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A Study on Cognitive Error Validation for LED In-Ground Traffic Lights Using a Digital Twin and Virtual Environment

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Abstract: Traffic accident prevention is considered one of the most crucial public safety issues due to the ongoing rise in traffic accidents. The installation of LED in-ground traffic lights is one strategy that has proven to be quite effective in preventing numerous traffic accidents, notably pedestrian accidents. The traffic signal helps reduce accidents for pedestrians, but there is a drawback in that such installations may lead to cognitive errors, such as the driver making a mistaken start or stop. Therefore, it is crucial to validate cognitive errors in advance of the widespread adoption of LED in-ground traffic signals. To this end, in this study, we (i) built an experimental environment that can be employed for various traffic tests using digital twins and virtual simulators; (ii) designed test scenarios and measurement plans for validation to conduct a validation test, and (iii) demonstrated cognitive errors through data from various experiments. As a result, it was proven that there is a possibility that the LED in-ground traffic lights may cause cognitive errors for drivers, and the causes of this were analyzed. In the future, this framework can be used to demonstrate various transportation problems and can contribute to improving the quality of public safety.

Keywords: in-ground traffic lights; safety validation; digital twin; virtual traffic simulator

MSC: 00A72

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1. Introduction

With the continuous increase in traffic accidents, these incidents have emerged as an important public safety problem that must be addressed with a multidisciplinary approach [1]. In particular, countries without a strong capacity to address health care, economic, and social problems disproportionately bear the burden expected from this, indicating a need to address traffic accidents as a public health priority [2]. In line with this, various social, institutional, and technological efforts are being made at the national and local levels [3–7]. For example, awareness creation, the strict implementation of traffic rules, and scientific engineering measures to prevent traffic accidents require considerable amounts of time but are effective in preventing traffic accidents [1].

Among the various types of traffic accidents, the rate of pedestrian accidents is increasing due to the recent spread of smartphones and their increased use by people as they walk [8,9]. Accordingly, various studies have been conducted to prevent traffic accidents that involve pedestrians [10–14], and LED in-ground traffic lights are a representative example that have actually had a strong effect in preventing accidents [15]. As shown in Figure 1, LED in-ground traffic lights blink in conjunction with the traffic signal, increasing the visibility of general pedestrians and vulnerable road users on the crosswalk during the day and night [16]. In other words, by installing LEDs and communication modules on braille blocks previously existing on crosswalks and streets, these devices serve as a new pedestrian signal. They also, therefore, act as a psychological stop line for pedestrians and a clear boundary line for drivers, inducing slow driving and preventing traffic accidents by suppressing and preventing jaywalking caused by the use of smart phones when crossing. In addition, this method can serve as a multi-functional traffic signal assistant for the vulnerable transportation modes in school zones and silver zones. With their installation, the rate of traffic accidents has actually decreased significantly [17]. In a study [18] that focused on the repeated occurrence of similar traffic accidents in a specific area, LED in-ground traffic lights were installed in 22 places where pedestrian accidents were frequent and the effects and efficiency were analyzed. It was found that the occurrences before and after installation at the same location, the numbers of injuries, and the numbers of deaths decreased by 41.2%, 38.6%, and 55.1%, respectively, as shown in Figure 1. In particular, comparing nighttime traffic accidents with locations in which LED in-ground lights were not installed, the number of accidents decreased by 62.7% [18].

Figure 1. LED in-ground traffic lights and the effect of installing them [18].

Although the social value of preventing traffic accidents and improving public safety through the establishment of a healthy traffic culture is sufficient and there are also economic advantages, such as ease of installation/maintenance and low cost, there is one risk when installing these lights: cognitive errors, such as misstarts and misstops by drivers, may occur. As drivers are accustomed only to existing traffic lights, they may mistake in-ground lights for existing traffic lights at night. Therefore, it is necessary to evaluate and validate the occurrence frequency of and conditions associated with such errors; that is, the influence of the LED in-ground traffic lights on drivers' cognitive information changes and the correlation with cognitive errors should be analyzed to derive the cause of these errors.

2. Literary Review

In general, in order to establish, apply, and evaluate transport policies, field tests are conducted through pilot driving trials in actual environments with the control of external factors to improve the effectiveness of the policies [19,20]. However, given the various limitations in terms of time, cost, and laws when installing and evaluating LED in-ground traffic lights in actual road environments, it is necessary to evaluate and analyze them in a virtual environment [21]. To this end, we built a traffic digital twin model and a virtual environment with conditions identical to those of an actual road environment and analyzed whether cognitive errors occurred during test driving trials in this environment.

A digital twin is one of the key technologies of the fourth industrial revolution and refers to a digital replica that mimics a physical system as it is [22]. The digital twin can be useful for solving various problems in the real world; for instance, in making predictions, undertaking optimization, and augmenting policy establishment [23,24]. For example, by building a digital twin of traffic or of a smart city, traffic conditions such as traffic congestion or accidents can be predicted and traffic policies established [25–27]. In addition, the digital twin and virtual simulation environment can be interoperated and used for driver training and validation [28].

However, research on such digital twins has mainly focused on analyzing current situations and predicting the future after the building of a model using knowledge and actual data [29,30]. In addition, many studies using virtual simulators have been conducted, but they are mainly used for general purposes, such as games or simulators for driver training [31,32]. Also, depending on the purpose, the resolution of the models may be low or the elements of the real world abstracted. Accordingly, the reflection of the actual traffic situation may be insufficient [33]. However, in order to validate elements such as cognitive errors, it is essential to build a high-resolution digital twin model and a high-performance virtual simulation environment, as an environment similar to the actual driving environment is required.

Therefore, in this study, we built a digital twin model of an actual area where LED in-ground traffic lights are installed and a virtual environment similar to actual car driving conditions to assess possible cognitive errors. To this end, validation accuracy could be increased by building a high-resolution digital twin model identical to the real sites, providing diverse secure experimental groups, and configuring appropriate experimental scenarios. In addition, using the built virtual environment and scenarios, we analyzed whether cognitive errors among drivers occur due to LED in-ground traffic lights by conducting test drives. Specifically, we analyzed the influence on changes in the cognitive information of drivers in such environments and derived causes through a correlation analysis with cognitive errors. Figure 2 shows the overall research framework used for recognition error verification in this paper.

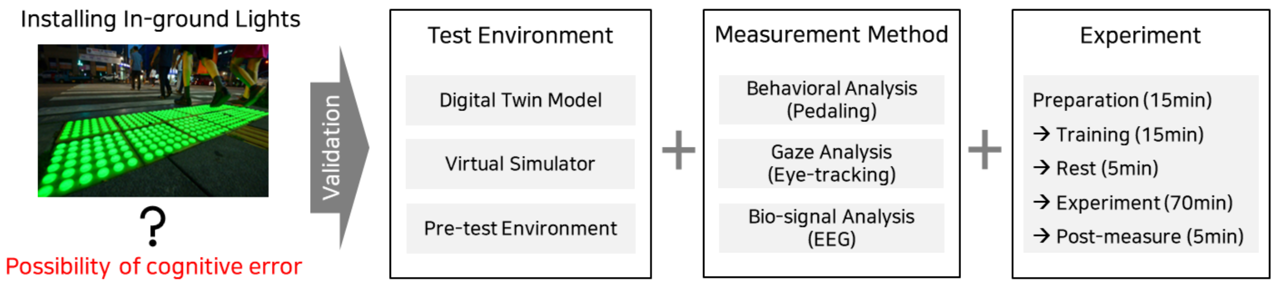


Figure 2. Overall research framework used for cognitive error validation in the paper.

