WatchOut: Facilitating Safe Driving Behaviors with Social Support

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Abstract
Bad driving behaviors are a major cause of the traffic accidents, many of them resulting in fatalities. Our study intends to encourage safe driving habits by increasing a driver's self-awareness about their own driving habits, as well as receiving supportive feedback on their driving behavior from a loved one as an intervention method. We built an Android prototype app to deliver feedback for bad driving maneuvers to both drivers themselves and to their corresponding supporters, and conducted a field study evaluation. The results from the survey showed that even though many of the drivers thought they drove safely before this experiment, they realized the app feedback on their driving behavior increased their knowledge of their own driving habits. Further, supporter feedback based on the app helped them drive safer. Based on the results, multiple design implications are drawn for improving driving habits through increasing self-awareness and providing support from loved ones.

Author Keywords
Driving Behavior Change; Social Reinforcement; Social Face; Driving Assessment

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g.,HCI): Miscellaneous;

Introduction

According to a recent report [11], the incidence of traffic accidents due to unsafe driving (such as mobile phones usage, drowsy driving, neglecting to look forward, bad braking, bad steering wheel operation) occupied more than 56% of the total traffic accidents in Korea. The general consensus is that unsafe and aggressive driving behaviors increase the risk of traffic accidents. This style of driving refers to a behavior that is motivated by impatience, annoyance, hostility, and/or an attempt to save time [10]. However, according to Kalra [5], driver behaviors are relatively safer when they are being monitored, or feedback of their events is provided, or their aggressive driving events are recorded.

Many approaches have been taken to assess and understand driving behaviors. The development of in-vehicle sensing technology has resulted in an improved, more objective measurability for driving style. For example, DriveSafe automatically detects car movement and makes a phone silent to prevent phone usage while driving. "SafeDrive rewards you” promotes safe driving by providing users with monetary compensation. DriveWell is a behavior-based application from Cambridge Mobile Telematics and helps drivers to improve their driving by accurately measuring driving quality using a smartphone [2]. DriveWell and most in-vehicle sensing apps, however, focus on the assessment of driving behaviors to increase a driver’s self-awareness, but do not consider social factors for driving behavior change. According to the social cognitive theory of Bandura [1], in a social context, people become more aware of normative behaviors through social learning, and this can motivate them for self-regulation of their behavior.

Therefore, in this study, we examine the effectiveness of the following in driving behavior changes:

- The self-awareness of a driver’s own driving habits with a smartphone sensor-based driving assessment
- How a person’s intimate social reinforcement (such as social attention and affection) can affect driving behaviors.

Our approach aimed to increase self-awareness of driving habits objectively, reinforced by social support, to both motivate behavior regulation and encourage continued regulation.

Related Work

HCI studies have been conducted to identify the effectiveness of social reinforcement in the behavioral changes of an individual. According to Skinner [9], a human learns and eventually changes his behavior through experiencing reinforcement and punishment. Reinforcement is one of the main methods to increase an individual’s desirable behaviors. Furthermore, social members, such as family, friends, and colleagues, can provide reinforcement to the person who tries to change his or her behavior [9]. Lee [6] revealed that, social reinforcements such as social attention, affection, and reputation could have a meaningful impact on an individual’s health behavior change.

Another kind of social reinforcement to change human behavior is that “Not wanting to cause discomfort for an individual.” Shin [8] revealed in his research that individuals are motivated to change their behavior due to not wanting to discomfort others, rather than the internal motivation to change their own behavior. In this context, we designed a model which consisted of a driver, a supporter who can provide affection to the driver (i.e., a reinforcer), and a mobile application that

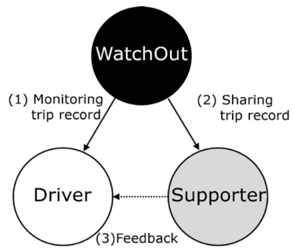

Figure 1: Overview of WatchOut experiment model.

