Long-Term Evaluation of Drivers' Behavioral Adaptation to an Adaptive Collision Avoidance System

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Objective: Taking human factors approach in which the human is involved as a part of the system design and evaluation process, this paper aims to improve driving performance and safety impact of driver support systems in the long view of human–automation interaction.

Background: Adaptive automation in which the system implements the level of automation based on the situation, user capacity, and risk has proven effective in dynamic environments with wide variations of human workload over time. However, research has indicated that drivers may not efficiently deal with dynamically changing system configurations. Little effort has been made to support drivers' understanding of and behavioral adaptation to adaptive automation.

Method: Using a within-subjects design, 42 participants completed a four-stage driving simulation experiment during which they had to gradually interact with an adaptive collision avoidance system while exposed to hazardous lane-change scenarios over 1 month.

Results: Compared to unsupported driving (stage i), although collisions have been significantly reduced when first experienced driving with the system (stage ii), improvements in drivers' trust in and understanding of the system and driving behavior have been achieved with more driver–system interaction and driver training during stages iii and iv.

Conclusion: While designing systems that take into account human skills and abilities can go some way to improving their effectiveness, this alone is not sufficient. To maximize safety and system usability, it is also essential to ensure appropriate users' understanding and acceptance of the system.

Application: These findings have important implications for the development of active safety systems and automated driving.

Keywords: behavioral adaptation, adaptive automation, human–automation interaction, training, trust in automation, reaction time

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INTRODUCTION

Vehicle driving is a very hazardous undertaking and is associated with a high accident rate. Taking place in a highly complex environment with a multitude of different dynamic objects, car drivers are subject to various dangerous traffic conditions. While the primary driving tasks may include remaining in one's lane, monitoring hazards, and responding quickly, car drivers are also required to have high operational and tactical abilities and skills to avoid risky situations when perceived (Bellet et al., 2009; Cabrall et al., 2016; Horswill & McKenna, 2004; Wetton et al., 2010). On the one hand, there is a large volume of published studies describing the role of the human in road traffic accidents as the greatest source of error (Huang et al., 2000; National Highway Traffic Safety Administration (NHTSA), 2008; Treat et al., 1979). On the other hand, it has been argued that when it is not possible to find a technical error behind accidents that could theoretically be avoided by the driver, road-accidents data analysis attempts to blame the driver by tracing the reason back to human error (Rumar, 1982).

Automobile automation has been introduced as an effort to address driver error and support them control their vehicles efficiently and safely in a more comfortable way by supporting drivers' perception, decision-making, and action implementation (Bauer et al., 2012; Itoh, Horikome et al., 2013). Although driving automation systems' performance- and safety-enhancing benefits are evident, new kinds of human errors have also been observed and reported in situations involving automation assistance (Merat & Lee, 2012; Parasuraman & Riley, 1997). Therefore, automobile automation should be carefully implemented within the concept of human-centered design in which the human must retain the final authority and is perceived as the main component of the system

(Billings, 1997; Inagaki, 2006) while considering human trust and complacency (Parasuraman & Manzey, 2010; Stanton & Young, 2000).

From a systems designer's point of view, humans may not perform as well as automation; thus, the current focus is to minimize the human role of control and increase the level of automation (Miller & Parasuraman, 2007; van der Wiel et al., 2015). For example, to provide effective support and ensure safety in highly critical situations, the designers may aim to design robust automation systems with higher authority of control action even without human directive (Inagaki, 2006; Wilson & Russell, 2007). Accordingly, some systems might be given the authority to override/prevent humans' action that is not appropriate or act on their behalf (Sheridan & Parasuraman, 2005). Although such systems can be effective from a safety perspective, they are not always desirable from the human factors perspective, as *machine-initiative* trading of authority may cause problems related to human trust and acceptance (Muslim & Itoh, 2017a; Singh et al., 1993). For example, systems with higher automation authority may surprise humans with actions they do not expect in the given situation leading to distrust in and, sometimes, conflict with automation. Such human factors related issues can potentially lead to creating human–automation interaction problems, which may result in system disruption, accident, and personal injuries (Norman, 1990; Strauch, 2017).

However, the performance and effectiveness of an assistance system, particularly in the long view of human–automation interaction, depends not only on the authority of the system and its sophistication and robustness, but also on driver's ability and willingness to cooperate with that system (Hoc, 2000). Humans, when they understand and cooperate with the system entities, can address a wide range of problems that are difficult or impossible to be handled by the human or system alone. In aviation, for example, while the use of automation significantly contributed to reducing airplane crashes compared to the early days of air travel, different kinds of airplane crash occurred due to pilots' overreliance on automation and conflicts and lack of cooperation between human pilots and autopilots (Casner & Hutchins, 2019; Sarter & Woods, 1992). An appropriate level of human–automation cooperation and understanding is thus required to achieve safe and effective human–automation interactions.