The remainder of the paper is organized as follows. Section 3 describes the construction of the digital twin and virtual environment for the validation of cognitive errors. Section 4 discusses the design and execution of the experiments based on the built environment. Section 5 analyzes the results obtained through the experiments. Finally, Section 6 concludes the paper.

3. Construction of the Environment for the Validation of Cognitive Errors

In this section, the overall construction of the environment for the digital twin model and virtual simulator for use in the experiment validating cognitive errors is presented.

3.1. Digital Twin Model Construction

Digital twins have various purposes, such as monitoring, analysis/prediction, and detection of real objects/systems. Depending on the purpose, the level of similarity of the model used may vary, but in general, it is very important to build a model that has high similarity with reference to the shape, motion, and data from the real world. Unlike general training and analysis/prediction approaches, we secured the most complete and sophisticated model for use in the experiments related to safety validation.

The detailed digital twin construction process was as follows. First, a target area for test driving was selected and a road/terrain model was built for it. In particular, a high-resolution 3D model was required so that the test subjects did not feel a sense of heterogeneity, and it was constructed to reflect the operating rules of the traffic system, such as actual signals and traffic flow characteristics, as much as possible. In this study, as shown in Figure 3, an existing district in Gangnam, Seoul, Republic of Korea, likely to be familiar to the test subjects, was selected. A specific test course was then selected and a digital twin model was built for this course. At this point, in order to use the SCANeR studio simulator, a professional driving simulator from AVSimulation, as a simulation engine, roads and terrain from the Gangnam area were synthesized in the simulator. Two intersection types were used, as shown in Figure 3. Intersection type one represented the case where the driver proceeds straight through an intersection with a right-turn-only lane, and intersection type two represented the case where the driver makes a right turn at an intersection without a right-turn-only lane. These two types of intersections were then appropriately arranged in the design of two driving courses.

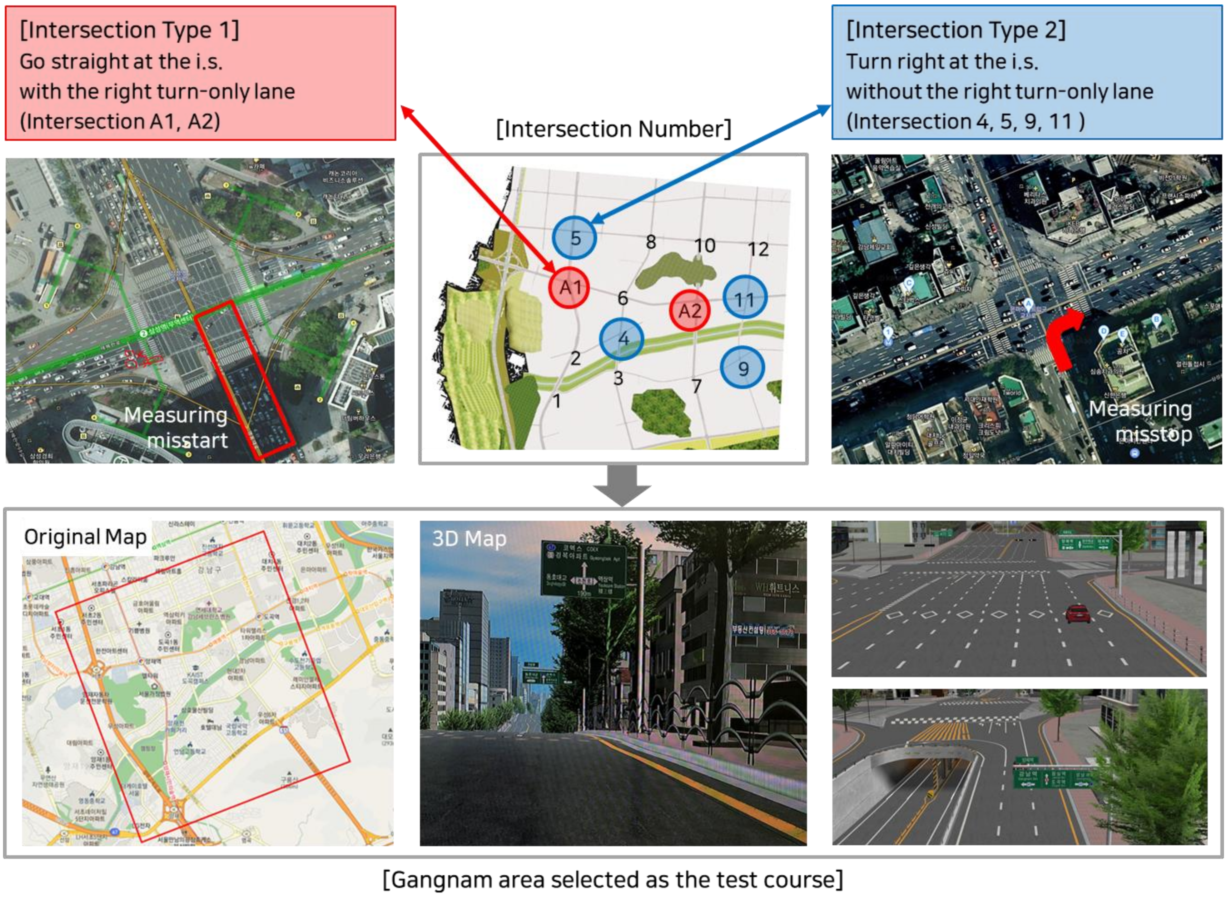


Figure 3. The two types of intersections used in the design of two courses (Gangnam area).

After implementing the road and course model in this way, it was necessary to implement LED in-ground traffic lights in the corresponding section. These were appropriately placed at intersections that actually have LED in-ground traffic lights and synthesized so that there was no sense of dissimilarity with reality. Figure 4 shows examples of how traffic lights were positioned in the digital twin model.

Finally, in order to improve the model, the surrounding traffic environment was implemented; that is, surrounding vehicles and pedestrians passed without a sense of heterogeneity together with the test subject. The surrounding traffic environment was also established based on the actual traffic volume so that the test subjects could immerse themselves as if in reality. This not only helped to adjust the test subject's driving speed but also guided them to the desired lane in the main scenario section. Through this process, the road digital twin model was finally completed.

