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Effect Evaluation of Forward Collision Warning System Using IoT Log and Virtual Driving Simulation Data

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Abstract: Advanced driver-assistance systems (ADAS) are primarily known for their positive impact in improving the safety of drivers. Previous studies primarily analyzed the positive effects of ADAS with short-term experiments and accident data without considering the long-term changes in drivers' safety perception. The human factor is the most dominant among factors that cause traffic accidents, and safety effect evaluation should be performed considering changes in human errors. To this end, this study classified the safety effect of ADAS-forward collision warning (FCW) on taxi drivers in Seoul into behavioral control and attitude change to perform analysis on respective factors. With regard to behavioral control, virtual driving simulation was used to analyze the reaction time of drivers and deceleration rate, and for attitude change, autoregressive integrated moving average (ARIMA) time series analysis was employed to predict the long-term perception change of drivers. The analysis results indicated that, in terms of behavioral control, ADAS-FCW reduces the cognitive reaction time of drivers in risk situations on the road, similar to the findings in previous studies. However, in terms of attitude change, ADAS-FCW has the adverse long-term effect of increasing violations in maintaining safety distance in the case of nighttime-drivers under 60 years old. As can be seen from these results, new technologies in the road safety arena can have a short-term effect of improving safety with behavioral control but may have a negative impact in the long term. The results of this study are expected to provide a theoretical basis for reference in the safety evaluation of ADAS and traffic safety facilities.

Keywords: ADAS; IoT platform; dangerous driving behaviors; autoregressive integrated moving average (ARIMA); safety effect estimation

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1. Introduction

Road traffic accidents are events that arise from complex factors, and causes can be classified into human factors, vehicle factors, and road environment factors [1]. The human factor accounts for the largest share among the factors of traffic accidents. With advancements in road design engineering and automotive engineering, traffic accidents caused by road environment factors and vehicle factors have been decreasing, whereas accidents caused by human errors do not show such a decreasing trend. Traffic accidents involving human factors in South Korea accounted for 97.4% of cases in 2019, an increase from 95.9% in 1996 [2]. One of the reasons for the minimal change in the number of accidents caused by human errors is the decrease in the physical abilities of older drivers following the increase in the elderly population [3]. However, we address these issues in the context of naturalistic challenges on the road.

A leading cause of road accidents related to human error is driver distraction. With the increasing use of cell phones, most drivers use cell phone applications while driving. Cell phone applications in the 21st century provide drivers with positive functions such as route setting and forward traffic information, but they have also been found to have the negative effect of distracting attention, such as in the case of using a cell phone and listening to music while driving [4–6].

Since 2010, there has been another change in the driving environment—vehicles started being equipped with advanced driver-assistance systems (ADAS) to support drivers while driving. ADAS technology was developed to improve the safety and convenience of drivers, starting with the commercial deployment of forward collision warning (FCW) and lane departure warning (LDW) systems.

In the past, methods of improving drivers' safety included improvement of road safety features or developing and implementing training programs for drivers. However, the introduction of ADAS has emerged as a new way of improving drivers' safety, and various types of ADAS have been developed with the increasing rate of ADAS use in vehicles.

Among these different types of ADAS, FCW was the first to be deployed. FCW provides drivers with a warning via sound and vibration before a collision with a vehicle or a pedestrian, and collision risk information is presented mainly through sound in South Korea, the warning time is 2.5 s before the collision). Thus, the positive function of the technology fitting to the development intention of FCW was the prevention of rear-end crashes. The results of traffic accident data analysis in the United States indicated that road accidents were reduced by up to 12% with FCW installation [7]. Additionally, estimation of the avoidance time of drivers by reproducing the crash situation on test tracks with FCW installation pointed to an instant decrease of 14.3% in rear-end crashes [8].

These positive functions of FCW have led South Korea to mandate the installation of FCW for commercial vehicles since 2018. However, unfortunately, there was no decrease in traffic accidents of commercial vehicles. The reason for no decrease in the number of accidents despite the introduction of new safety technology may be the adverse function of human factors following the adoption of the technology. In a survey of drivers of vehicles fitted with ADAS including FCW, it was found that owing to reduced physical requirements during driving with ADAS installation, drivers paid less attention while driving [9].

Through various long-term studies, it was found that, unlike the case of road safety features in which the effects apply to nonspecific multitudes of drivers passing through a specific point and where only the positive functions of reducing traffic accidents are presented [10–12], ADAS differed in terms of the method and scope of its impact on drivers, as outlined in Table 1.

Table 1. Differences between conventional road environment improvements and ADAS on road safety.

Classification	Road Environment Improvement	ADAS Effect
Target	Stationary	Dynamic
Effect	Behavioral control	Behavioral control and perception change
Method	Affect all vehicles passing the point of improvement	Installed in a vehicle to affect a single driver

ADAS is installed in vehicles to enable quick detection of dangerous situations for a single driver and supports vehicle control to avoid accidents. In the long run, it may not provide only the positive functions of reducing traffic accidents to drivers and may have different effects depending on the characteristics of drivers. For further development of ADAS technology, it is necessary to evaluate the effect of ADAS on drivers' routine driving behavior in the long term as well as the short-term impacts.

In this paper, FCW, the system with the highest use among ADAS, was used as a target technology, its safety effect was comprehensively evaluated from various perspectives, and an evaluation methodology for new ADAS technology is presented.

2. Classification of Effects Depending on FCW Installation Based on TPB

Before analyzing the short-term and long-term effects of FCW installation, a theoretical look at the human factors is necessary. Although human behavior can be attributed to various causes, it can be classified into three types according to the theory of planned behavior

(TPB) [13]. As shown in Figure 1, a person's behavior is determined by the combined actions of attitude, norm, and behavioral control factors. In the field of transportation, a driver's attitude is influenced by perceptions such as habits and education [14,15], and behavioral control is changed by facilities such as speed bumps, equipment, and devices [16]. The norm is affected by laws, regulations, and deterrence [17].

