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Research Article

Mode confusion of human–machine interfaces for automated vehicles

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Abstract

In this study, we designed two user interfaces for automated vehicles operated in the modes that correspond to the Society of Automotive Engineers automation levels 0–3. The first is a level-centred interface that allows the driver to increase or decrease the automation level step-by-step. The second is a function-centred interface that has independent driving controls in the longitudinal and lateral directions. We implemented prototypes for the two interfaces and conducted driver-in-the-loop experiments on a driving simulator to verify their effectiveness in the driver's mode awareness. For events on the road, the participants took actions to control the vehicle, which might cause mode changes, and answered the modes he/she believed. The experimental results show that the mode confusion rate of the level-centred interface is twice higher than that of the function-centred interface. Also, visual feedbacks can reduce the mode confusion rate dramatically. The results show that a function-centred user interface combined with adequate visual and/or auditory feedback is essential to improve driver's mode awareness when driving an automated vehicle.

Keywords: autonomous vehicles, intelligent vehicles, user interfaces, human–machine interface, human–robot interaction, human-computer interaction, mode confusion; situation awareness

1. Introduction

According to the WHO's global status report on road safety 2015 (WHO, 2015), about 1.25 million people die each year on the world's roads as a result of road traffic crashes and between 20 and 50 million more suffer non-fatal injuries. Road safety studies indicate that human error is the major cause of road traffic accidents. Medina *et al.* (2004) suggested that as much as 75% of all roadway crashes can be attributed to human or driver error. The National Highway Traffic Safety Administration reported that 94% of fatal crashes in the USA are caused by driver error (Singh, 2015). Driver errors include slips, lapses, mistakes, and violations (Reason, 1990; Stanton, 2009). Slips and lapses are defined as attentional and memory failures, respectively, while mistakes are made due to planning failures. Full explanations of each of these error types may be found in reference section (Reason, 1990). Driver errors are made for a number of reasons, including distraction, confusion, disengagement, fatigue, and violation, and are responsible for many crashes, injuries, and fatalities.

Automated vehicles have the potential to improve road safety by supporting or supplementing the driver in various situations. These vehicles are equipped with both advanced driver assistance system (ADAS) as well as an intelligent co-pilot system to provide appropriate support to the driver in all traffic situations, from normal to safety-critical emergency situations. Typically, automated vehicles have several different levels of automation ranging from manual to partially and fully automatic (Hoeger *et al.*, 2011; Gasser & Westhoff, 2012; NHTSA, 2013; SAE International, 2016).

Automation can decrease driver workload and increase performance but also degrade situation awareness (De Winter *et al.*, 2014). As known well, there has been some controversy regarding the effects of automation. For example, in a mid-level of autonomous driving, supervising the system can increase driver workload and fatigue. If drivers are engaged in non-driving tasks, situation awareness deteriorates for automated driving compared to manual driving. However, automated driving can result in improved situational awareness compared to manual driving if drivers are motivated or instructed to detect objects in the environment (De Winter *et al.*, 2014). Also, automated vehicles may benefit novice drivers who can make mistakes not often made by more experienced drivers, with respect to vigilance and driving tasks. For this reason, in recent years, most automotive manufacturers, and even IT companies like Google, have devoted concerted effort to develop the next generation of automated or autonomous vehicles (Markoff, 2010).

Although automated systems promise increased safety and reduced human error, a number of substantive human factor challenges must be addressed before these types of automated systems can become a practical reality. These challenges include the potential for negative adaptations occurring due to misunderstanding of, misuse of, or overreliance on the system, or changes in attention and distraction from the driving task (Trimble *et al.*, 2014). In particular, as the driver's role shifts from active vehicle control to passive monitoring of the automated system and environment, the driver's situational awareness in detecting system state changes or in perceiving critical factors in the environment becomes very important (Bainbridge, 1983; Endsley, 1996).

Norman (1981) emphasized the need for special attention to mode errors in the design of computing systems. The author pointed out that misclassification of the current computing system mode could lead to input errors, which may have serious

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consequences. One reason for mode errors is the failure of the human operator of the system to keep track of the mode changes (Woods, 1988). Another reason is that the rules of interaction change with mode changes (Norman, 1988). There has been substantial research conducted on mode confusion and the resulting automation surprise experienced by users of highly automated systems (Sarter & Woods, 1995; Sarter *et al.*, 1997). Various methods have been used to evaluate the properties of human-automation interfaces and to determine the potential for mode confusion via automated theorem proving or model checking (Butler *et al.*, 1988; Degani & Heymann, 2002; Heymann & Degani, 2007; Bolton *et al.*, 2014). Degani and Heymann (2002) and Heymann and Degani (2007) proposed an approach and methodology for the analysis and generation of user interfaces, with a special emphasis on human–automation interaction. In this method, the correspondence between the behaviour of the machine and the abstracted information provided to the user is formally described and analysed by considering the machine, the user's tasks, the user interface, and the interface model of the machine. The authors also presented a systematic procedure for generating information content for the interface that is both correct and succinct. They identified inaccurate mental models as among the major causes of mode confusion. However, they did not discuss the mode confusion caused by vague or inappropriate displays of the system status on the user interface. This type of problem is related to human cognition and cannot be detected using formal methods; thus, the potential for mode confusion must be verified experimentally.

Regarding mode confusion in vehicle automation, early studies have focused on adaptive cruise control (ACC) systems (Furukawa *et al.*, 2003; Horiguchi *et al.*, 2006; Horiguchi *et al.*, 2007; Lee *et al.*, 2014; Ahn *et al.*, 2015; Eom & Lee, 2015a, b; Lee & Ahn, 2015). Horiguchi *et al.* (2006, 2007) found that if different modes show similar responses, it is difficult for users to distinguish them. Based on the observation, they proposed a new approach to estimate the possibility of mode confusion using mode vectors encoding the input–output relations and applied it to ACC systems. Since the similarity between mode vectors results in mode confusion, they proposed a method to add some extra outputs to the modes that are represented by the same vector. Furukawa *et al.* (2003) conducted an experimental study of mode awareness using a dual-mode ACC system with high- and low-speed modes. They identified information that could be effective in supporting mode awareness in complex situations if some direct information concerning the system state is concealed. Through the experiments, they found that a clear visual display of the system state is highly effective in reducing mode confusion and that overlapping the ranges of the high- and low-speed modes improves the drivers' mode awareness as well as the ease of mode transition. Lee *et al.* (2014), Ahn *et al.* (2015), Eom and Lee (2015a, b), and Lee and Ahn (2015) studied the mode confusion of ACC systems in a simulated environment. They proposed a new human–automation interaction design methodology in which they determined the compatibility between the machine and interface models using proposed criteria, and if the models are deemed to be incompatible, one or both is/are modified to make them compatible. Also, the authors developed a new driver interface for ACC systems based on a formal method, conducted a set of driver-in-the-loop experiments to observe possible instances of mode confusion, and redesigned the user interface to minimize their occurrence. The experimental results showed that the clarity and transparency of the user interface were as important in reducing mode confusion as the correctness and compactness of the mental model.