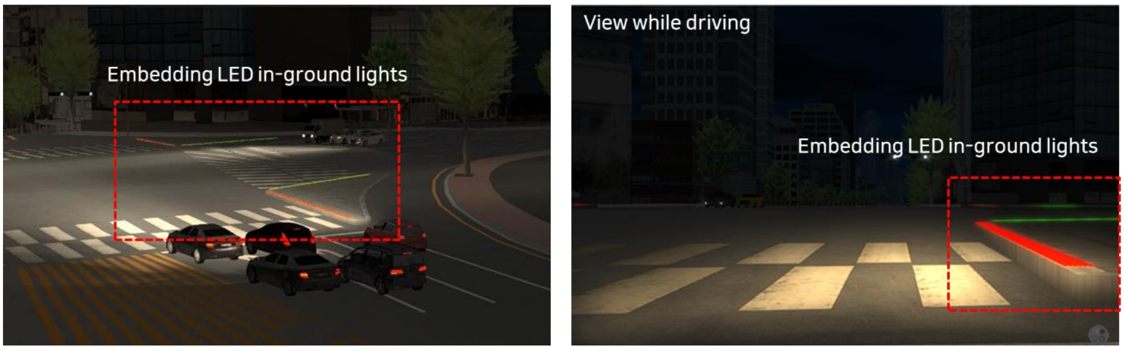


Figure 4. Implementation of LED in-ground traffic lights at intersections.

3.2. Virtual Simulator Construction

Various specialized driving simulators, such as SCANeR studio [34], UC-win/Road simulator [35], and STISIM drive [36], can be used to build a road digital twin. As mentioned earlier, SCANeR studio was used as a virtual environment. In addition to applying the previously built digital twin model to this simulator, the steering wheel, seat, and navigation system were built to resemble those of an actual vehicle to provide a realistic driving experience. Specifically, a remodeled vehicle was used as the cabin of the simulator, and a three-channel video screen and a motion platform with two degrees of freedom were also utilized. At this time, as shown in Figure 5a, various navigation systems were analyzed and, based on them, a virtual navigation system was designed. It was designed to provide guidance through a display at the HUD location so that the driver had no sense of heterogeneity and to increase intuitiveness. Figure 5b shows the finalized overall experimental environment, including the digital twin and the virtual simulator.

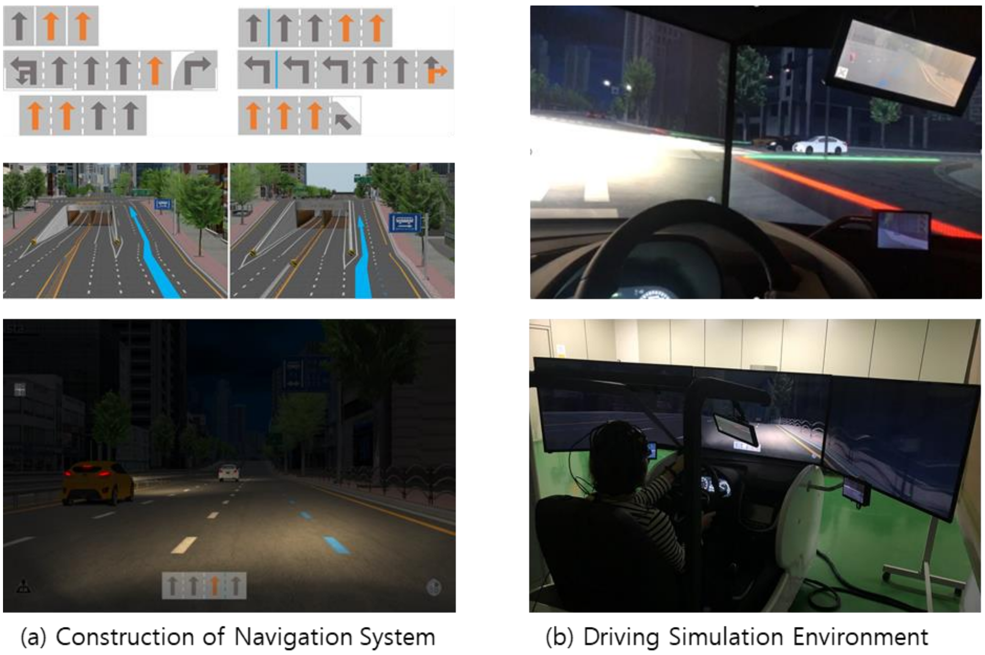


Figure 5. Virtual simulation environment.

4. Experiments

Next, using the virtual environment described above, experiments were designed and conducted to assess whether LED in-ground traffic lights would lead cognitive errors to occur.

4.1. Experimental Design

4.1.1. Design of Measurement and Evaluation Methods for Test Subjects

Before conducting the experiment, it was necessary to design measurement and evaluation methods for the test subject. First, for the driver, an eye tracker and an electroencephalogram (EEG) measuring device were used to measure biometric information and reaction information. This also allowed us to measure the possibility of a misstart through the driver's steering wheel/pedal operation and vehicle behavior. Table 1 shows the specific parameters used for driver monitoring.

Table 1. Various parameters for driver monitoring.

Category	Parameter	Acquisition Tool
Vehicle and environmental information	- Acceleration and deceleration - Vehicle speed - Longitudinal and lateral acceleration - Traffic information	Signal of simulator
Response information	- Steering response - Pedal response - Driver's cognitive status - Driver's stabilization status	APS and BPS Steering torque and angle

Then, an evaluation plan for the test subject was designed. To do this, a preliminary questionnaire was designed to recruit test subjects of various inclinations for a qualitative evaluation. There were 87 questions on the pre-questionnaire in three categories. First, there were 22 items pertaining to driver information, which were used to collect basic personal information and to devise a driving-related basic propensity score. Second, there were 28 questions about risky driving behavioral factors, including speeding, inability to cope with traffic situations, reckless driving, drunk driving, and distraction factors. Finally, there were 37 questions related to the determinants of driving behavior, such as problem avoidance, seeking stimulation, interpersonal anxiety, interpersonal anger, and aggression. The survey was conducted in advance to recruit test subjects in consideration of the driver propensity characteristics. It was also used to analyze the test subjects afterwards.

Also, for an objective evaluation of the driver, it was necessary to design a method for classifying and applying bio-signals. As shown in Figure 6, such a method was used to evaluate the driver through the collection of bio-signals at the event point (section) at which their reaction was to be observed during the test drive. Conditions for the driver evaluation were divided into three categories: perception, decision making, and action. In order to evaluate the driver objectively in accordance with these three conditions, measurement indicators were subdivided, as shown in Figure 7, and tests corresponding to each indicator were designed. Thus, a quantitative evaluation was conducted in advance for the three states through a line connection test, a lateral tracking test, a traffic sign discrimination test, a situational memory test, and a stimulus response test.