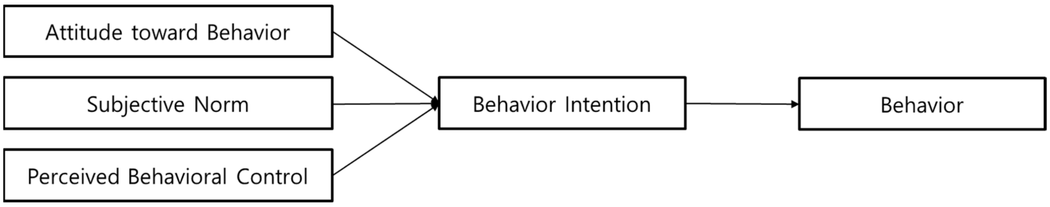


Figure 1. The theory of planned behavior (TPB).

Warning of collision risk by FCW is included in behavioral control and can be classified as a short-term effect on a dangerous situation on the road. As shown in Table 2, changes in drivers' habits due to FCW installation can be classified as long-term effects on attitude changes, and because FCW installation is not related to laws, regulations, and deterrence, the norm is excluded from the classification.

Table 2. Classification of ADAS effect by theory of planned behavior (TPB) factor.

TPB Factors	ADAS Effect	Range of Effect
Attitude Toward Behavior (*ATB*)	Driving habits, perception	Persistent, long-term
Subjective Norm (*SN*)	-	
Perceived Behavioral Control (*PBC*)	Vehicle control under dangerous situations	Instant, short-term

As shown in Equation (1), behavior occurs with combined effects from the respective factors of *ATB*, *SN*, and *PBC*.

$$B_i = ATB_i + SN_i + PBC_i \tag{1}$$

where,

B_i: performing a specific behavior i
ATB_i: attitude or perception toward a specific behavior i
SN_i: subjective norm for a specific behavior i
PBC: behavioral control for a specific behavior i

In this study, there was no effect of FCW on the subjective norm, and FCW only affected the attitude toward behavior and perceived behavioral control. Because *ATB* and *PBC* have different and independent influence ranges, only the participants (analyzed subjects) were matched, and the analysis methods and analysis items were independently applied.

As shown in Table 3, *PBC* analysis involved a front-end collision scenario through driving simulation and analyzed the instantaneous effect at a critical moment. *PBC* analysis allowed us to analyze the effect of reducing cognitive response time, which is the positive function of FCW.

The *ATB* analysis aggregated the number of FCW alerts per day using IoT devices mounted on vehicles. Through this, you could check the change in driving behavior after installing FCW. Through *ATB* analysis, it was possible to quantitatively analyze the adverse effects of FCW in terms of human factors, such as attention decline and changes in driving habits.

Table 3. Analysis contents and data for each TPB factor.

TPB Factors	Analysis Contents	Measure of Effectiveness	Analysis Data
PBC	Estimation of instantaneous effects in collision risk situations using virtual simulation	Cognitive reaction time, deceleration, collision	Four scenario driving results for each participant (total of 70 people)
ATB	Estimation of the number of changes in dangerous driving behaviors	Number of forward collision warnings	Daily IoT log data from September 2017–August 2018 (for forecasting) Annual log statistical data from September 2018–August 2020 (for verification)

3. *PBC* Analysis Method and Result

3.1. Reasons for Analysis Using Virtual Driving Simulation

To analyze the effect of FCW on vehicle control for the driver during at-risk situations, an experiment was conducted using a driving simulator. Virtual driving simulation is a preferred means in empirical studies in transportation research because it can reproduce a situation according to the design of the researchers and can prevent safety accidents that may arise from real-world experimentation.

Virtual driving simulations have been used in previous studies on smartphone-based ADAS effect [18] and comparisons before and after ADAS installation [19–21]. For *PBC* analysis, the experimental results from the cases of previous studies can be referred to, but in this study, for comprehensive evaluation of the effect of FCW by using the same analysis targets for *ATB* and *PBC*, and to reflect the characteristics in the driving of Korean drivers, the experiment was performed using virtual driving simulation.

3.2. Equipment Used for Virtual Driving Simulation Experiment

The hardware used in the experiment was I-drive 3ch., 2DOF MP, as shown in Figure 2. It is composed of a personal computer-based image generator (PCIG), 32-inch 3-channel LCD monitor, 1/4 vehicle shape cabin with 100% real vehicle parts, control force and loading system (CFLS), and active steering wheel system (ASWS) logic. The software used was Uc-Win/Road Ver. 13.0, and analysis was performed by saving basic data (e.g., driving speed, driving time, collision status, mileage, and driving coordinates of drivers participating in the experiment) at 0.02-s intervals.

Figure 2. Driving Simulator used in the experiment.

3.3. Scenario Design

The experimental scenario was designed for independent effect analysis for each element. The selected effect measures for effect analysis of FCW were as follows: cognitive reaction time (s), deceleration from the start of the breaking until the end of breaking (m/s^2), and number of collisions with the front vehicle (times) as shown in Figure 3.

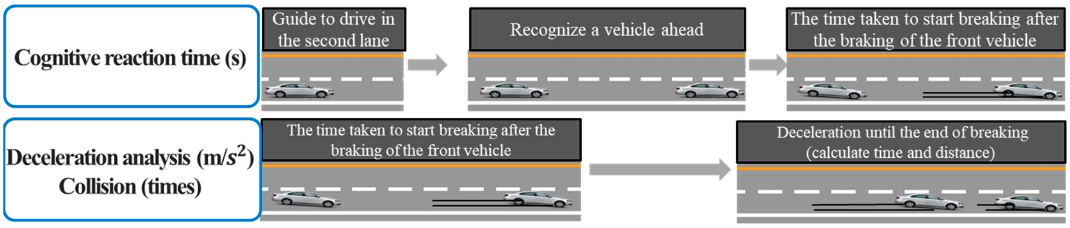


Figure 3. The measure of effectiveness of *PBC* analysis.