With respect to mode confusion in highly automated vehicles, Heymann and Degani (2013) described a hierarchy of automated driving aids and their functionalities, with a focus on ACC and lane centring, which is generally called lane keeping (LK). They presented specific models of operation and suggested display concepts to facilitate efficient interaction. However, they neither implemented these models nor tested their displays in driver-in-the-loop experiments for verification. In the intelligent transport (HAVEit) project (Hoeger *et al.*, 2011), the researchers developed and verified a survey of users' cognitive modes and mode transition of the system to realize an effective joint system and human–machine interface (HMI). They also evaluated the usability of the user interface in automated vehicles, which allows the lateral control systems to be activated only when the longitudinal control system is active (Heymann & Degani, 2013). However, they have not conducted research to investigate whether this type of interface is effective for the driver's mode awareness and, if not, to identify alternatives to achieve better mode awareness. Lau *et al.* (2018) investigated the impact of two interface designs, simple and advanced, on driver behaviour in a level 3 automated driving systems. They examined driver's responses resulting from the system-initiated requests to intervene provided by the interfaces through human-in-the-loop experiments on a driving simulator. It was found that the advanced interface captured drivers' attention significantly faster and helped them prepare for intervention better than the simple interface. These results highlight the importance of applying good HMI design practices to support driver performance and the need for effective HMI guidelines, standards, and assessment methods for the HMI design for automated driving systems. However, they have not designed and examined the HMI for level 0–3 of automated vehicles. Miller *et al.* (2014) evaluated four different automation conditions—fully autonomous vehicle, autonomous steering, autonomous speed control, and no automation—based on their post-transition accident avoidance, situational awareness, and feelings of trust in and comfort with autonomous or partially autonomous driving. The results show the reaction time in the autonomous steering condition was longer than those of the other conditions. This work presented a method for experimenting and evaluating situational awareness in multilevels of automated vehicles. Dönmez Özkan *et al.* (2021) reviewed a state-of-the art on mode awareness from the related domains of automated driving, aviation, and human–robot interaction. They presented a summary of existing mode awareness interface solutions as well as existing techniques and recognized gaps concerning mode awareness. They found that existing interfaces are often simple, sometimes outdated, yet are difficult to meaningfully expand without overloading the user, and the predictive approach is a possible promising strategy to lessen the need for mode awareness via separate indicators.

In this study, we design two types of HMI—level-centred and function-centred—for automated vehicles and verify their effectiveness with respect to the driver's mode awareness through driver-in-the-loop experiments. We develop two HMIs in reference to the definition of the Society of Automotive Engineers (SAE) automation levels 0–3 (SAE International, 2016) and the existing HMIs. The level-centred interface increases or decreases the automation level one by one (Hoeger *et al.*, 2011; Heymann & Degani, 2013). In contrast, the function-centred interface has independent buttons to activate the ACC and LK systems, and thus, the automation level is increased or decreased as a result by turning on/off each control direction. First, we design two typical interfaces with reference to existing HMIs. Then, we analyse two different interfaces using a formal method (Heymann & Degani, 2007;

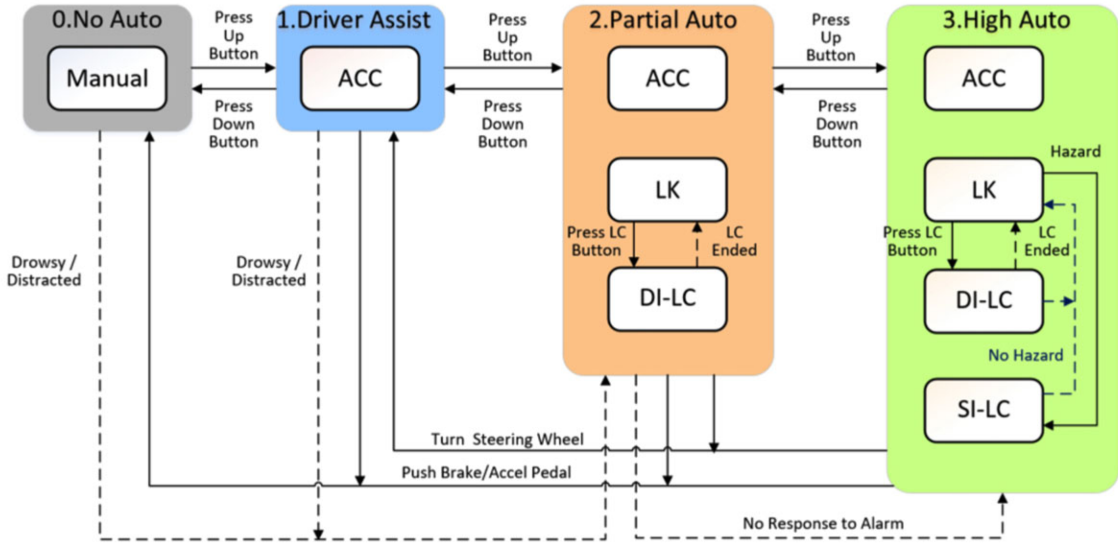

Figure 1: The level-centred interface model of an automated vehicle consists of four modes and their transitions. The four modes, No Auto, Driver Assist, Partial Auto, and High Auto, correspond to the SAE levels 0, 1, 2, and 3, respectively. Mode transition is either manually triggered by the user or automatically triggered by the system, indicated by solid and dotted lines, respectively.

Eom & Lee, 2015a). Next, we conduct experiments on a simulated automated vehicle to observe instances of mode confusion when using the two interfaces. Finally, we summarize and discuss the experimental results.

2. User Interface Models of Automated Vehicles With Multiple Levels of Automation

The HMI can be formally described and analysed by considering the following four elements: the machine, the user's tasks, the user interface, and the user's conceptual model of the machine (Horiguchi *et al.*, 2007). Since most machines do not display all of their internal states or events to users, in this context, the internal states and their transitions are clustered and abstracted before being displayed on the user interface. This cluster of states is referred to as a mode. From the user's perspective, a machine is recognized via the user interface in a mode-transition system that comprises modes, events, and transitions among modes. This mode-transition model of the interface is referred to as an interface model. The interface model of automated vehicles must be designed to enable the user to perform driving operations correctly and quickly (Heymann & Degani, 2007).

In this study, we designed, evaluated, and compared two different interface models—the level-centred interface and the function-centred interface—based on the definitions of the SAE for multiple driving automation levels (SAE International, 2016) and the existing interfaces. The level-centred interface increases the automation level step-by-step. For example, only the ACC system is active in level 2, and both the ACC and LK system are active in level 3. If the ACC system is not active, the vehicle cannot make the transition to level 3. The level-centred interface was designed based on the interfaces developed in the HAVEit project (Hoeger *et al.*, 2011) and by Lexus. In contrast, the function-centred interface has independent buttons to activate the ACC and LK systems. This means that the automatic driving controls exist independently in the longitudinal and lateral directions. The automation level is increased or decreased by turning on/off each control direction. The function-centred interface was designed by Benz and BMW and used in an experimental study (Miller *et al.*, 2014).

2.1. Level-centred interface model

In this study, we designed a level-centred interface model with reference to the user interface of the HAVEit project (Hoeger *et al.*, 2011). As shown in Fig. 1, this model has four operational modes, and the mode is changed by pressing the up and down button on the steering wheel. Basically, the No Auto, Driver Assist, Partial Auto, and High Auto modes correspond to the SAE levels 0, 1, 2, and 3, respectively (SAE International, 2016). These modes also correspond to the driver-assisted, semi-automated, highly automated, and fully automated modes in the HAVEit project, respectively (Hoeger *et al.*, 2011).

(i) Mode 0 (No Auto) indicates the manual mode in which the driver controls the vehicle always using the steering wheel and pedals with the support of warning systems, such as forward-collision warning (FCW), lane departure warning (LDW), and blind-spot warning.
(ii) Mode 1 (Driver Assist) refers to the driver-assisted mode in which a vehicle is controlled by the ACC system in the longitudinal direction. However, it does not support an LK function whereas the level 1 supports one of the LK and ACC functions.
(iii) Mode 2 (Partial Auto) is a partially automated mode in which both the ACC and LK system are active so that a vehicle can be controlled automatically in both the longitudinal and lateral directions. In this mode, the driver-initiated auto lane change (DI-LC) system is also available, unlike the level 2. Here, the DI-LC system means an automatic lane change (LC) system initiated by the driver's manual input, for example, by pressing a button.
(iv) Mode 3 (High Auto) is the highly automated mode in which both the ACC and LK systems, as well as the system-initiated auto lane change (SI-LC) system, are active. Here, the SI-LC system means an automatic LC system initiated by the system without the driver's intervention.

Table 1: User-triggered transitions in the level-centred interface model.