Normal Driving	N
Sudden Acceleration	A
Sudden Braking	B
Sharp Right Turn	R
Sharp Left Turn	L
Excessive Speed	S
Accelerometer X/Y/Z axes	Ax, Ay, Az
Gyroscope X/Y/Z axes	Gx, Gy, Gz
Longitude, Latitude	Lon, Lat
Provider Speed	Speedp

Table 1: Notations that has been used throughout the paper

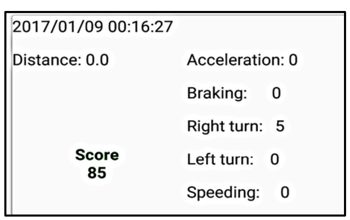

Figure 2: Assessed driver's trip report

interacted between the driver-supporter pair to determine whether the individual's driving behavior changed through feedback from the system and from the supporter (i.e., discomfort due to safety concerns of loved ones). The overview of our research model is illustrated in Figure 1.

System Design

We developed a novel mobile application called WatchOut to assess bad driving habits, increase the awareness of a driver's own driving behaviors, and identify the influence of intimate' social reinforcement.

According to the data released by the U.S. General Service Administration [12], the six most unsafe driving behaviors are as follows: improper speed, violating the right of way, driving left of center, turning improperly, passing improperly, and following too closely. Based on this information, we defined the following bad driving behaviors in our test condition: 1) Rapid acceleration, 2) Slamming on the brakes, 3) Hard left cornering, 4) Hard right cornering, and 5) High speed.

The detection of a driver's driving style based on the user's actual driving behavior can be incorporated through machine learning techniques [7], threshold-based event detection methods [13], or through statistical analysis of the inherent propensities of the driver [4]. The threshold-based event detection method was used in our experiment.

To design the detection algorithm, we collected multiple templates for each dangerous driving maneuver including sudden acceleration, slamming on the brake, and hard right and left cornering. We use the notations in Table 1 to refer to these behaviors in the rest of the paper. We recorded 3-axis accelerometer and 3-axis gyroscope readings at 2 Hz sampling rate. The phone was fixed vertically to the wind shield facing the back seat. An average of four templates were recorded for each behavior. We did not collect templates for high speed because it could be calculated based on the distance traveled divided by the time of travel using location coordinates. Recorded sensor signals were smoothed using a simple moving average to remove noise from car vibration. Based on these data sets, we observed the patterns for each behavior by visualizing the various statistical features that were extracted for each sensor signal. We found that longitudinal acceleration was best at indicating acceleration and braking movements. Lateral acceleration and angular velocity around the vertical axis were more indicative of turning. Based on our observation, the amount of force and angular velocity exerted for each event is summarized in Table 2.

Longitudinal Maneuver		Lateral Maneuver	
Exerted force	Exerted force SD	Exerted Force	Angular Velocity
3.8 g	1.45 g	3.5 g	0.5 rad/s

Table 2: Thresholds of longitudinal and lateral maneuvers

According to our phone placement, the longitudinal acceleration conforms with A_z and the lateral acceleration and rotation around the vertical axis conform with A_x and G_y respectively. For speeding detection, we used the location coordinates to calculate distance and speed. We collected location data every second. Every excessive speeding interval where the speed exceeded the 70 km/h limit was considered as over speeding. Our algorithm then aggregated all adjacent windows detected as excessive speed as one speeding event. We chose 70 km/h, which is the maximum speed limit within the city in Korea.

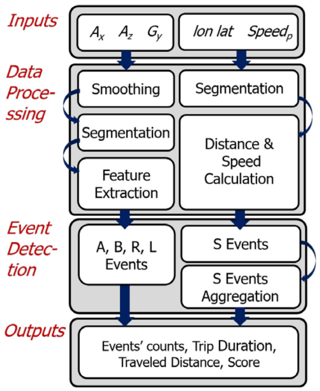

Figure 3: Overview of the detection method.

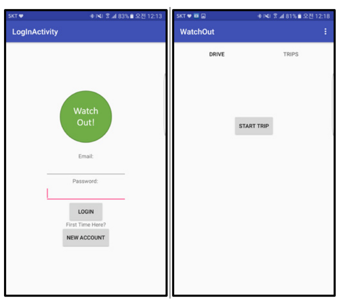

Figure 4: Interface of WatchOut mobile app

Window size	Predicted	Ground truth label N	A	B	R	L	Precision (%)	Recall (%)	Accuracy (%)
10 sec	N	6	0	0	0	0	100	75	92
	A	2	6	0	0	0	75	100	
	B	0	0	4	0	0	100	100	
	R	0	0	0	4	0	100	100	
	L	0	0	0	0	4	100	100	

Table 3: The accuracy of dangerous behavior detection for A, B, R, L events with respect to the window size.