At the start of the scenario, the study participants drove on a road with a speed limit of 50 km/h, and the driving lane was maintained on the second lane. The reason why the speed limit was selected as 50 km/h was to be the same as the speed limit on the roads in Seoul where the study participants normally drive. The Seoul Metropolitan Government has implemented the "Safety Speed 5030" that sets the speed limit for roads in the city to 50 km/h for main and auxiliary arterial roads and 30 km/h for collector roads.

As shown in Figure 4 below, when the distance between the unexpected vehicle and the participant's vehicle becomes 100 m, the unexpected vehicle changes lanes from the first lane to the second lane (Step 1). The unexpected vehicle accelerates slowly at 0.41 m/s^2 until it reaches a safe distance of 50 m after 15 s of the lane change. After completion of acceleration there is a hold time of 5 s (Step 2). The safety distance of 50 m was calculated based on the driver's cognitive reaction time. For the cognitive response time, the 85th percentile driver value of 2.5 s is applied, but in an unexpected event, the cognitive response time increases by 35% [22]. By applying a cognitive reaction time of 3.5 s, a safe distance of 50 m at a driving speed of 50 km/h was set. As the length of the safety distance increases, the number of collisions decreases. If the safety distance is short, unnecessary deceleration of the driver occurs before an unexpected situation occurs, which may affect the overall experimental results (cognitive reaction time, deceleration, number of collisions). The safety distance was selected with a leisurely 50 m based on the 85th percentile driver value.

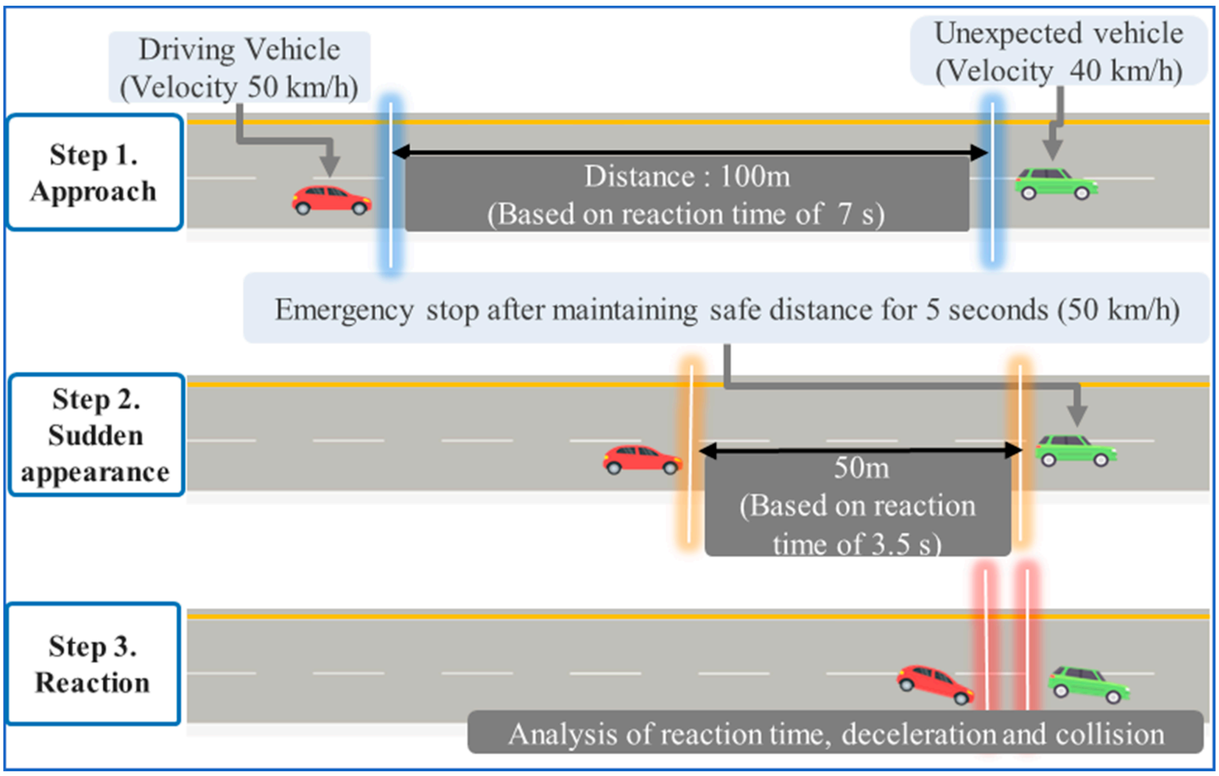


Figure 4. Driving simulation scenario.

The unexpected vehicle performs an emergency stop, and the participant's cognitive reaction time, deceleration, and collision status were analyzed at the emergency stop of the unexpected vehicle (Step 3). Scenarios were divided into day/night, and a total of 4 experiments were conducted per study participant when FCW was installed and when FCW was not installed. Weather conditions were based on sunny days, and environmental variables that could affect driving such as weather conditions and road pavement were not considered.

3.4. Study Participants

The drivers who participated in the experiment were 70 taxi drivers from Seoul who had installed and used FCW since 2017. They were affiliated with a taxi business corporation in Seoul and worked in alternating shifts of daytime (06:00–18:00) and nighttime (18:00–06:00). The *PBC* analysis participants were the same as those of the *ATB* analysis.