Mode	Driver's Operation: Press Up Button	Press Down Button	Press High Button	Press Cancel Button	Push Brake Pedal	Push Gas Pedal	Turn Steering Wheel	Compatible
NA	DA							Yes
DA	PA	NA			NA	NA		Yes
PA	HA	DA			NA	NA	DA	Yes
HA		PA			NA	NA	DA	Yes

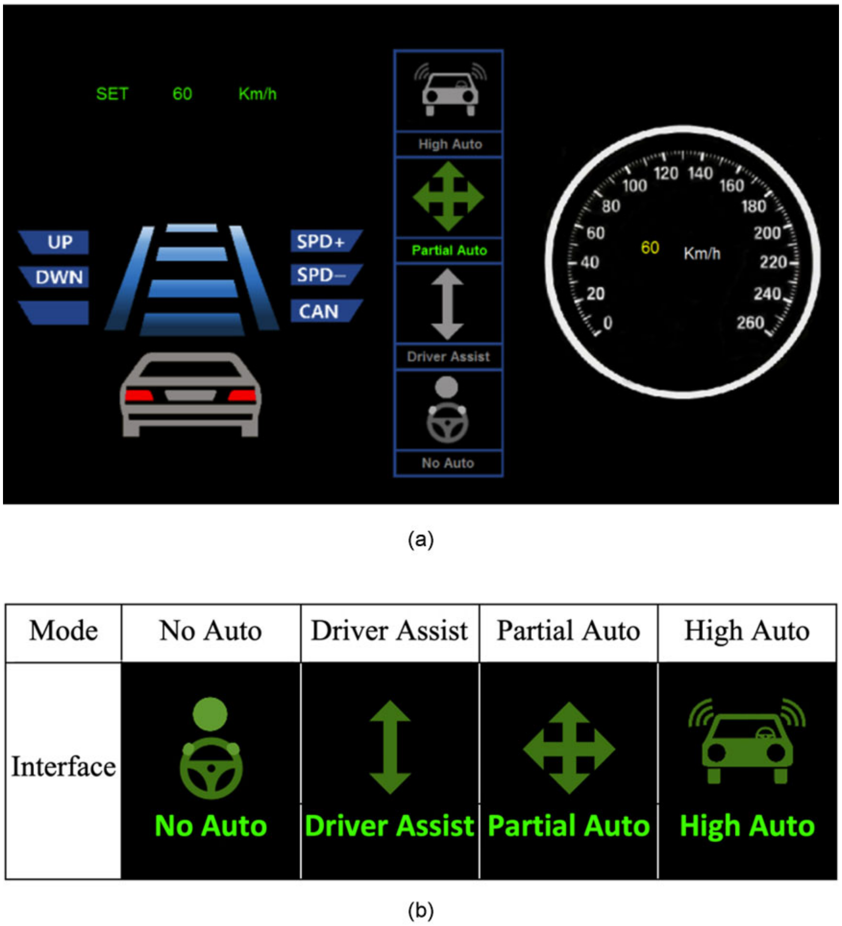

Figure 2: Design of the level-centred interface for an automated vehicle. (a) The GUI in the gauge cluster and (b) icons for operational modes.

The driver can change the mode one step up or down by pushing an up or down button on the steering wheel. Also, when the driver depresses the brake or gas pedals in the Driver Assist, Partial Auto, or High Auto mode, the mode is automatically transitioned to No Auto. Also, when the driver turns the steering wheel when in the Partial Auto or High Auto mode, the mode is transitioned to Driver Assist. If the driver is inattentive or drowsy, an arousal alarm is raised, and the system is temporarily transitioned to the Partial Auto mode. If the driver does not respond to the 'take-over request' (TOR) alarm, the mode is transitioned to the High Auto mode and the minimum-risk state (MRS). If the driver does not respond to the alarm by operating input devices, the vehicle adopts the High Auto mode and the MRS. The MRS is a last resort provision to guarantee the driver's safety when the driver does not respond to a TOR. The vehicle gradually decelerates to a standstill, while LK remains active for a certain period and auto LC is triggered to perform lane changing and parking on the edge of the road.

Next, we analyse and evaluate the correctness of the interface model designed above. We check whether there were any incompatible mode transitions in the interface model, which may cause mode confusion, and redesign the interface model if any incompatible mode transitions exist. We applied a simplified formal method using the state and mode transition table for an interface model, proposed in our earlier work (Eom & Lee, 2015a). In this approach, first, we build a state and mode transition table for an interface model, which contains all states and modes, all events triggered by the user or system, and their resulting transitions. Next, we check whether an interface model satisfies the following two criteria: (i) The response of the machine to user-triggered events must be deterministic; that is, when starting in the same mode, identical user events should produce identical

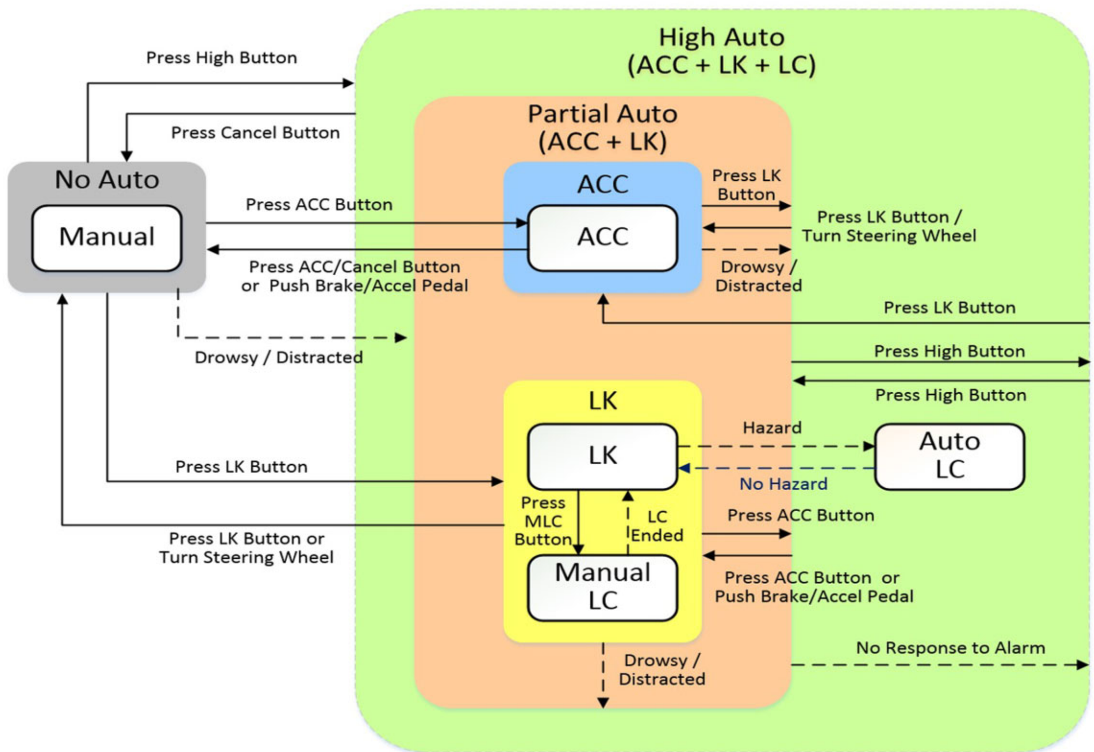

Figure 3: The function-centred interface model of an automated vehicle consists of five modes and their transitions. The five modes are No Auto, ACC, LK, ACC + LK, and ACC + LK + LC, which combine longitudinal and lateral controls. Mode transition is either manually triggered by the user or automatically triggered by the system, indicated by solid and dotted lines, respectively.

Table 2: User-triggered transitions in the function-centred interface model.

Mode	Driver's Operation: Press ACC Button	Press LK Button	Press High Button	Press Cancel Button	Push Brake Pedal	Push Gas Pedal	Turn Steering Wheel	Compatibility
NA	ACC	LK	ACC+LK+LC					Yes
ACC	NA	ACC+LK	ACC+LK+LC	NA	NA	NA		Yes
LK	ACC+LK	NA	ACC+LK+LC	NA			NA	Yes
ACC+LK	LK	ACC	ACC+LK+LC	NA	LK	LK	ACC	Yes
ACC+LK+LC	LK	ACC	ACC+LK	NA	LK	LK	ACC	Yes

transitions between system modes. (ii) Mode changes that are not present in the interface model must not be triggered by users. Table 1 summarizes the mode transitions activated by user-triggered inputs. We found no incompatible transitions in the level-centred interface.

