C. & Hankey, J.M. Human factors field evaluation of automotive headway maintenance/collision warning devices. *Human Factors*, **39**, 216–229, 1997.
http://dx.doi.org/10.1518/001872097778543930

[9] Shahar, R., Actuarial Research on the Effectiveness of Collision Avoidance Systems, 2013, available at http://www.ron-ai.com/maagar.php?op=page&id=12, (accessed 2 November 2015).

[10] National Transportation Safety Board, *The Use of Forward Collision Avoidance Systems to Prevent and Mitigate Rear-End Crashes* (NTSB Report NTSB/SIR-15/01), Washington, DC: NTSB, 2015.

[11] Williams, T., *NTSB Calls for Immediate Action on Collision Avoidance Systems for Vehicles; Cites Slow Progress as Major Safety Issue*, NTSB Press Release, 2015, available at http://www.ntsb.gov/news/press-releases/Pages/PR20150608b.aspx

[12] Ren Z.Q., Wang, C. & He, J., Vehicle detection using Android smartphones. *7th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*. Bolton Landing: New York, 2013.

[13] IDC, Smartphone Shipments Reach Second Highest Level for a Single Quarter as Worldwide Volumes Reach 355.2 Million in the Third Quarter, 2015. available at http://www.idc.com/getdoc.jsp?containerId=prUS25988815 (accessed 28 October 2015).

[14] ITU, ICT facts and figures. 2015. available at http://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2015.pdf

[15] Albert, G., Musicant, O. & Lotan, T.A., "Safety Suit" for smartphone apps: what do the experts say? *The 4th International Conference on Driver Distraction and Inattention (DDI2015)*, Sydney, Australia, November, 2015.

[16] Astley, S.M., Evaluation of computer-aided detection (CAD) prompting techniques for mammography. *British Journal of Radiology*, 78, pp. 20–25, 2005.
http://dx.doi.org/10.1259/bjr/37221979

[17] Bliss, J.P., Investigation of alarm-related accidents and incidents in aviation. *International Journal of Aviation Psychology*, 13, pp. 249–268, 2003.
http://dx.doi.org/10.1207/S15327108IJAP1303_04

[18] Bliss, J.P. & Acton, S.A., Alarm mistrust in automobiles: How collision alarm reliability affects driving. *Applied Ergonomics*, 34, pp. 499–509, 2003. http://dx.doi.org/10.1016/j.apergo.2003.07.003

[19] Hauer, E. & Bamfo, J., Two tools for finding what function links the dependent variable to the explanatory variables. *International Cooperation on Theories and Concepts in Traffic*, Lund: Sweden, 1997.

[20] Aarts, L. & Van Schagen, I., Driving speed and the risk of road crashes: A review. *Accident Analysis and Prevention*, **38**(2), pp. 215–224, 2006. http://dx.doi.org/10.1016/j.aap.2005.07.004