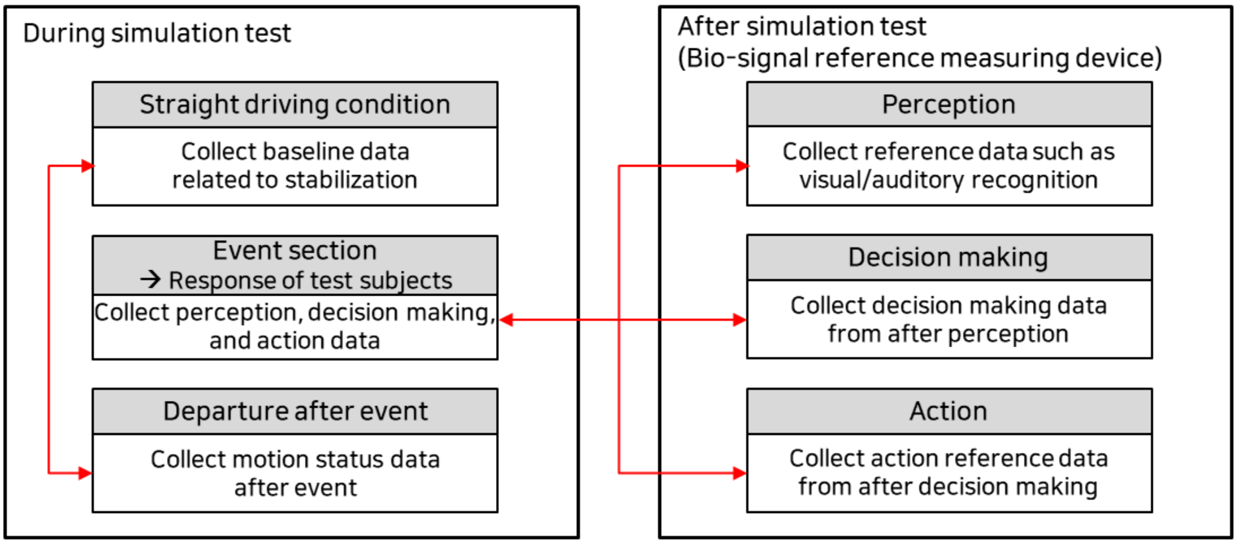


Figure 6. Design of the evaluation for the bio-signals of the test subjects.

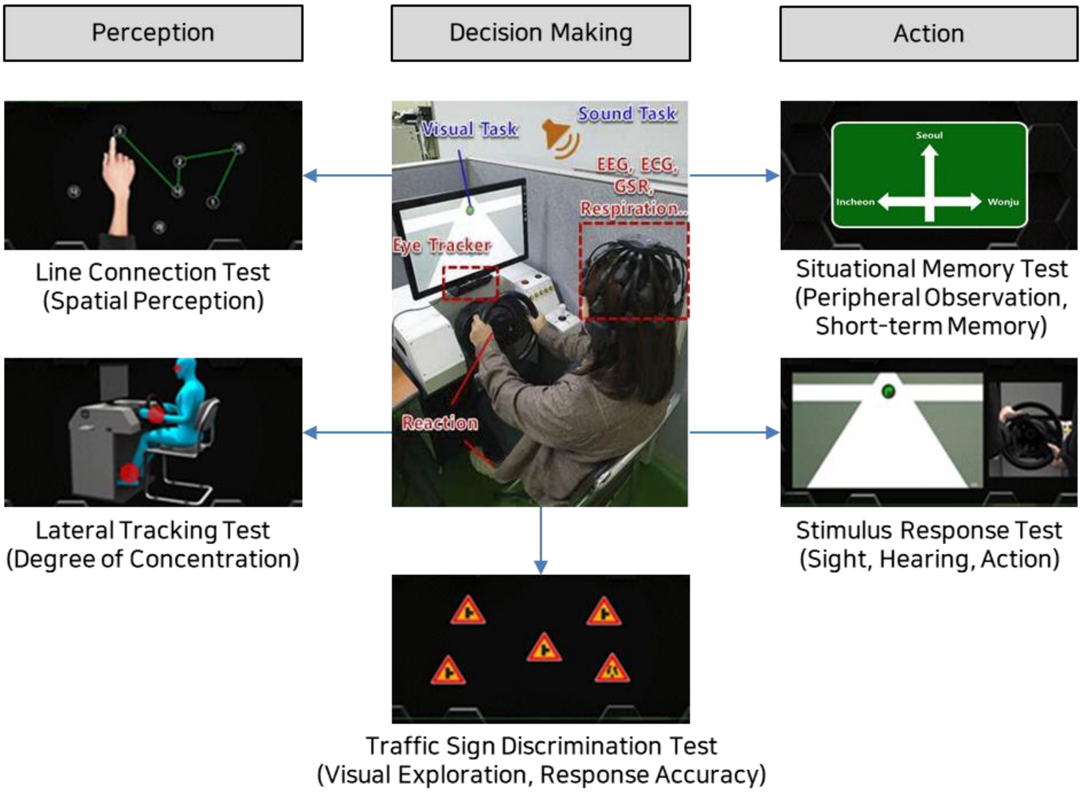


Figure 7. Various tests to evaluate the three states (perception, decision making, action).

4.1.2. Design of Scenarios

After designing the measurement and evaluation methods for the test subjects as described above, it was necessary to design specific test scenarios. In order to validate various situations, a total of three cognitive error-occurrence scenarios during road driving were designed. The first was a scenario that validated the situation involving the misstart of the vehicle while the driver waited after stopping completely. The purpose of this was to test for the presence or absence of an erroneous start due to the driver's misrecognition when the green light of the in-ground traffic lights at the crosswalk was turned on while the vehicle was completely stopped. The second scenario was one in which a misstart was validated after deceleration. The purpose in this case was to test for the presence or absence of a departure due to the driver's misrecognition of the in-ground signal when the green light of the in-ground traffic lights was lit during a slow approach. Finally, the third scenario was a validation scenario to test for a misstop of the vehicle when the driver was turning right. The purpose of this was to test for the presence or absence of a stop due to the driver's misrecognition when the in-ground lights turned red as they made a right turn. Details of scenarios are shown in Figure 8.