Finally, we designed a graphical user interface (GUI) for the level-centred interface model in a gauge cluster, as shown in Fig. 2. The No Auto, Driver Assist, Partial Auto, and High Auto modes are represented by the symbols and text in the centre of the gauge cluster, while the internal states of the ACC, LK, and LC systems are represented by the figures located on the left in the gauge cluster. We used different colours for the text and illustrations and located them to optimize driver awareness of the vehicle status and operational mode.

2.2. Function-centred interface model

In contrast to the level-centred interface, the function-centred interface model was designed so that the automated driving systems, such as the ACC and LK systems, are operated independently in the longitudinal and lateral directions, as illustrated in Fig. 3. This type of interface has traditionally been adopted by most automotive manufacturers such as Mercedes-Benz and BMW. We configured this model with five modes: Modes 0–4 labelled No Auto, ACC, LK, ACC + LK, and ACC + LK + LC, respectively.

- (i) Mode 0 (No Auto) is a manual driving mode and corresponds to the Mode 1 (No Auto) of the level-centred interface.
- (ii) Mode 1 (ACC) corresponds to the Mode 2 (Driver Assist) of the level-centred interface as well as the SAE level 1.
- (iii) Mode 2 (LK) corresponds to the SAE level 1 in which an ADAS can assist the driver with either steering or braking/accelerating, but not both simultaneously. The level-centred interface does not have any mode that matches this mode.
- (iv) Mode 3 (ACC + LK) corresponds to the Mode 3 (Partial Auto) of the level-centred interface.

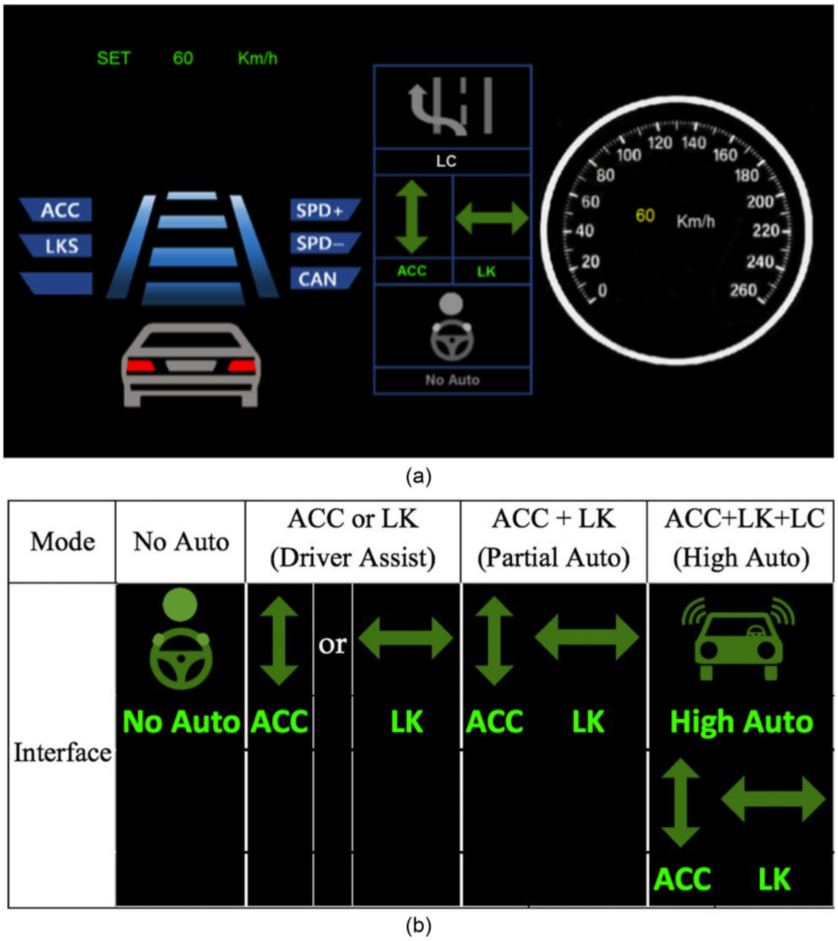

Figure 4: Design of the function-centred interface for an automated vehicle. (a) The GUI in the gauge cluster and (b) icons for operational modes.

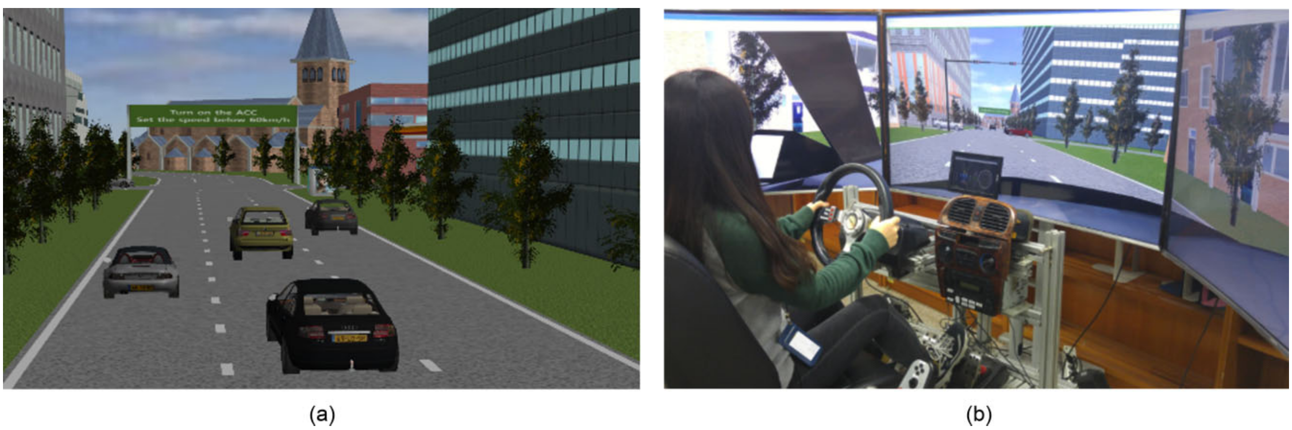

Figure 5: Participant driving on the simulator during the experiment. (a) A virtual road environment and (b) the driving simulator.

(v) Mode 4 (ACC + LK + LC) corresponds to the Mode 4 (High Auto) of the level-centred interface.

Each mode is transitioned manually by pressing buttons or pedals, as shown in Fig. 3. The buttons for ACC, LK, and LC are toggle buttons. For the user's convenience, when the LC button is held down while LC is off, the ACC and LK functions are simultaneously activated. In the ACC + LK and ACC + LK + LC modes, the mode is transitioned to LK if the ACC button is pressed whereas it is transitioned to ACC if the LK button is pressed. If the driver presses either the brake or gas pedal while ACC is on, the ACC function is turned off, and the mode is transitioned to LK. If the driver turns the steering wheel more than a specified angle while LK is on, the LK function is deactivated, and the mode is transitioned to ACC. As in the case of the level-centred model, if the driver is inattentive or drowsy, an alarm is raised, and the system enters the ACC + LK mode. If the driver does not respond to the TOR alarm, the mode is transitioned to the ACC + LK + LC mode and the MRS in which the vehicle is driven to a safe area. Table 2 sum-