As shown in Table 4, in terms of the usual working hours, the study participants comprised 37 daytime drivers and 33 nighttime drivers. In terms of age, there were 30 drivers aged 60 or above and 40 drivers aged under 60. A total of 70 study participants participated in all 4 *PBC* experiment scenarios.

Table 4. Descriptive statistics of study participants' age and working hours.

Age Range of Participants	Daytime Drivers		Nighttime Drivers	
	No.	Percentage (%)	No.	Percentage (%)
Thirties	2	5.4	4	12.1
Forties	5	13.5	9	27.3
Fifties	12	32.4	8	24.2
Sixties	18	48.6	12	36.4
Sum	37	100.0	33	100.0

3.5. Results of PBC Effect Analysis in FCW Installation

3.5.1. Effect on Cognitive Reaction Time

Without FCW installation, in the rear-end crash scenario, the cognitive reaction time from the start of the scenario and deceleration was 1.66 s during daytime, as shown in Figure 5, but in the case with FCW installation, the reaction time decreased to 1.46 s. In the case of nighttime, the reaction time also decreased from 1.95 s without FCW installation to 1.66 s with FCW installation. This confirms that FCW sends the stimuli to the driver in advance in case of a dangerous situation, which leads to a faster cognitive reaction time. As for comparisons between drivers aged under 60 and drivers aged 60 or above, the default (without FCW installation) cognitive reaction time of drivers aged under 60 was shorter than that of drivers aged 60 or above. With FCW installation, the cognitive reaction time decreased by 14.5% during daytime and by 17.5% during nighttime for drivers aged 60 or above, showing a larger decrease than that of drivers aged under 60, whose cognitive reaction time was reduced by 10.4% during daytime and by 13.3% during nighttime. The sample size was 70, and the variances were analyzed as 0.35, 0.27, 0.33, and 0.25 for each scenario.

In terms of the statistical test, as shown in Table 5, for both types of normality verification (Shapiro–Wilk and Kolmogorov–Smirnov tests), the *p*-values (significance probability), the test statistic, were below 0.05. The *p*-value of the corresponding samples for the difference between with and without FCW installation was 0.00, indicating that the effect of reduced cognitive reaction time was achieved owing to FCW installation for both daytime and nighttime.

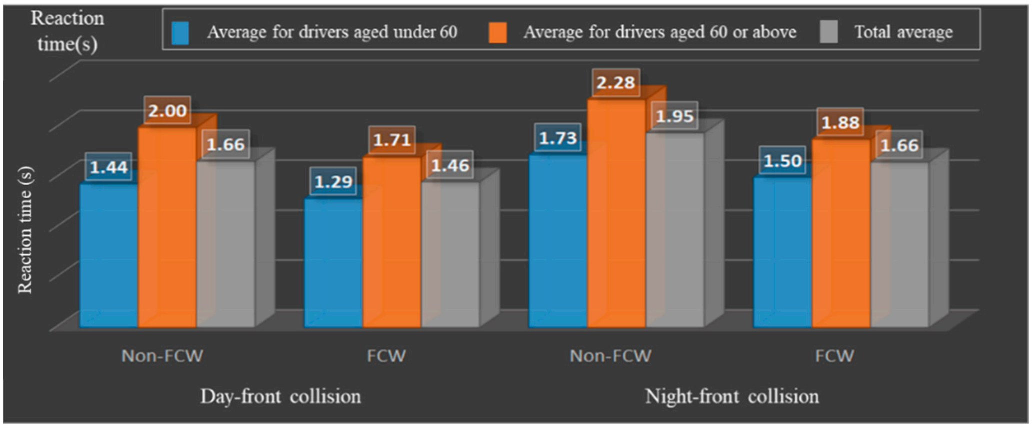


Figure 5. Cognitive reaction time values before and after the installation of the FCW system.

Table 5. Result of reaction time(s).

Classification		Daytime		Nighttime	
		Non-FCW	FCW	Non-FCW	FCW
Degree of freedom		69	69	69	69
Sample mean		1.66	1.46	1.95	1.66
95% confidence interval of mean	Lower limit	1.58	1.39	1.87	1.60
	Upper limit	1.75	1.52	2.03	1.72
Median		1.73	1.51	1.97	1.66
Variance		0.12	0.07	0.11	0.06
Standard Deviation		0.35	0.27	0.33	0.25
Normality verification	Shapiro-Wilk p-value	0.001	0.020	0.002	0.008
	Kolmogorov-Smirnov p-value	0.001	0.097	0.010	0.058
Correspondence sample t-test p-value		0.000		0.000	

3.5.2. Effect on Deceleration

As shown in Figure 6, the mean value of deceleration was 5.05 m/s^2 for daytime and 5.15 m/s^2 for nighttime without FCW installation. When FCW was installed, the mean deceleration was 4.76 m/s^2 for daytime and 4.68 m/s^2 for nighttime, indicating a decrease in deceleration by 5.7% and 9.1%, respectively. The decrease at nighttime was larger than that of daytime and, in particular, the decrease of drivers aged 60 or above at nighttime was the largest at 10.2%. This is correlated with the cognitive reaction time, and it can be judged that because the cognitive reaction time was reduced, the time margin up to the time of collision also increased, which also affected deceleration. The sample size was 70, and the variances were analyzed as 0.26, 0.27, 0.30, and 0.27 for each scenario.

In the statistical test, as shown in Table 6, the effect of reduced deceleration with FCW installation was observed both in the daytime and nighttime.

3.5.3. Number of Collisions

Considering the cognitive reaction time and deceleration of the driving simulation scenario, when the distance to the front vehicle is analyzed from the start of the scenario with a timetable, as shown in Figure 7, the distance to the front unexpected vehicle continues to decrease up to the point of the perception of a dangerous situation (cognitive reaction time), and the vehicle brakes after the perception of the dangerous situation. In the case without FCW installation at nighttime, one event of collision occurred, but after FCW installation, no events of collision occurred. After FCW installation, the safety distance from the front of the vehicle increased during both daytime and nighttime, confirming highly effective accident prevention due to FCW installation.