After counting the total number of events, three points were subtracted from a total of 100 points for each bad driving behavior. The screen view of the driver's counted point and the overview of our detection method are illustrated in Figures 2 and 3.

We compared the accuracy of detection based on different window sizes including 5, 10, and 20 (2.5, 5 and 10 seconds), which varied according to the minimum and maximum event length from our ground truth data. The minimum event length was associated to some acceleration events and the maximum length was observed for braking and turnings. The detection algorithm achieved higher accuracy in terms of precision and recall as the window size became closer to the maximum event length. The accuracy for 5, 10, and 20 window size was 67, 74, and 92%, respectively, which is defined as the portion of correctly detected events. The detailed accuracy results for 20 window sizes in terms of precision and recall and with respect to each event is shown in Table 3.

Experimental Design

We recruited eight teams for the experiment, each composed of a driver and one driver's supporting member to test the effects of social support. First, we recruited licensed drivers who own their car and drive every day. Then, every driver invited one intimate person to support the interventions. Generally, drivers do not want to make their intimate person worried (not wanting to discomfort other), so we limited the driver's supporter to their partner, family member, or very close friend. The participants (N= 16) were students and workers whose age ranged from teens to 50's. We included three married couples, two parent-child couples, one unmarried couple, one sibling couple, and one pair of friends. There were five male drivers and three female drivers, and the supporters consisted of seven women and one male participants. We conducted this field experiment from 7 to 11, December, 2016. All participants received $17 for participating.

After downloading the application, drivers created an account and activated the app by pressing the "Start Trip" button before each trip. The interface of the WatchOut mobile app is shown in Figure 4. The app measured unsafe driving behaviors and provided the visualized information for the driver. When a driver finished their trip successfully, the driver's last trip record was saved in the "Trips" tab. Every driver received a score on a scale from 0 to 100. The score started at 100 points and three points are subtracted per one bad behavior. In addition, the app counted each unsafe driving behavior and indicated how many mistakes the driver made.

The driver's behavior and performance were shared with their supporters through the WatchOut app. Supporters used the same account as the driver, and all of the driver's trip history was always available when the supporter wanted to review it. To protect the driver's personal privacy, the app did not provide information about the driver's route to their supporters. Every evening, we sent a text message to the supporters to remind them to checked the driver's visualized driving records for the day and provide daily feedback to the driver. Caring members shared their

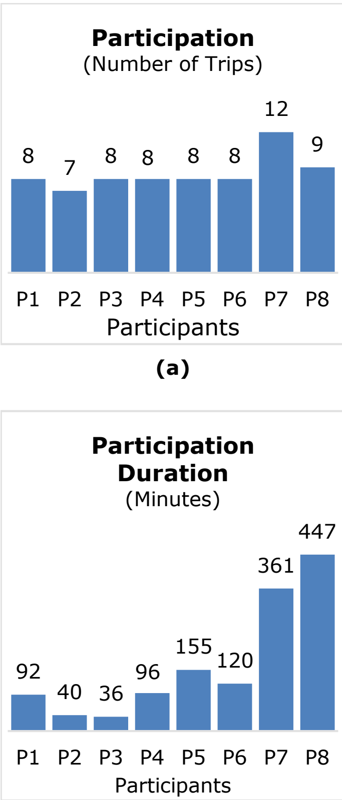

Figure 5: The amount of driver (Pi) participation in the experiment based on the number of their trips (a) and the total duration of driving (b).

feelings and concerns about the driving behaviors to the drivers via direct face-to-face interaction or via media such as mobile chatting service. After the experiment, we performed a survey and interview to evaluate the feasibility of our approach using the WatchOut app and explored further implications.

Evaluation

Participants used our prototype app for four days. To better compare the participants based on their driving behaviors, we accumulated their behaviors' counts separated by the driving behavior types. The values were normalized based on the time traveled. Another visualization was normalization based on the distance traveled.

Participants were asked to respond to the statement using a six-point Likert scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree). The four major factors we asked drivers include pervious knowledge of their own driving habits, increased awareness of their own driving behavior after using the app, the role of supporter's interventions for driving safer, and the effectiveness of our app in providing feedback. The factors we asked supporters include the impact of their feedback on drivers before this experiment, and the effect of our app on providing feedbacks to the drivers. We also asked about the satisfaction of the information that the WatchOut app provided and the additional features that they would like us to add in the future.