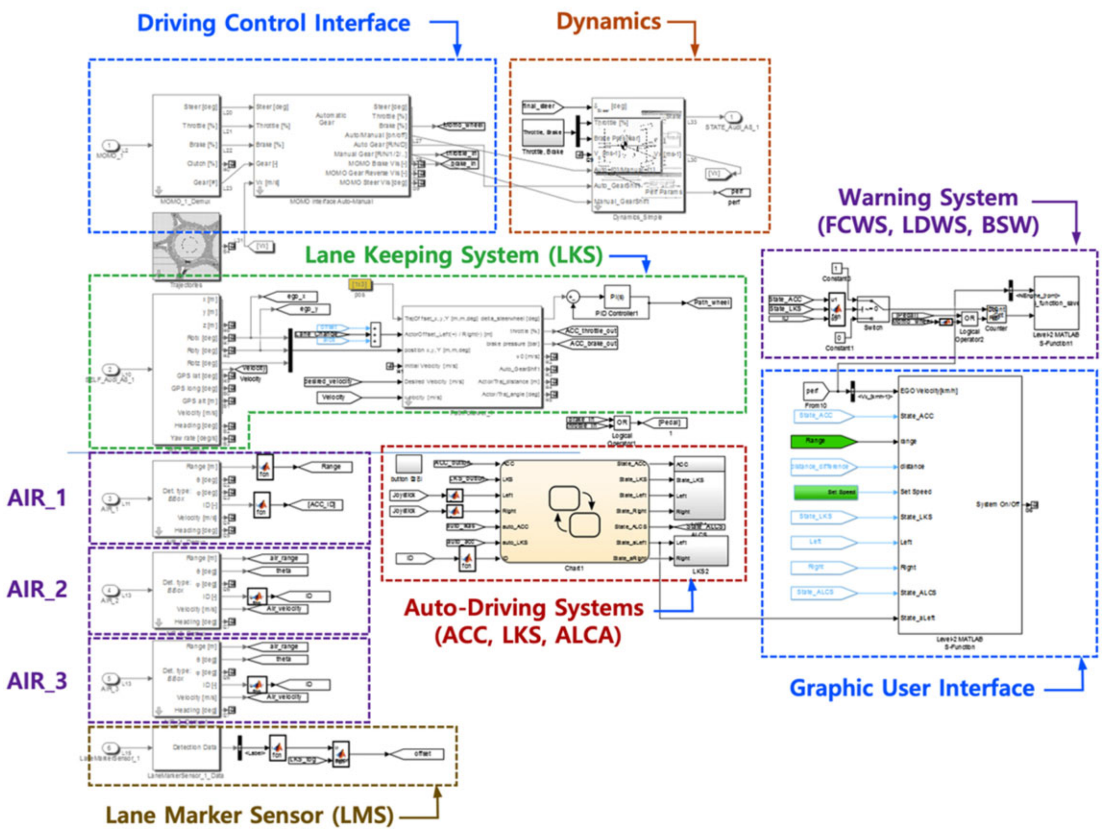

Figure 6: Overall system architecture of the simulated vehicle equipped with the automated driving systems: Implementation using Matlab and Simulink in PreScan.

marizes the mode transitions activated by user-triggered inputs. We found no incompatible transitions in the function-centred interface (Eom & Lee, 2015a).

As shown in Fig. 4, we designed a GUI for the function-centred interface model in a gauge cluster. No Auto, ACC, LK, and LC are represented by the symbols and text, and, as in the level-centred interface, we located these in the centre of the gauge cluster, while the internal states of the ACC, LK, and LC systems are represented by the figures on the left in the gauge cluster. We used different colours for the text and illustration in the centre of the gauge cluster to help the user to distinguish between the modes easily and to be aware of the driving situation.

3. Driver-in-the-Loop Experiments

3.1. Participants

The 48 participants consisted of 36 male and 12 female adults aged between 23 and 31 years (mean = 26.6, SD = 2.0). We used a basic questionnaire to obtain personal information from the participants, all of whom had a valid driver's license, 1 or more years of driving experience, and normal or corrected-to-normal vision. The average driving experience of the participants was 4.0 years (SD = 2.5), driving 2.0 days per week (SD = 1.6). 54% of the participants are aware of vehicle automation. Most vehicles have cruise control by default, some have ACC and LDW, and no cars have automation beyond L3. Most of them are unfamiliar with the definition of SAE automation levels.

3.2. Apparatus

The experiments were performed on a fixed-base drive simulator using the TNO PreScan software as shown in Fig. 5 (Eom & Lee, 2015a). The simulator had three 55-inch curved screen displays that produced 130° (horizontal) x 30° (vertical) field of view for a front view and a 10-inch display for a gauge cluster. The input device was a Logitech G27 racing wheel with brake and gas pedals. The buttons on the wheel were configured to control various operations in order to perform mode switching in the automation systems.

In the driving simulator, we implemented all components for a vehicle with multilevels of automation, including the GUI and the warning, ACC, LK, and LC systems, based on PreScan using Simulink and Matlab as shown in Fig. 6. PreScan is a physics-based simulation platform that offers a variety of sensor emulation functions to facilitate the rapid development of active safety or ADAS. PreScan provides an actor information receiver (AIR) sensor which is a virtual active scan sensor that can replace a certain physical scanner, such as radar or laser scanners. Two AIR sensors with short and long ranges emulating radar sensors were used for longitudinal vehicle control systems such as FCW and ACC systems. A lane-marker sensor (LMS) was used to implement a LK system which performs lateral vehicle control. Not only a LMS but also two AIR sensors simulating a long-range radar and a 360° short-range lidar sensors were used to implement a LC system that controls a vehicle in the lateral direction to change lanes automatically. The role of the lidar AIR sensor is to detect vehi-

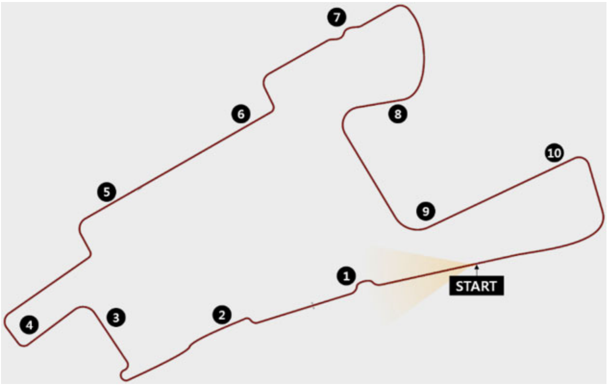

Figure 7: Experimental road and event areas.

cles in the side lanes. The ACC system outputs the throttle position and brake pressure, whereas the LK and LC systems output the angle of the steering wheel. These output values are delivered to the vehicle dynamics module, which calculates the vehicle behaviours, such as the velocity and acceleration. Finally, a GUI was implemented using Matlab. In this interface, the driving–control interface module is automatically activated when the Logitech G27 racing wheel is connected to the gas and brake pedals. The vehicle dynamics, AIR_1, AIR_2, AIR_3, and LMS modules are automatically activated by the links between the vehicle and the sensors provided by PreScan.

3.3. Scenario

To conduct the driving simulation, we used PreScan to design a road model with three lanes. Figure 7 shows this road, which was modelled after the Detroit Street Circuit of the USA Grand Prix, which consisted of actual city streets. In the proposed scenario, we designed ten events, each to occur in a specific region. Table 3 shows the designed traffic situation, the expected driver operation, and the changes in the system mode of each event. The modes in parentheses are those of the function-centred interface model.

The host vehicle began its travel in the middle of three lanes. As the host vehicle approached a specific location, one or more of the surrounding vehicles exhibited predetermined behaviours, such as sudden acceleration of braking. The surrounding vehicles were driven by a driver model called the 'Path Follower' in PreScan, and the host vehicle was driven by the experiment participant. In each experiment, each vehicle followed a predetermined path. We included the following ten events, as illustrated in Fig. 8, in the experimental scenarios.

3.4. Procedure

This study was approved by the Institutional Review Board of Kookmin University. Before the experiment, participants filled out a consent form and a basic questionnaire. Then they were informed about the research goals and experimental procedures. They were explained about the definitions of the operational modes and transitions associated with an intelligent vehicle with various levels of automation as described in Section 2. In addition, the user interfaces were explained and demonstrated in detail. The experimenter ensured that participants understood the logic of the user interface and then repeated presentations until they recognized the mechanism. In addition, some specific instructions were given for the experiment. For example, subjects must drive on city roads at 60 km/h or less, not make a car tread on lane marks, and close their eyes and remove their hands and feet from the steering wheel and pedals when ordered to close their eyes. Then they practiced driving in the simulator. It took 20 minutes for each participant to complete this process before the experiment.

In order to get rid of the learning effect, experiments were conducted using the level-centred and the function-centred interfaces for different participants in different orders. Depending on the design scenario, a certain event occurred after the host vehicle arrived at a specific location. In response to each event, participants tried to control the vehicle by pressing a button, pressing a brake or gas pedal, and turning the steering wheel. The experimenter observed the participants' behaviour and the resulting mode changes in the system.