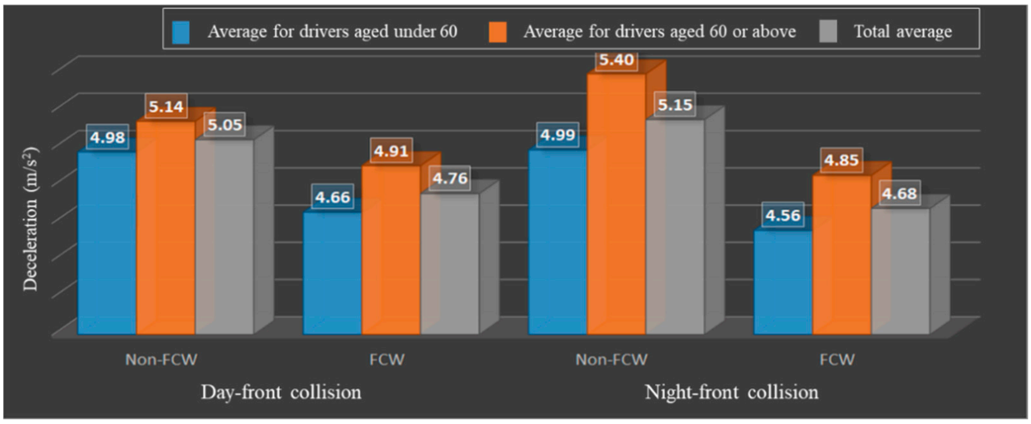
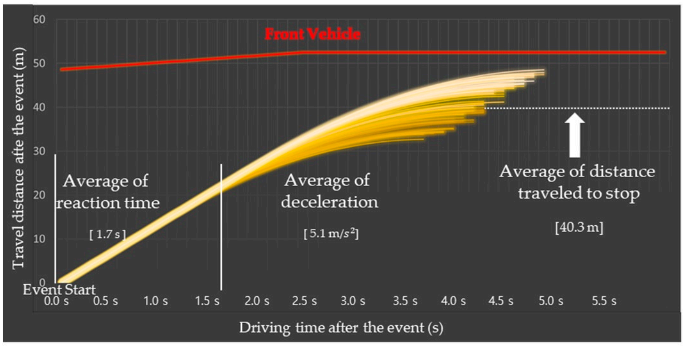


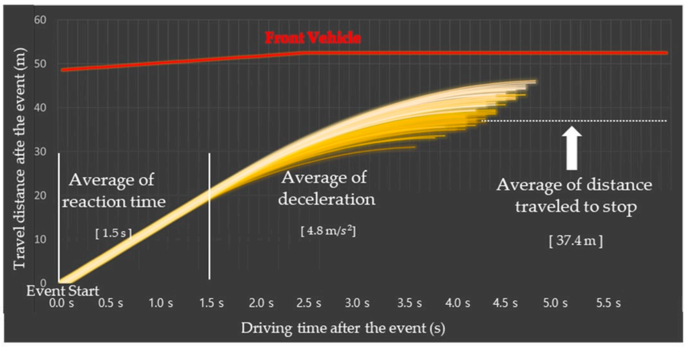
Figure 6. Deceleration values (m/s^2) in a dangerous situation before and after installation of the FCW system.

Table 6. Result of Deceleration (m/s^2).

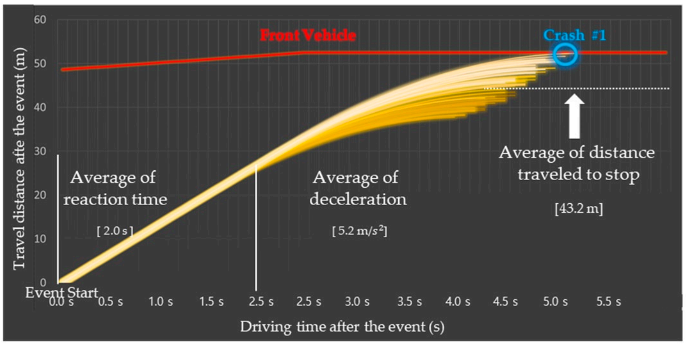
Classification		Daytime Non-FCW	Daytime FCW	Nighttime Non-FCW	Nighttime FCW
Degree of freedom		69	69	69	69
Sample mean		5.05	4.76	5.15	4.68
95% confidence interval of mean	Lower limit	4.98	4.69	5.08	4.61
	Upper limit	5.11	4.82	5.23	4.74
Median		5.07	4.72	5.13	4.67
Variance		0.07	0.07	0.09	0.07
Standard Deviation		0.26	0.27	0.30	0.27
Normality verification	Shapiro-Wilk *p*-value	0.014	0.139	0.013	0.185
	Kolmogorov-Smirnov *p*-value	0.043	0.189	0.040	0.200
Correspondence sample *t*-test *p*-value		0.000		0.000	



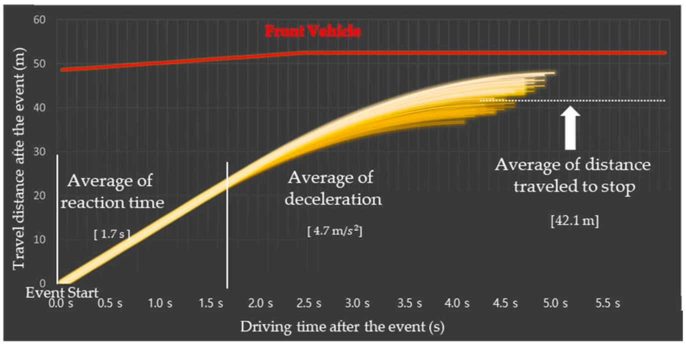
(a) Result of senario 1 : Driving without FCW at daytime



(b) Result of senario 2 : Driving with FCW at daytime



(c) Result of senario 3 : Driving without FCW at nighttime



(d) Result of senario 4 : Driving with FCW at nighttime

Figure 7. Vehicle travel distance and collision status after the event.