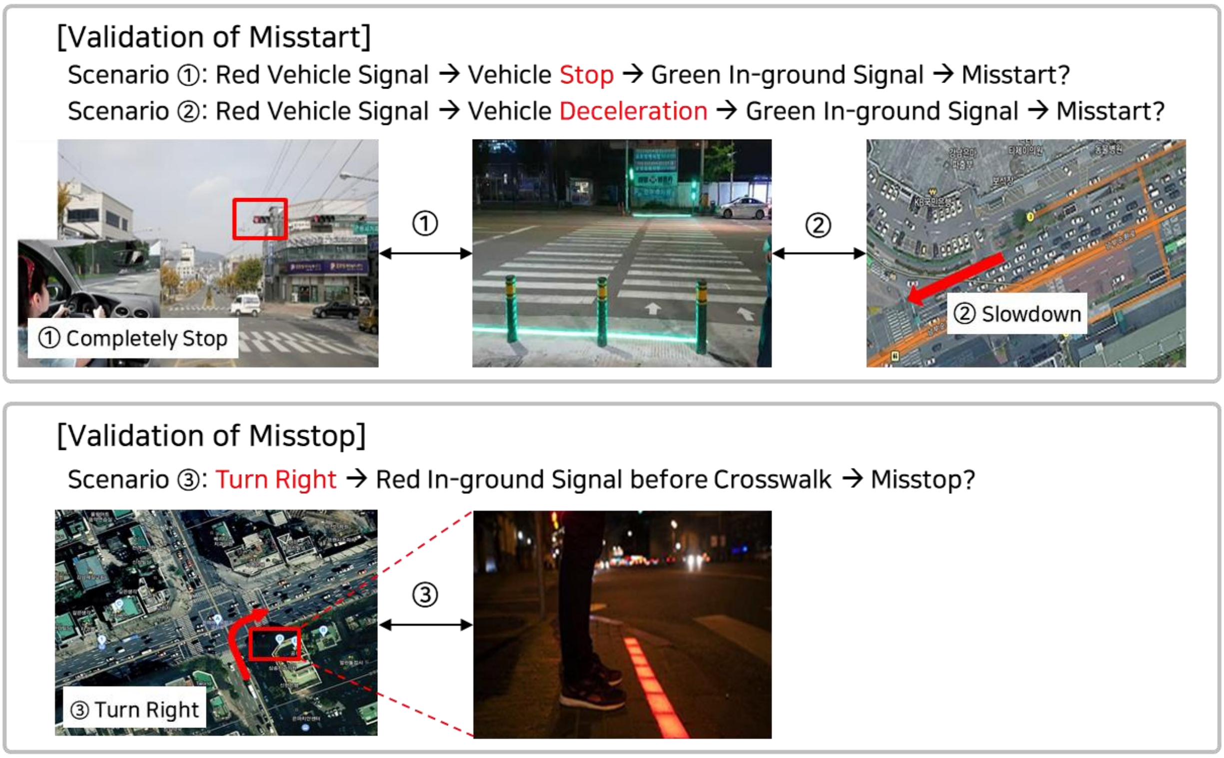
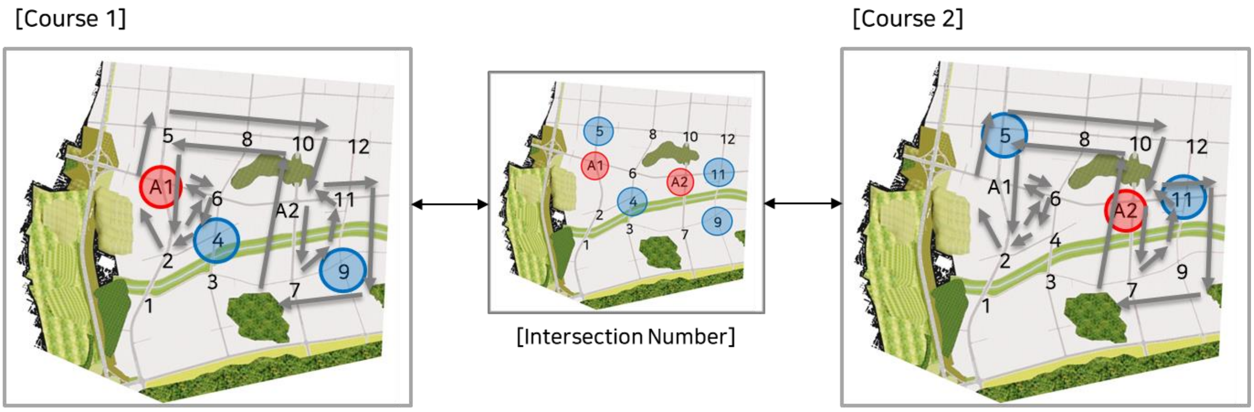


Figure 8. Design of three scenarios for recognition error validation.

4.2. Experimental Progress

Based on the above experimental design, this section presents the detailed experimental process. A total of 30 subjects, 15 male and 15 female, were recruited. The ages of the group were evenly distributed from the 20s to the 60s, with an average age of 44.6 years and an average driving experience of 20.8 years. In addition, the purpose of the experiment was not divulged to the subjects at the time of their recruitment. During the experiment, the average driving speed was calculated and found to range from 40 to 80 km/h, and the driving time for each of the two courses was estimated to be about 30 min. The specific test process consisted of preparation (15 min), training (15 min), resting (5 min), experimental (70 min), and post-evaluation (5 min) steps and the total time required per person, including practice time, was estimated at about two hours.

The next step was to organize the test drive courses. Two maps were created by mixing the test group and the control group, and the test was conducted by evenly distributing the two maps by age group, as shown in Figure 9. At this point, for the two courses, 15 people were included in the changing of the leading and trailing courses. Also, as shown in Figure 9, a total of 12 events for the LED traffic lights occurred in courses one and two while driving. Thus, in total, 720 events could be tested by combining the 360 cases of the test group and the 360 cases of the control group as the 30 subjects drove through the courses.



Type	Course Order & Intersections with LED In-ground Traffic Lights																											
Course 1	A1	6	4	2	A1	5	8	10	A2	7	9	11	A2		A2	11	9	7	A2	10	8	5	A1	2	4	6	A1	T1: 4 / T2: 2
Comparison	↕		↕		↕	↕			↕				↕		↕	↕	↕		↕				↕				↕	Comparison of LED traffic lights on the same intersection
Course 2	A1	6	4	2	A1	5	8	10	A2	7	9	11	A2		A2	11	9	7	A2	10	8	5	A1	2	4	6	A1	T1: 4 / T2: 2

Figure 9. Two types of courses and arrangement of traffic lights.

In addition, it was necessary to measure the test data for each test subject while conducting the test. Specifically, misstart-related data were collected from vehicle operation information (e.g., steering wheel, brakes) in the simulator as cognitive error data. In addition, as cognitive information data, data related to driver cognition were collected using the aforementioned eye tracker and EEG devices during the simulation. The experiments were performed with the conditions described above. MATLAB and EEGLAB were used for data analysis in this paper.

5. Results Analysis

5.1. Data Preprocessing

After the test drives were finished and the data were collected, data preprocessing and analysis were required prior to validation. Through the test drives, a total of 662 cases were extracted, excluding data losses and the control group, from the total of 720 events. At this time, for each case, the road/behavior data, driver gaze data, and bio-signal data were extracted and preprocessed.

5.1.1. Road and Behavioral Data

First, as shown in Figure 10, the time of each scenario point (from P1 to P12) was extracted from the driving trajectory of each test subject. A 120 s section was extracted from each scenario point, taking into account the time that elapsed when approaching the starting point at a low speed and the departure delay caused by the driver's misperception. In addition, the states of the vehicle signals and LED in-ground traffic lights to be observed were extracted from a total of two driving courses, with 12 scenarios for each course. At this time, there was an in-ground signal in the test group scenario, but there was no in-ground signal in the control group.

Next, the driver's behavior for each scenario was analyzed, as depicted in Figure 11. The driver saw changes in the traffic signal and took appropriate action, such as braking and accelerating. This paper analyzes these behaviors for each scenario to determine the driver's misrecognition.