After completing each event, the interface gauge cluster was covered, and the driving simulation was interrupted to ask participants questions about the mode change and the reason behind it. Then, the interface was uncovered, and the participants were asked the same questions. Their answers were recorded during the experiment. Participants used some automated driving functions while driving without any clue about the correct answers. At the end of the driving experiments, participants were asked if they experienced any mode confusion and why. Each experimental session lasted a total of 40 minutes.

Table 3: Event and their expected mode transitions in the experimental scenario.

Event no.	Traffic situation	Expected driver operations	Expected mode transitions	
			Before	After
1	V_2 suddenly emerges at the intersection	Brake	Partial Auto (ACC + LK)	No Auto (LK)
2	Traffic accident in front of V_1	Turn wheel	Driver Assist (LK)	Driver Assist (No Auto)
3	V_1 smoothly stops due to traffic lights	Brake	Partial Auto (ACC + LK)	No Auto (LK)
4	The driver closes his/her eyes (Drowsiness)	Close eyes	Driver Assist (ACC)	Partial Auto (ACC + LK)
5	V_1 suddenly stops due to traffic lights	Brake	Partial Auto (ACC + LK)	No Auto (LK)
6	The lanes are covered with snow	Take over	Partial Auto (ACC + LK)	No Auto (No Auto)
7	V_1 automatically changes lanes	NA	High Auto (ACC + LK + LC)	High Auto (ACC + LK + LC)
8	V_1 speeding up	Accelerating	High Auto (ACC + LK + LC)	No Auto (LK)
9	Merging lanes from three to two lanes	Take over	Partial Auto (ACC + LK)	No Auto (No Auto)
10	Under construction sign	Steering	Driver Assist (ACC)	Driver Assist (ACC)

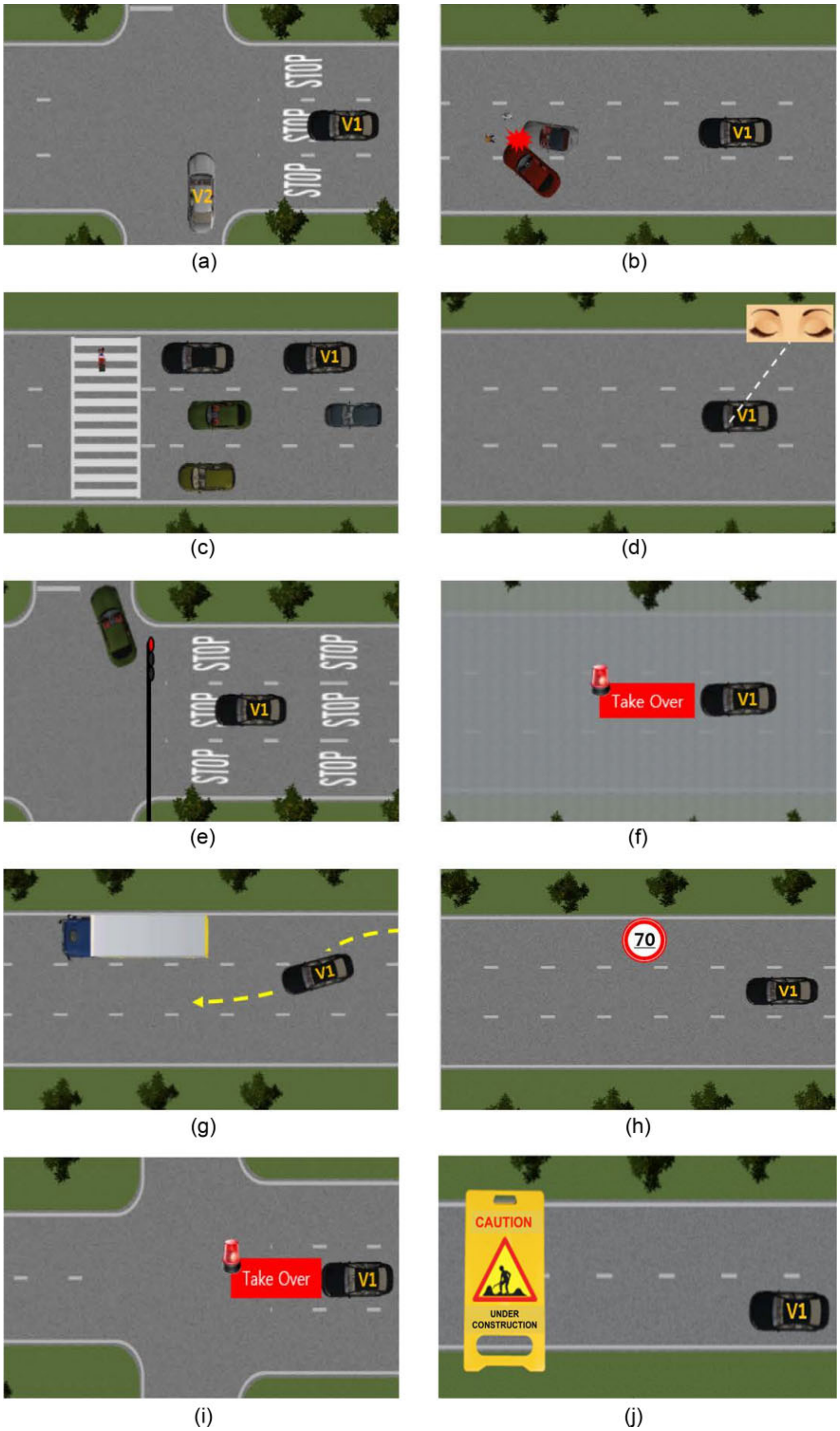

Figure 8: Ten events used in the driver-in-the-loop experiments: (a) Event 1: V_2 suddenly emerges at the intersection; (b) Event 2: V_1 arrives at the scene of a traffic accident site; (c) Event 3: V_1 stops smoothly in response to a red traffic light; (d) Event 4: Driver closes his/her eyes (drowsy state); (e) Event 5: V_1 encounters a red traffic light and must stop suddenly; (f) Event 6: The driver should take over control because the lanes are covered with snow; (g) Event 7: V_1 automatically changes lanes in the High Auto mode; (h) Event 8: V_1 must accelerate; (i) Event 9: V_1 must turn the steering wheel because of a decrease in the number of lanes; and (j) Event 10: V_1 must stop because of a construction zone.

4. Results

4.1. Experiment results

4.1.1. *Mode confusion rates*

For each event in the experiments, we obtained the following data: the participant's operation, the actual mode after operation, the mode the participant predicted without looking at the user interface, the reason the participant thought and expected that he/she was in that mode, and the mode that the participant recognized after looking at the user interface. We examined the mode-confusion rates with respect to two independent variables: the type of interface models and whether the participant glanced at

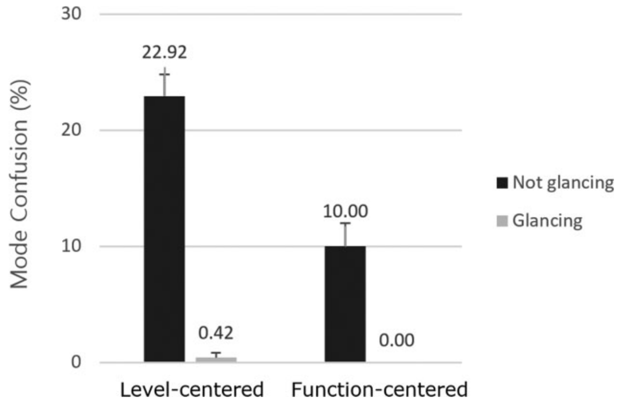

Figure 9: Mode confusion rates obtained for the two investigated interfaces of users glancing and not glancing at the display.

the display. We considered the two types of the user interface (i.e. level-centred and function-centred models) and two possibilities for glancing at the display (i.e. glancing and not glancing). Figure 9 shows the mode-confusion rates for the participants. When the participants could not see the display, the mode confusion rates for the level-centred and function-centred interfaces were 23 and 10%, respectively. However, they were reduced to 0.42 and 0.00% if the display was visible. Irrespective of whether the participant glanced at the display, the confusion rate for the function-centred interface model is lower than that of the level-centred model. Also, the confusion rate when glancing at the display is lower than the case when not glancing at the display. To assess the significance of these two factors, we also carried out an analysis of variance of the measurements using SPSS software. The difference between the level-centred and function-centred interface models is significant ($F_{1,47} = 14.1, P < 0.05$), as was the difference between glancing and not glancing at the display ($F_{1,47} = 86.1, P < 0.05$).