4. *ATB* Analysis Method and Result

4.1. Reasons for Time Series Analysis of IoT LOG Data

Previous studies on *ATB* analysis mainly relied on surveys [14,15], but owing to the development of IoT technology, driver behaviors can be tracked in real time, enabling the acquisition of more accurate results. In this study, based on IoT log data, time series analysis was implemented to investigate *ATB* according to FCW installation status.

With regard to IoT log data, ADAS-FCW had been installed in the vehicles of the taxi drivers who participated in the *PBC* analysis since 2017, as shown in Figure 8, and information on the collision risk with the front of the vehicle was continuously recorded. The recorded information was transmitted to the IoT platform in real time.

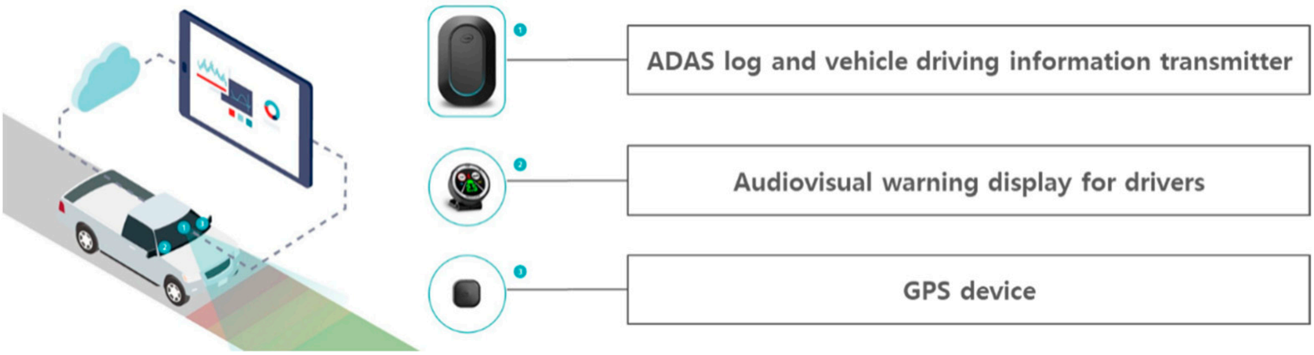


Figure 8. ADAS-FCW data on dangerous driving behaviors.

Prior to analyzing the collision risk information collected as above for one year, it was necessary to understand the characteristics of drivers' perceptions and behavioral changes. Factors that affect drivers' perceptions, such as education, do not have a persistent effect of changing the behaviors of drivers but require periodic training and stimulation [23]. This is because the effect returns to a certain value after a certain time [24].

The IoT log data collected in this study were also collected over a limited period of one year, so prediction of the future behavioral changes was required. The estimate techniques included linear and non-linear regression, historical average algorithms [25], smoothing techniques [26,27], and autoregressive linear processes [28–32]. It has been reported that a time series analysis-based technique such as autoregressive integrated moving average (ARIMA) is one of the most precise methods for the prediction of driving behaviors compared to the other available techniques mentioned above [33,34]. Therefore, time series analysis using the ARIMA model was performed for analysis of the effect of FCW on *ATB*.

4.2. Data and Classification

For the collection of IoT log data, information on vehicle number, time, speed, GPS coordinates (X,Y), ADAS code, and shift time were collected, as outlined in Table 7, and information was tabulated on a daily basis for each driver.

The data collection period was September 2017–August 2018 (1 year), and the 70 *PBC* study participants were divided into 4 groups, as shown in Table 8. The number of participants in each group was allocated according to their actual age and working hours.

Table 7. Sample of IoT log data.

ID	Vehicle Number	Corporation	Date	Time	GPS X Coordinate	GPS Y Coordinate	ADAS_CODE	Speed	Shift
A-2509437	6831	A-Sang	20180410	5347	37.65004	127.0555	Forward Collision Warning	90	Night
A-2509438	6831	A-Sang	20180410	5356	37.65187	127.0552	Right-lane departure	85	Night
A-2509440	6831	A-Sang	20180410	10,007	37.65899	127.0532	Collision Warning	65	Night
A-2509441	6831	A-Sang	20180410	10,045	37.65179	127.0553	Left-lane departure	83	Night
A-2512363	6831	A-Sang	20180427	35,436	37.65553	127.0549	Forward Collision Warning	96	Night
A-2512365	6831	A-Sang	20180427	35,728	37.66279	127.0449	Right-lane departure	76	Night
A-2518297	6836	A-Sang	20180414	224,138	37.63483	127.024	Pedestrian collision warning	10	Night

Table 8. Working hours and number of people in the *ATB* analytics group.

Group	Working Hours	No. of Participants
Daytime drivers aged under 60	06:00~18:00	19
Daytime drivers aged 60 or above	18:00~06:00	18
Nighttime drivers aged under 60	06:00~18:00	21
Nighttime drivers aged 60 or above	18:00~06:00	12
Sum		70

4.3. Model Development

4.3.1. Model Development Process

The ARIMA model was used for analysis and prediction of the univariate time series data of *ATB* with uniform interval.

$$W_t = \mu + \frac{\theta(B)}{\varphi(B)} a_t$$

where,

t: the indexes time
W_t: the response series
μ: the mean term
$\varphi(B)$: the autoregressive operator
$\theta(B)$: the moving average operator
a_t: the independent disturbance

The analysis was performed in three stages. In the first stage, the identification stage, the stationary status of the time series data was confirmed, and all four groups (daytime drivers aged under 60, daytime drivers aged 60 or above, nighttime drivers aged under 60, and nighttime drivers aged 60 or above) were fixed in the first differences (stationary). One or more models were tentatively selected using data on the occurrence of a dangerous event while driving for the period of one year. Accurate estimates of the parameters of the models were then obtained with the least-squares method.