Result

Figure 5 illustrates each driver's amount of participation in the experiment, in terms of the number of trips each participant traveled and the total participation time. The participants' average occurrences of dangerous behaviors per trip is shown in Figure 6.

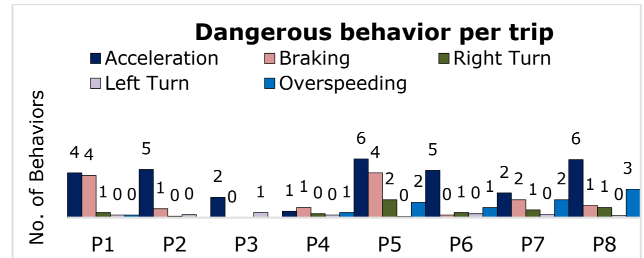

Figure 6: Average dangerous behavior occurrences per trip for each driver

Sudden acceleration is the most frequent behavior among participants, followed by sudden braking.

Social Reinforcement in Driving Behavior

From this experiment, we found that the scored objective feedback provided by WatchOut and by the driver's supporters let the driver know more about their driving habits; it helped to positively change driving behaviors. The agreement score provided by the drivers was 4.75 (SD=1.28), indicating that the Wachout app allowed them to better understand their driving habits. The average score for the questions that referred to self-recognition about driving behaviors and how the app helped them to drive more safely was 4.63 (SD=1.5).

Regarding the drivers' opinions about their supporters' role, drivers agreed that the supporters became aware of the driver's behaviors and that in turn affected their driving. One driver responded, *"I was concerned that somebody might know about my bad habits. Because of that I was driving more carefully."* (P7) Driver's agreement score about a related question also was 4.25 (SD= 1.28).

Driver's satisfaction was 4.25 (SD=1.28) regarding the feedback they received from supporters based on WatchOut. Driver agreed that the objective feedback from supporters helped them drive more safely. One driver mentioned that *"During driving, I was concerned about the feedback that I had received the day before*." (P3)

Supporters also generally disagreed (M=2.62, SD=1.18) that the feedback they gave to the driver before the experiment was effective; however, with the information that WatchOut provided, they agreed (M=4.75, SD=0.46) that they could provide the driver with more objective and effective feedback than before.

Social Face in Driving Behavior

We have found that not only does social reinforcement influence drivers, but also their social face is important in keeping good driving behaviors. According to Erving [3], the face is a mask that changes depending on the audience and the variety of social interactions. Social faces are emotionally attached to people. Thus, people try to maintain their social face and are afraid of losing it [3]. In this context, driver's hope to look good to their closest person and to be regarded as a responsible person. A driver who is member of a parent-child pair said *"I tried to drive very carefully because I wanted to set a good example for my child."* (P6) A driver in a couple said*, "If I get a low score, I prove that I am driving badly to my wife, so I tried to drive more safely.*" (P4)

Discussion and Future Work

During the participant's interview, we found that the scoring itself motivated drivers to better behave due to self-regulation and to gamification effect to some event. Even though gamification was not one of our study aspects of behavior regulation, it turned out to be another useful mechanism to consider. One driver said, *"During the experiment I felt driving was like a kind of game. I set the goals such as 'make all 0's' or 'Let's minimize a* sudden turn.' This made my driving more careful." (P4)

Because of the short duration of the experiment, we could not precisely determine whether WatchOut really changed their driving behaviors. Instead, our study showed that social factors can possibly change driving behaviors. Future research will need to cover a longer period to examine lasting behavioral changes.

Several new features can enhance the effectiveness of driving behavioral change. Participants pointed out "locating behavior occurrences on the map" and "measuring other bad driving behaviors, such as sudden lane changes and smart phone usage while driving" as important. Reflecting this feedback, we will design better features for the next study. In addition, privacy protection should be considered in the future app. For example, insurance companies might demand to see previous driving behaviors or want to monitor in order to adjust insurance premiums. To protect personal, sensitive information, a privacy mechanism is needed.

Finally, in this study we examined only the driver's behavioral change in a driver-supporter pair relationship. Future work, may compare the pair group with the driver group without social reinforcement. Moreover, future work may investigate the outcome's dependence on the relationship between driver-supporter and the power relationship between the two partners.

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