4.1.2. Mode confusion error analysis

Tables 4 and 5 present the mode confusion rates for the two interface models evaluated in this study. To help us determine how the participants recognized changes in the mode of the automated systems during the experiments, these tables compare the actual modes with the modes recognized by the participants. As shown in Table 4, for the level-centred interface, 99.6 and 78.8% of the mode changes were recognized correctly with and without glancing at the display, respectively. As shown in Table 5, for the function-centred interface, 100 and 91.3% of the mode changes were recognized correctly with and without glancing, respectively. Therefore, these results indicate that it was easier for participants to use the function-centred interface than the level-centred interface. In both the level-centred and function-centred interfaces, the mode confusion rate after glancing at the display was significantly reduced compared to that before glancing. Therefore, we can conclude that the design of the user interface was clear and distinct with respect to their perception by drivers.

With the level-centred interface, before the display was viewed, the highest mode confusion rate occurred in the Driver Assist mode. After being viewed, only one mode confusion instance occurred in the Partial Auto mode. Some participants who referred to the Driver Assist mode as the No Auto mode believed that the mode was changed to No Auto by manually controlling the steering wheel in the High Auto and Partial Auto modes. Those who considered the Driver Assist mode as the Partial Auto mode were confused about the definitions of the two modes. Confusion while in the No Auto mode occurred because the participants had forgotten their previous action. Instances of mode confusion occurred mostly after Event 4, where the mode changed automatically from any other mode to Partial Auto mode when the participant was driving while drowsy. The participants were aware of the mode before closing their eyes either because they did not trust the system, or they forgot the mode transitions while drowsing.

With the function-centred interface, before the display was viewed, the highest mode confusion rate occurred in the ACC + LK mode. The participants thought of the ACC + LK mode as the No

Table 4: Mode confusion rates before and after glancing at the level-centred interface in the experiments.

		Recognized Modes									
		No Auto		Driver Assist		Partial Auto		High Auto		Mode Confusion	
		Before	After	Before	After	Before	After	Before	After	Before	After
Actual Modes	No Auto	87%	100%	5%	0%	8%	0%	0%	0%	13%	0%
	Driver Assist	36%	0%	52%	100%	12%	0%	0%	0%	48%	0%
	Partial Auto	16%	0%	7%	2%	77%	98%	0%	0%	23%	2%
	High Auto	0%	0%	0%	0%	0%	0%	100%	100%	0%	0%

Table 5: Mode confusion rates before and after glancing at the function-centred interface in the experiments.

		Recognized Modes											
		No Auto		ACC		LK		ACC+LK		ACC+LK+LC		Mode Confusion	
		Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Actual Modes	No Auto	96%	100%	2%	0%	2%	0%	0%	0%	0%	0%	4%	0%
	ACC	5%	0%	95%	100%	0%	0%	0%	0%	0%	0%	5%	0%
	LK	6%	0%	0%	0%	92%	100%	2%	0%	0%	0%	8%	0%
	ACC+LK	5%	0%	2%	0%	15%	0%	76%	100%	2%	0%	24%	0%
	ACC+LK+LC	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%	0%	0%

Table 6: Questions and responses after an experiment with the level-centred interface.

Questions	Response					Likert 5-point scale	
	Strongly disagree	Disagree	Undecided	Agree	Strongly agree	Mean	SD
1. This vehicle helped the driver to recognize the surrounding environment correctly.	0%	8%	21%	63%	8%	3.71	0.83
2. The interface effectively transmitted driving information.	0%	0%	25%	58%	17%	3.92	0.64
3. I experienced mode confusion while driving.	4%	29%	17%	33%	17%	3.29	1.17
4. This automated vehicle is satisfactory.	0%	25%	29%	33%	13%	3.33	0.99
5. This automated vehicle is safe.	0%	25%	33%	21%	21%	3.38	1.07
6. This automated vehicle is convenient.	0%	13%	25%	38%	25%	3.75	0.97
7. This automated vehicle is reliable.	0%	17%	29%	38%	17%	3.54	0.96
8. I would use this vehicle often.	8%	21%	33%	29%	8%	3.08	1.08
9. I would use this vehicle if it were free of charge.	0%	0%	13%	29%	58%	4.46	0.71
10. This vehicle is similar to the automated vehicle that I expected.	17%	17%	25%	25%	17%	3.08	1.32

Table 7: Questions and responses after an experiment with the function-centred interface.

Questions	Response					Likert 5-point scale	
	Strongly disagree	Disagree	Undecided	Agree	Strongly agree	Mean	SD
1. This vehicle helped the driver to recognize the surrounding environment correctly.	0%	0%	25%	67%	8%	3.83	0.55
2. The interface effectively transmitted driving information.	0%	0%	17%	63%	21%	4.04	0.61
3. I experienced mode confusion while driving.	29%	38%	25%	8%	0%	2.13	0.93
4. This automated vehicle is satisfactory.	0%	4%	29%	50%	17%	3.79	0.76
5. This automated vehicle is safe.	0%	8%	29%	46%	17%	3.71	0.84
6. This automated vehicle is convenient.	0%	0%	17%	46%	38%	4.21	0.71
7. This automated vehicle is reliable.	0%	4%	33%	33%	29%	3.88	0.88
8. I would use this vehicle often.	0%	8%	29%	38%	25%	3.79	0.91
9. I would use this vehicle if it was free of charge.	0%	0%	0%	46%	54%	4.54	0.50
10. This vehicle is similar to the automated vehicle that I expected.	0%	17%	25%	38%	21%	3.63	0.99

Auto, LK, and ACC + LK + LC modes in Event 4. This mode confusion occurred for the same reasons as in the level-centred interface. Also, the confusion between ACC + LK and ACC occurred because the participants forgot their previous actions. Likewise, the confusion while in the No Auto and ACC occurred because the participants had forgotten their previous action. The participants considered the LK mode as No Auto mode were confused because they did not trust the system. A participant regarded the LK mode as the ACC + LK mode due to the definitions of the two modes.

In Event 4, we asked a specific question regarding how the automated system operated when the driver dozed at the wheel. All of the participants responded that the mode was changed to Partial Auto or ACC + LK regardless of the interface type, and they expected that the system would ring an alarm in order to wake a driver who was dozing at the wheel.

4.1.3. *Carry-over effect analysis*

Since the same subjects participate in all experimental treatments, there is a possibility that a previous treatment can change behaviour in a subsequent experimental treatment. This is known as a ‘carryover’ effect. The carryover statistic measures the effect of one treatment on the next treatment. For example, suppose that the reference treatment has a strong effect, and the test treatment has a weak effect. If the washout period is not long enough, the residual effects of the reference treatment in the first period can cause the effects of the test treatment in the second period to appear stronger than they actually are. To confirm that the carryover effect is significant, the P-value for the carryover effect is compared with the significance level (α) which of 0.05 is common. If the P-value is less than α, the carryover effect is statistically significant. To analyse the carryover effects on our experiments, we performed an equivalence test for a 2×2 crossover design using Minitab. The carryover effect is not statistically significant because the estimated carryover effect is 0.452 and the P-value is 0.498 ($P > 0.05$).