Second, the ARIMA model was applied on the estimation stage and the accuracy of the model was tested based on diagnostic statistics. The optimal model was selected based on the following diagnosis.

(i) Low Akaike information criteria (AIC). AIC is estimated by AIC = (−2log L + 2(p + q), where "p" is the autoregressive parameter and "q" is the moving average parameter. "L" is the likelihood function.
(ii) Insignificance of autocorrelations for residuals. If a model is an adequate representation of a time series, it should capture all the correlations in the series, and the white noise residuals should be independent of each other.
(iii) Significance of the parameters. Significance tests for parameter estimates indicate whether some terms in the model might be unnecessary.

Third, in the forecasting stage, future values of the time series after one year were forecasted.

4.3.2. Model Evaluation

The mean absolute percent error (MAPE), as defined below, was used as a measure of the accuracy of the models:

$$\text{MAPE} = 100 \times \left(\frac{\sum_{i=1}^{n} (|Y_F - Y|/Y)}{n} \right)$$

Y_F: forecasted variable
Y: actual variable
n: number of variables

SAS 9.4 software (SAS Institute, Inc.) was used for time series analysis and developing ARIMA models and forecasting.

4.3.3. Building ARIMA Models

The "p" and "q" parameters were identified based on the significant spikes in the plots of the partial autocorrelation function (PACF) and the autocorrelation function (ACF) of the different time series. While identifying the best fit ARIMA models, appropriate values of "p" and "q" were chosen corresponding to a minimum value of the selection criterion, that is, AIC and Schwarz–Bayesian information criteria (SBC). The results are shown in Table 9.

Table 9. Optimized ARIMA model by driver group.

Parameters	ARIMA Model	AIC	SBC
Daytime drivers aged under 60	(1,1,1)	346.6	356.3
Daytime drivers aged 60 or above	(1,0,1)	144.3	154.2
Nighttime drivers aged under 60	(1,1,1)	279.2	287.1
Nighttime drivers aged 60 or above	(1,1,0)	317.2	331.8

4.4. Results of ATB *Effect Analysis in FCW Installation*

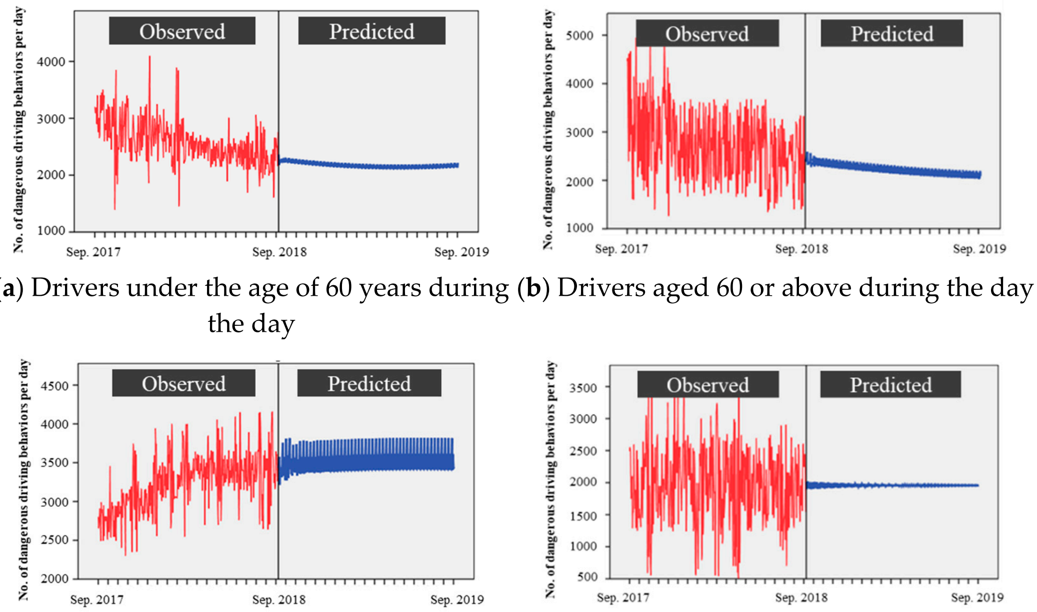
As shown in Table 10, the daily average number of front collision warnings changed differently depending on the driver group after FCW was installed for driving. In the case of the daytime drivers aged under 60 and daytime drivers aged 60 or above groups, a decrease in the number of warnings was observed over the long term. Conversely, in the case of the nighttime drivers aged under 60 group, the number of warnings actually increased over the long term, and there was no change in the nighttime drivers aged 60 or above group.

To verify the accuracy of the model, the actual value of the average number of forward collision warnings for each period September 2017–August 2018, September 2018–August 2019, and September 2019–August 2020 was compared with the predicted value. As a result of verification, there was an error within ±5%, and the MAPE value was analyzed to be less than 5.41.

The predicted daily number of forward collision warnings is shown as a graph in Figure 9. As with the change in the average value per period, it can be seen that warnings to the drivers under the age of 60 at night continued to increase.

Table 10. Results of prediction of changes by driver group.