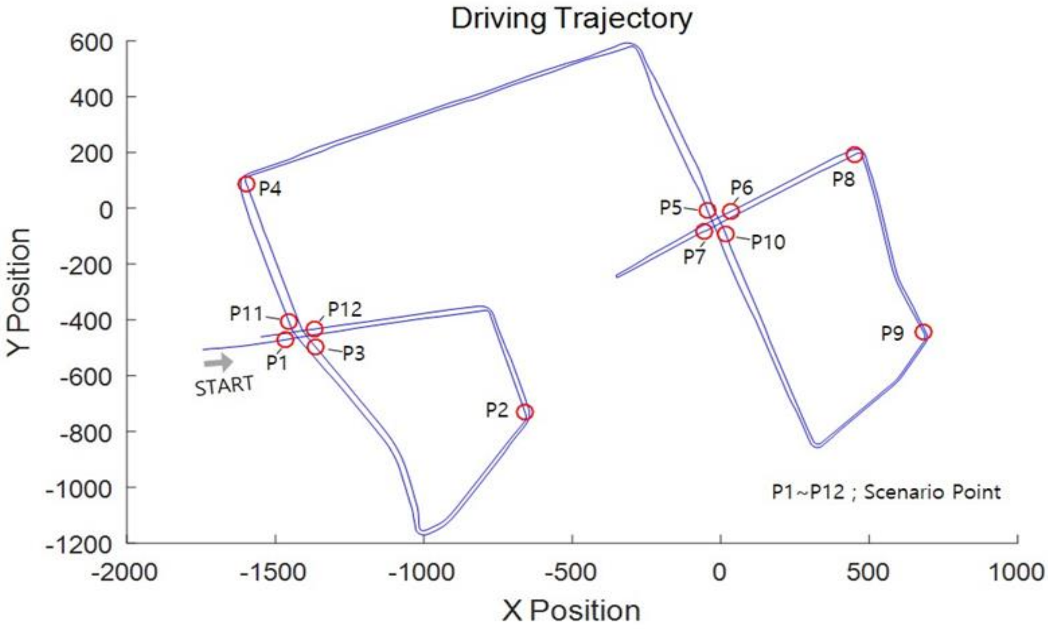


Figure 10. Extraction of 12 scenario points from the driving trajectory.

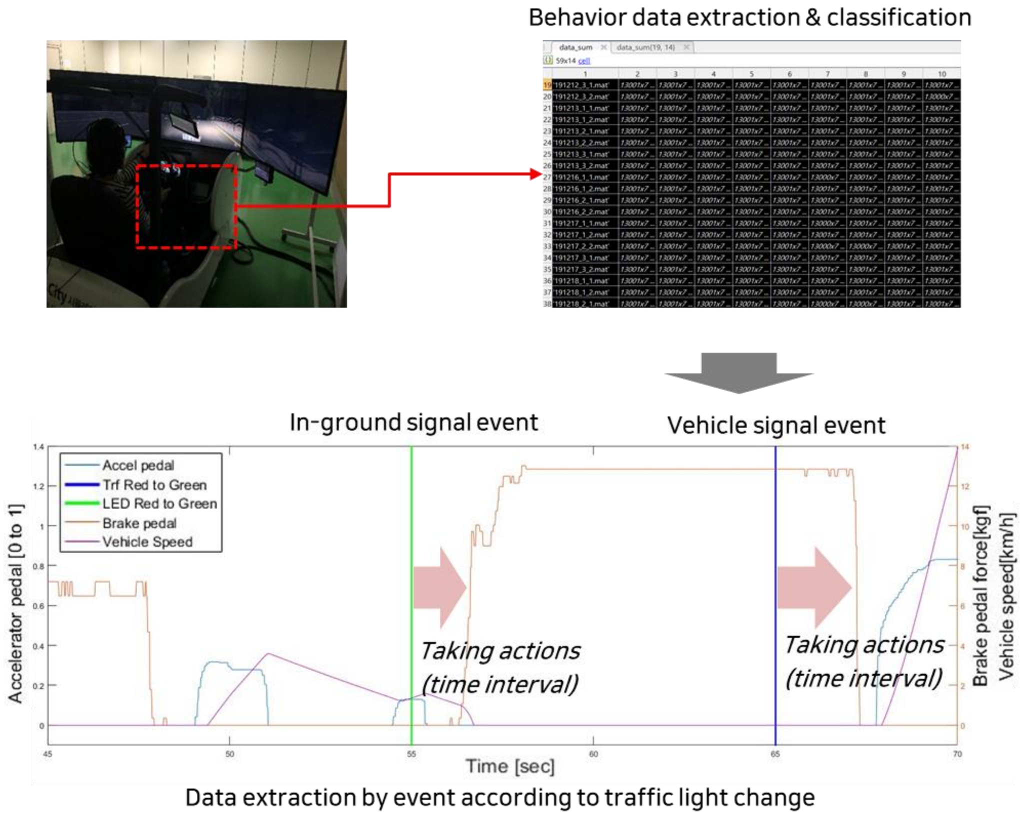


Figure 11. Data preprocessing for behavior analysis according to the properties of the road.

First, given that Scenario one was a scenario in which the driver's misstart was observed when the vehicle was completely stopped, the driver's behavior in each case was analyzed in terms of whether or not there was an intention to start. Thus, when the in-ground traffic light was green, the vehicle signal was red, and the driver's stepping on the brake pedal decreased, it was determined that the driver had an intention to start. Next, considering that scenario two was a scenario in which the driver's misstart was observed in a situation where they were approaching the stop line at a low speed, the driver's behavior was also analyzed in terms of whether or not the driver had an intention to start. At this time, it was determined that the driver had a will to start not only for the same state found in scenario one but also when the speed increased when the driver stepped on the accelerator. Finally, as scenario three was a right-turn scenario at an intersection, the driver's deceleration and stop patterns (longitudinal acceleration) and lateral behavior (lateral acceleration, steering angle, and steering angular velocity) were observed in relation to whether or not there was a pedestrian signal on the ground. Unlike scenarios one and two, right turns were compared through statistical figures to distinguish them from deceleration for turning.

Meanwhile, based on the previously obtained road data, behavior data were classified, synchronized, and stored. In order to classify the behavioral data according to the signal change, the signal-change time point and the main behavior-change time point were distinguished and extracted. In addition, in order to analyze the driver's behavior when passing over in-ground signals while driving, 24 parameters were extracted by combining six statistical measures (mean, median, variance, standard deviation, maximum, minimum) for each of the four major behavioral factors (longitudinal acceleration, lateral acceleration, steering angle, steering angular velocity).

5.1.2. Gaze Data

Next, the driver's gaze data were analyzed. First, classification was conducted to determine the level of attention paid to the corresponding area by distinguishing the traffic light in front and the traffic light on the ground. These data—specifically, the hit time for the corresponding area and the rate for the gaze time for the designated area—were then classified and extracted. Figure 12 shows the foreground for the driver's gaze data and the area settings for the classification of the gaze data.