4.2. Questionnaire survey

4.2.1. *Summary of questionnaire results after each experiment*

After performing the experiment with each interface, the participants completed a questionnaire consisting of seven questions related to their subjective evaluation (i.e. whether the participant was confused during the experiment, the reason for his/her confusion, the action that he/she took when confused, and whether the interface effectively transferred the state of the vehicle). We analysed the questionnaire responses using a Likert five-point

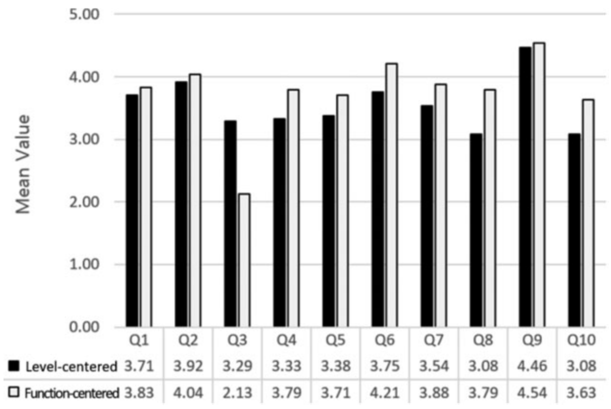

Figure 10: Comparison of questionnaire results between the level-centred and function-centred interfaces.

scale. Tables 6 and 7 summarize the responses of the participants regarding the level-centred and function-centred interfaces, respectively. In addition, Fig. 10 compares the questionnaire results for the two interface models. As shown in Table 7, for the level-centred interface, 67% of participants experienced instances of mode confusion. The participants reported that this mode confusion occurred because the mode transitions differed when they controlled the pedals and steering wheel in the Partial Auto and High Auto modes. For example, when the driver turns the steering wheel while in the Partial Auto or High Auto mode, the mode transitions to the Driver Assist mode. However, if the driver depresses the pedals, the mode transitions to the No Auto mode. Therefore, while driving, the participants must remember what they control and how mode transitions occur. In addition, the participants answered that except for the No Auto mode, it is difficult to intuitively understand the terms that indicate each mode. For the function-centred interface, 33% of participants experienced instances of mode confusion, as shown in Table 7.

As also shown in Table 8, for the participants who experienced mode confusion in the level-centred and function-centred interface models we asked three additional survey questions concerning the reason for his/her confusion, the action that he/she took when he/she was confused, and whether the mode confusion exposed them to danger. In the first question, 46% of participants in both interfaces experienced instances of mode confusion due to the complexity and difficulty of the operation methods of the automated systems. 26% of participants responded that the mode terms for the level-centred interface were not acceptable and required some effort to remember their meanings. 16% of participants responded that they felt mode confusion and did not know what to do in response to their confusion. Regarding the second question, most of the participants tried to drive manually when they experienced mode confusion. Some participants resolved the confusion by taking proper actions after glancing at the display. For the third question, 64% of participants experienced mode confusion when using the level-centred interface, as compared to four when using the function-centred interface. This result indicates that the level-centred interface is prone to mode confusion, and thus to increased risk of danger.

4.2.2. *Summary of questionnaire results after all experiments*

After all the experiments had been completed, the participants were asked to complete a questionnaire to compare the two interfaces. The participants' responses, as summarized in Table 9, show that for all questions, the participants indicated that the function-centred interface was better than the level-centred interface. They reported that, in the function-centred interface, the modes were clearly distinguished by having to turn on/off each button. In addition, the participants preferred the LK mode in the function-centred interface system and recommended that the LK system be installed in automated vehicles. On the other hand, the participants reported that the driving workload in the level-centred interface required that they remember the number of buttons that had been pressed as the systems were combined, and the mode terms did not clearly explain each mode. Finally, regarding mode preference, more than half selected the Partial Auto mode in which both the ACC and LK system were available.

4.2.3. *Limitations*

Several limitations are apparent in the present study.

First, there is a pre-learning effect on the user interface. The function-centred interface is very similar to the current vehicle interface; thus, the subjects are more familiar with the function-centred interface than the level-centred one. However, it is impossible to exclude such pre-learning effects from the participants because the function-centred interface has long been widespread worldwide.

Second, there is a bias on the subject's age and gender. We recruited a sample of participants from South Korea and many from the university campus. The average age of the participants was 26.6 (SD = 2.0) years, whereas that of whole Korean drivers was 46.6 (SD = 14.7) years in 2021 (Korean National Police Agency, 2019). The male-to-female gender ratio was 3:1 in the experiments, whereas the gender ratio of Korean drivers was 4:3 in 2021.

Table 8: Questions and responses after experiencing the mode confusion.

Questions	Response	Number of participants	
		Level-centred	Function-centred
1. Why was he/she was confused?	Incorrectness of cluster's information	8%	0
	Forgetting previous actions	4%	0
	Difficulty of operation	33%	13%
	Lack of understanding mode terms	13%	13%
	Did not know how to do after	8%	8%
2. Which action did he/she take when confused?	Manually drive	46%	16%
	Do nothing	8%	4%
	Drive while glancing at the display	13%	13%
3. Does the mode confusion expose people to danger?	Yes	64%	16%
	No	4%	16%

Table 9: Questions and responses after all experiments were completed.

Questions	Number of participants		
	Level-centred	Function-centred	Etc.
1. Which interface effectively transmits the information?	13%	88%	0%
2. In which vehicle do you experience more mode confusion?	71%	21%	8%
3. Which vehicle do you feel is easy to operate?	29%	71%	0%
4. In which vehicle can you handle a crisis quickly?	33%	46%	21%
5. In which vehicle do you feel less workload?	21%	75%	4%
6. In which vehicle do you maintain lanes easily?	17%	79%	4%
7. Which vehicle is more convenient?	21%	79%	0%
8. Which vehicle is safer?	17%	67%	17%
9. With which vehicle are you most satisfied?	13%	88%	0%
10. Which mode would you prefer to use often?	No Auto		0%
	ACC		13%
	LK		17%
	ACC + LK		63%
	ACC + LK + LC		8%

Therefore, there is a significant difference in age and gender distribution between the sample and the population.

Third, the experiment results obtained from simulator research differ from those shown in the real world. The simulator results need to be evaluated with regard to their generalizability to the real world. Driver behaviour data collected in artificial scenarios under controlled conditions may not be like driver behaviour in real-world situations. It is, therefore, necessary to verify the validity of the simulator results. This work remains as future work.

5. Conclusions

In this study, we developed two interface models for an automated vehicle with options to operate in four and five different automation modes, respectively, and then conducted driver-in-the-loop experiments to examine the effectiveness of these interfaces with respect to driver's mode awareness. The results can be summarized as follows:

(i) Intuitive and familiar interface model: The experimental results show that the function-centred interface was a more comprehensive user interface than the level-centred interface. The overall mode confusion rates for the level-centred and function-centred interfaces were 23 and 10%, respectively. Since the level-centred interface is not familiar to the people and represents various combinations of automated functions, it is not intuitive and thus may cause more mode confusions than the function-centred interface, which is an extension of the current ADAS.

(ii) Visual and auditory feedback: When the drivers saw the display after completing each event, the mode confusion rates for both level and function-centred interfaces were reduced dramatically. We could confirm that the role of the feedback was very important for drivers to recognize the vehicle state or mode. Of course, this visual feedback can be replaced with auditory feedback. However, the effect of auditory feedback fades away in the long term while it is expected to be the same as that of visual feedback in the short term.

Therefore, for easier and safer driving of automated vehicles, a function-centred interface with appropriate visual and auditory feedback is more desirable in terms of being more intuitive and easier to understand. To this end, various advanced user interface technology can also be introduced into the interface (Lee & Yoon, 2019; Atif *et al.*, 2020; Li *et al.*, 2020; Bustos *et al.*, 2021; Chang *et al.*, 2021; Dhiman & Röcker, 2021; Lee & Yoo, 2021; Wang *et al.*, 2021).

In this work, the experiments were performed, assuming that the severity of mode confusion was the same in all situations. However, the severity of accidents due to mode confusion may vary depending on the situation. Therefore, it is necessary to create scores for the severities of mode confusion and use them in experiments and comparison of the interfaces. Moreover, there is a need to develop a driver monitoring method that detects whether the driver is currently in mode confusion (Zhang *et al.*, 2017; Kopuklu *et al.*, 2021; Bogdoll *et al.*, 2022; Hu *et al.*, 2022). In addition, if the system detects a driver's mode confusion, it should warn the driver so that the driver can cope with it. If the driver fails to cope, the system should be able to manage the situation instead of the driver.

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Conflict of interest statement

None declared.

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