Parameters	Period	Actual Values	Forecasted Values	Error in Prediction	MAPE
Daytime drivers aged under 60	September 2017–August 2018	2794	2884	3.1%	5.41
	September 2018–August 2019	2744	2738	−0.2%	
	September 2019–August 2020	2538	2435	−4.2%	
Daytime drivers aged 60 or above	September 2017–August 2018	2894	2950	1.9%	2.32
	September 2018–August 2019	2513	2481	−1.3%	
	September 2019–August 2020	2113	2013	−5.0%	
Nighttime drivers aged under 60	September 2017–August 2018	2864	2804	−2.1%	4.17
	September 2018–August 2019	3321	3379	1.7%	
	September 2019–August 2020	3499	3567	1.9%	
Nighttime drivers aged 60 or above	September 2017–August 2018	1943	1951	0.4%	2.99
	September 2018–August 2019	1991	2043	2.5%	
	September 2019–August 2020	1967	1997	1.5%	



(**a**) Drivers under the age of 60 years during the day (**b**) Drivers aged 60 or above during the day

(**c**) Drivers under the age of 60 years during the night (**d**) Drivers aged 60 or above during the night

Figure 9. Changes in dangerous driving behaviors after the installation of the FCW system.

5. Discussion

After FCW installation, there were positive effects in *PBC* and *ATB* in terms of safety on daytime drivers. However, for nighttime drivers aged under 60, their usual driving behavior changed with FCW installation, and the risk of traffic accidents increased over the long term.

Although FCW reduces the possibility of accidents in dangerous situations by affecting the *PBC* of drivers, in the long term it can affect the *ATB* and increase the risk of traffic accidents. This result can be interpreted that in the case of nighttime drivers, they tend to be overly reliant on FCW, which leads to an increase in their dangerous driving behaviors, and this situation requires additional countermeasures for improvement in the attitude and habits of nighttime drivers.

Distraction and inattention of drivers can be judged to have an impact on their safety, and the results of recent studies indicate that driver distraction has a more negative effect on safety than other factors such as alcoholism and fatigue [35,36]. In particular, in the case of young drivers, when driving for a long period, their attention is greatly reduced compared to that of older drivers, and the cause of this decreased attention is their confidence in driving ability [37]. As FCW improves the driving ability for each driver, it can actually have a detrimental effect on driver attention. In fact, in 2016, there was an accident that led to the death of a Tesla driver from a crash with a large trailer, due to ADAS sensor error, when the driver had the autonomous driving mode (ADAS highway autopilot function) on for driving. The driver in the accident was negligent of the driver's basic duty to safety while heavily relying on the vehicle function.

In comprehensive consideration of the study results and accident cases, ADAS including FCW can improve safety in situations of collisions by improving driving ability in direct aspects such as driver cognitive reaction time and steering ability. However, in the long run, ADAS may have a negative impact on the driving habits of drivers and cause accidents.

6. Conclusions and Outlook

The effect of FCW installation varies depending on driver-specific characteristics and, thus, in some cases FCW can actually have negative effects. Taking into account the ADAS functions suitable for each driver's driving ability and usual driving habits, considerations should be made on driver-specific safety support functions, ADAS training for improvement in driving habits, and additional safety devices.

In the *PBC* analysis of this study, environmental variables (weather conditions, road pavement conditions) that may affect the behavior of drivers were not reflected. There was a technical limitation in reflecting the conditions of rain and snow, which are highly likely to cause a traffic accident while driving, in the simulation without any difference from reality. In the future, it is necessary to conduct research that can optimize and apply weather conditions and road pavement conditions in simulations.

In the *ATB* analysis, due to the Personal Information Protection Act, only detailed IoT logs for one year could be used in this study, and only the average data for each period was available for the data for the next two years. In the future, if the scope of data utilization is expanded in research for public interest, detailed analysis will be possible.

Also, road information (road geometry, weather, pavement quality, road operation status) could not be reflected, owing to limitations in the data collection methods in this study. In South Korea, an IoT pavement quality management system (PQMS) platform is under development, as shown in Figure 10. This new PQMS platform will enable the collection of road information that could not be incorporated in this study. With the incorporation of road information collected through the developed platform in further studies, a high-quality effect evaluation will be achieved.

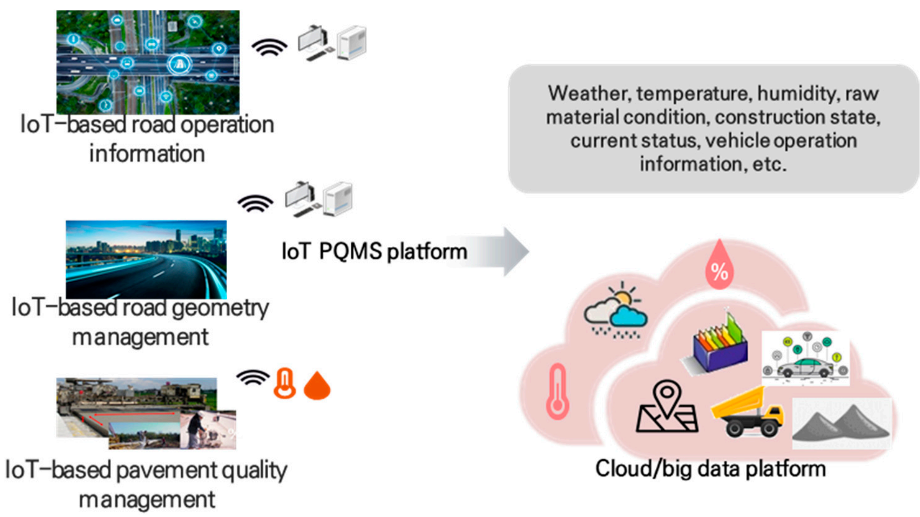


Figure 10. Data connection and analysis by using the IoT platform in fields ranging from road construction to operation.

The comprehensive evaluation method proposed in this study can change the evaluation method for newly developed technologies, thereby ensuring the effectiveness and safety of the research and development results of these techniques.

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