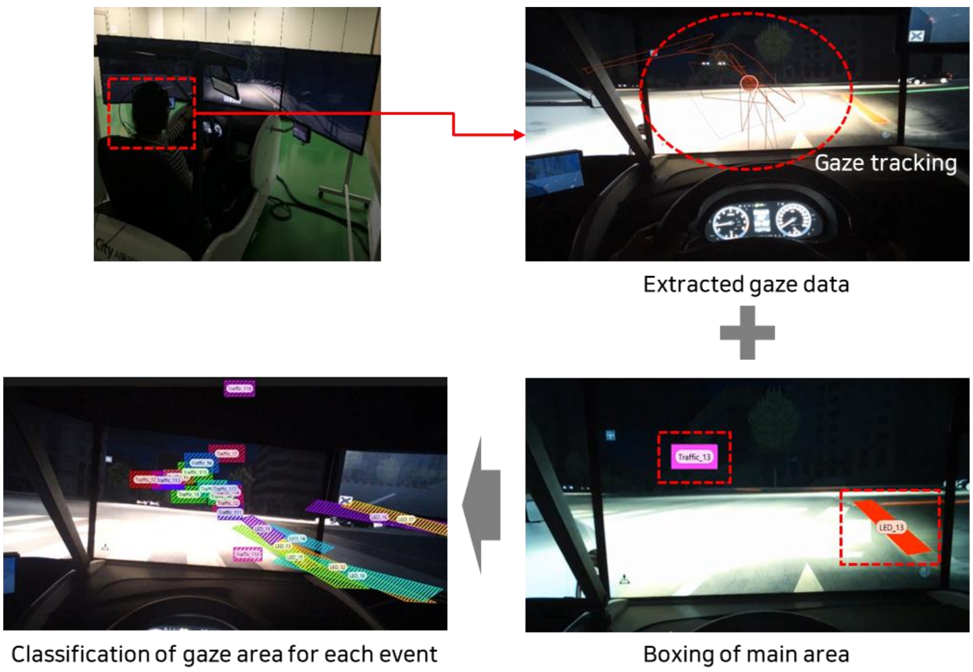


Figure 12. Extraction and preprocessing of gaze data.

5.1.3. Bio-Signal Data

Next, it was necessary to analyze the bio-signal data of the test subjects. This study used the Quick-20 r device by Cognionics Company, in which channel positions are arranged in a 10–20 montage with two variable-placement ExG channels. For the event-related potential (ERP) analysis, data from 20 locations were acquired, as shown in Figure 13.

After confirming the active section for the event occurrence through the ERP analysis, we conducted a statistical analysis in the corresponding section. First, an EEG analysis was conducted to assess each subject's immediate stress and anxiety. Then, from the data for the 20 channels measured during the preliminary tasks, usable signals were classified based on impedance and noise for each channel was removed. In addition, a high-pass filter was applied to classify noise and eliminate poor signal channels. Finally, the absolute power values and activation ratio values of theta, alpha, and beta waves for each channel were obtained through a power spectrum analysis. Figure 13 shows the overall process from bio-signal extraction to preprocessing.

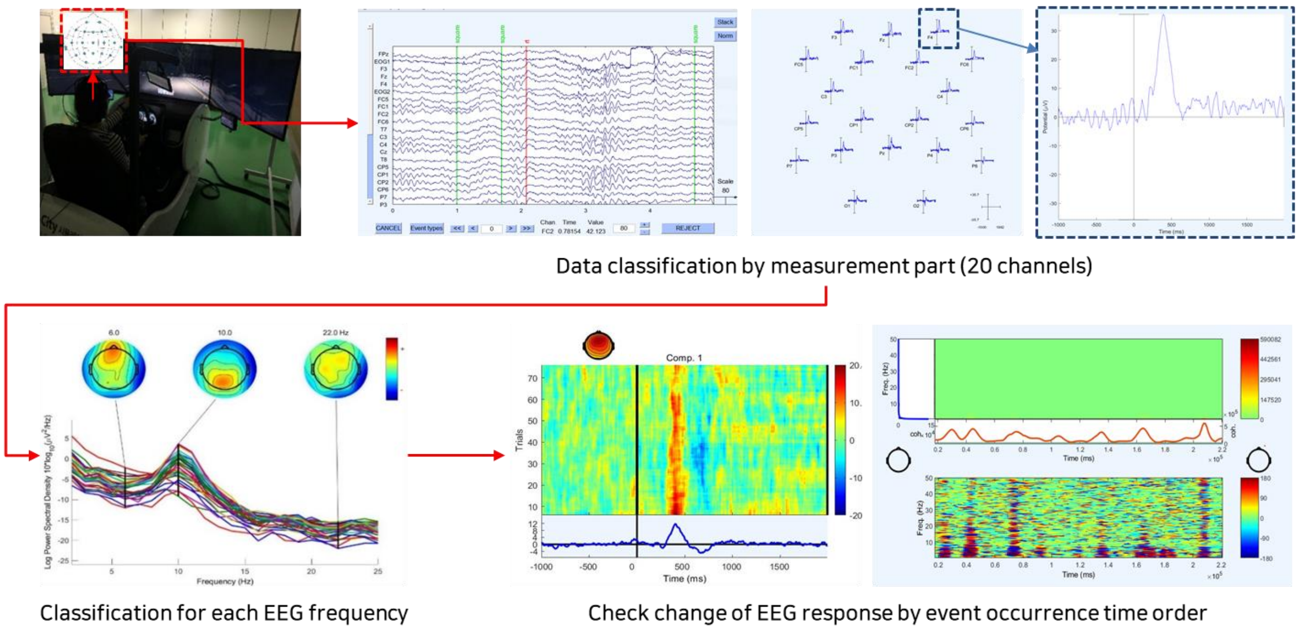


Figure 13. Extraction and preprocessing of EEG data.

5.2. Data Analysis

5.2.1. Pre-Validation of Simulator Test Results

Before analyzing the cognitive error results, the effect of the test sequence on the driver in each case was validated in advance. This was a test of the hypothesis that the behavior patterns of the early and late stages may show differences due to the test subjects' adaptation to the simulator and learning effect; that is, this was undertaken to ascertain whether there were any pattern differences and to test the two groups simultaneously without classifying them separately during the main analysis. To this end, differences in behaviors between the test group and the control group with the same course and conditions were analyzed. For example, we analyzed differences in driving patterns in the same section between group A (15 people), who followed course one, and group B, (15 people) who followed course two. First, we analyzed each driver's behavior for each course through Welch's two-sample *t*-test. This is a two-sample location test that is used to test the (null) hypothesis that two populations have equal means. It was confirmed that the individual analysis was unreliable due to an insufficient number of samples for each course. It was also confirmed that there was no difference, as no significant result was obtained as a result of checking the *p*-value in the overall test obtained with more than 50 samples. Thus, it was confirmed that there were no differences in the driver behaviors according to the test sequence.

5.2.2. Validation of Misstarts

As a result of the validation test of misstarts when the driver stopped in scenarios one and two, it was found that a total of 7 false start cases out of 224 events occurred when there was an LED in-ground traffic light. In this section, we discuss the cognitive errors that caused actual misstarts in detail. The causes of the misstarts were analyzed through a comparison of two groups of test subjects: those who committed a misstart and those who did not. First, this was analyzed using the gaze information. A hypothesis was established that there was a difference in the time spent watching traffic lights between the misstart group and the non-misstart group. As a result of this analysis, it was confirmed that there was a statistical difference. The time spent watching the LED in-ground traffic lights was 3.47% longer in the misstart group than in the non-misstart group, and the time spent looking at the vehicular signal in front was 1.47% longer. It was found that the time the misstart group spent looking at the traffic lights was 4.94% longer (Table 2).

Table 2. Analysis of traffic light gaze data.

Category	Normal Group Mean (%)	Misstart Group Mean (%)	Difference Mean (%)	*t*-Test *p*-Value
Front + in-ground signal gaze time	4.79	9.73	4.94	0.02
In-ground signal gaze time	2.91	6.38	3.47	0.07
Front signal gaze time	1.88	3.35	1.47	0.14

The next step was a stress/concentration and stability/adaptation analysis using the biometric information. A hypothesis was established that there would be differences in stress/concentration and stability/adaptation outcomes between the misstart group and the general group. As a result of the analysis, however, it was confirmed that there was no statistical difference. However, although not statistically significant, it was confirmed that the misstart group had high stress and low values for stability. At this time, one interesting finding was that, as the event continued, theta wave (stability) and beta/alpha wave (stress) outputs also gradually increased, meaning that, as the test time elapsed, stress increased with long-term testing and the drivers' adaptation to driving (Table 3).

Table 3. Analysis of biometric information.

Category		Stress (Beta/Alpha Wave)				Stability (Theta Wave)			
		Normal (%)	Misstart (%)	Difference (%)	*t*-Test *p*-Value	Normal (%)	Misstart (%)	Difference (%)	*t*-Test *p*-Value
With in-ground signal	Event 3	0.27	0.42	0.15	0.15	5.32	3.28	−2.04	0.03
	Event 5	0.32	0.48	0.16	0.25	4.25	5.10	0.85	0.41
	Event 7	0.45	0.39	−0.06	0.24	6.58	5.80	−0.78	0.15
	Event 11	0.48	0.47	−0.01	0.35	7.23	6.20	−1.03	0.08
	Total	0.38	0.44	0.06	0.37	5.84	5.10	−0.74	0.13
Without in-ground signal	Event 3	0.32	0.34	0.02	0.35	4.97	4.82	−0.15	0.12
	Event 5	0.54	0.37	−0.17	0.19	4.52	5.43	0.91	0.09
	Event 7	0.56	0.47	−0.09	0.37	6.23	5.45	−0.78	0.12
	Event 11	0.49	0.61	0.12	0.27	6.97	6.31	−0.66	0.07
	Total	0.48	0.44	−0.04	0.26	5.67	5.50	−0.17	0.14
Difference	Event 3	−0.05	0.08	0.13	-	0.35	−1.54	−1.89	-
	Event 5	−0.22	0.11	0.33	-	−0.27	−0.33	−0.06	-
	Event 7	−0.11	−0.08	0.03	-	0.35	0.35	0	-
	Event 11	−0.01	−0.14	−0.13	-	0.26	−0.11	−0.37	-
	Total	−0.1	−0.01	0.09	-	0.17	−0.41	−0.58	-

The last step was an analysis using a questionnaire. In this step, only the data for those who passed the questions testing the sincerity of the responses were extracted and analyzed, and a total of 25 subjects participated in this step. As a result of the analysis, it was found that the difference in the propensity of the misstart group compared to the normal group was not statistically significant. However, as a result of inferring the differences between them by listing them based on the p-value, it was judged that the misstart group tended to be relatively prudent or careless. Also, although they tended to speed, it was judged that they had a tendency to obey the law and showed aggression (Table 4).

Table 4. Analysis of questionnaires.

Category	Normal Group Mean (%)	Misstart Group Mean (%)	Difference Mean (%)	t-Test p-Value
Aggression	2.42	2.90	0.49	0.23
Drunk driving	1.29	1.00	−0.29	0.25
Interpersonal anger	2.48	2.79	0.31	0.40
Reckless driving	1.81	2.05	0.24	0.47
Problem avoidance	1.78	1.96	0.19	0.47
Speed driving	2.04	2.29	0.25	0.49
Unskilled driving	2.24	2.43	0.19	0.65
Immaturity in handling traffic situations	2.25	2.18	−0.07	0.78
Interpersonal anxiety	2.24	2.36	0.12	0.79
Seeking stimulation	1.94	1.92	−0.02	0.94
Distraction	2.59	2.66	0.07	0.99

5.2.3. Validation of Misstops

In scenario three, complete stops due to misrecognition of the LED in-ground traffic lights when turning right did not occur. In other words, it was difficult to clearly confirm the effect of the in-ground lights because it was challenging to distinguish between a natural slowdown and a slowdown due to the in-ground traffic lights when the driver was turning right. However, using scenario three, the presence or absence of the lights was validated as having an effect on the driver when passing through the area. In order to analyze the behavioral change according to the presence or absence of the lights, a hypothesis was established that there would be a difference in the behavior of the groups who passed through an intersection with the LED in-ground traffic lights and those who passed through an intersection without these lights. Subsequently, as a result of this validation through Welch's t-test, the lights were found not to have affected driver behavior as the drivers drove through this course. It was also found that only 1 parameter out of the total of 24 parameters could confirm the hypothesis.

6. Conclusions

LED in-ground traffic lights are one of the most effective ways to prevent pedestrian accidents. However, there is a problem in that cognitive errors, such as misstarts or misstops by a driver, may occur due to their installation, and prior assessments of such cognitive errors are essential before installing these lights in earnest. Therefore, this paper attempted to assess drivers' in-ground traffic light recognition errors using a digital twin model and a virtual driving environment. To this end, a digital twin and virtual simulator-based test environment that enabled real-world traffic tests was established. In addition, various test scenarios and measurement methods for validation were designed and experiments were conducted to test for cognitive errors.

Through the experiment, it was confirmed that there is a possibility that the in-ground traffic lights will cause drivers to start incorrectly. In particular, it was found that those who displayed a strong speeding tendency, aggression, and negligence were likely to engage in false starts. As a result of the gaze analysis conducted here, this could be judged in connection with the fact that the misstart group spent a considerable amount of time watching the traffic lights. In addition, as a result of a bio-signal analysis, it was found that the misstart group had high stress and high anxiety, confirming that concentration and anxiety when driving influenced whether they committed cognitive errors. It was also found that the lights could cause a false start when the vehicle was stopped, but they did not significantly affect the driver's behavior while driving. However, although the lights did not affect driver behavior, it was found that they could steal the driver's gaze when they were stopped.

Based on the experimental results here, this study found that efforts are needed to recognize the possibility of cognitive errors and prevent them before the widespread installation of these light systems. It also found that the digital twin-based traffic demonstration environment constructed in this way can be used for establishing new traffic policies, applying new traffic technologies, and other experiments related to traffic accident prevention. Finally, by supplementing and expanding such an environment in the future, we will establish a general transportation demonstration framework and use it to demonstrate various transportation problems, thereby contributing to improving the quality of public safety by making traffic situations safer.

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