How humans act, interact, and cooperate with automation is closely linked to their understanding of and trust in the system (Casner & Hutchins, 2019). Although automation may perform correctly, automation's failure to handle some situations due to lack of human cooperation caused by misunderstanding and inappropriate trust has been reported (Parasurarnan & Mouloua, 1996). Such mishaps make human–automation interaction, which covers the human understanding of and cooperation with automation as well as human capability and limitation to perform the physical and cognitive actions smoothly and safely, one of the most significant challenges that determine and may undermine the expected effectiveness and benefits of automation in all aspects of human–machine systems (Carroll & Olson, 1988).

As a way to improve human–automation interaction and cooperation, adaptive automation—in which the level of automation can be increased and decreased based on human's capability, task complexity, and risk—has been developed (Dijksterhuis et al., 2012; Inagaki, 2003; Tattersall & Fairclough, 2003). Adaptive automation has been proven effective in environments with wide variations in human cognitive abilities and workload, such as aviation in which aircraft control can be dynamically allocated between human pilots and autopilots in either a task-dependent manner (takeoff, climbing, cruising, and landing) or a situation-dependent manner (routine and critical conditions; Inagaki, 2003; Parasuraman et al., 1992). The cognitive abilities of highly skilled and trained human pilots enable them to develop an accurate mental model of the system, which reduces the possibility of inappropriate interactions (Hoc & Lemoine, 1998). In the automotive domain, the limited ability of car drivers to appropriately interact with the dynamic levels of adaptive automation when needed may pose a significant challenge (Kaber & Endsley, 2004; Young et al., 2007).

Previous research that has investigated the effectiveness of adaptive automation in automobile safety found that the ability of drivers to interact with multiple assistance functions is highly related to their level of understanding, which significantly influences the overall performance and increases the likelihood of automation-related errors (Muslim & Itoh, 2018a). For example, a high number of automation-related collisions have been observed when conflicts occurred between drivers' action and automation control due to drivers' misunderstanding of the different degrees of automation interventions used in adaptive collision avoidance systems (Muslim & Itoh, 2019a). Therefore, the questions here are how to improve drivers' cognitive abilities in interacting with adaptive automation; and how to address human factors issues, for example, trust and understanding, that might trigger inappropriate drivers' behavioral adaptation to driving automation systems and undermine efforts to address road traffic safety issues using assistive technology?

The present study attempts to address the abovementioned research questions by supporting the drivers' behavioral adaptation to and understanding of the adaptive driver assistance system for a more accurate mental model and safe and effective human–automation interactions using long-term driving simulation study. The goal was to test the claim, consistent with previous findings (Muslim & Itoh, 2018a), that the effectiveness of an adaptive collision avoidance system would be less when the drivers encountered critical events while supported by the system with a poor understanding of the automated functions than when those events occurred while the drivers are trained to interact appropriately with the system. It was also anticipated that drivers' mental models associated with their performance improvements would be most noticeable in how drivers assess, trust, and accept the system.

METHOD

Experiment Setup

A driving experiment was conducted on a motion-base driving simulator (Honda, DA-1105, 2005) comprising a cockpit with a single adjustable driver chair, a motorized steering wheel (Ø = 38 cm), brake and gas pedals, and an automatic transmission system (Figure 1). The driver field of view was projected using 120° curved screen (85 × 30 inches), and side and rear views were displayed in three small LCD screens (5 × 4 and 5 × 2.3 inches, respectively). The simulation data was recorded at 100 Hz using an external computer where the experimental scenarios and the driver assistance system were designed and installed. All drives were conducted on a 6-km-long limited access highway setting comprising two lanes in each direction with a median barrier to separate between directions. The centerline between lanes was marked with a dashed white line.

Forty-two human subjects (12 females; 30 males; M_{age} = 33.2 ± 13.9 years) of different nationalities with a valid Japanese driver's license and an average driving frequency of 4.2 times/week were recruited for the driving experiment. All participants reported at least 3 months of international driving experience. They signed an informed consent sheet and received remuneration (4,150 JPY) for their participation in the driving experiment, which was approved by the Ethical Committee of the Department of Systems and Information Engineering, University of Tsukuba, Japan.

Tasks

The participants were asked to fasten the seatbelt and drive as safely as they would normally do in real-world driving. They had to hold the steering wheel with both hands at any position they like and to keep the vehicle speed at 80 km/hr in the left-hand lane (the slow lane according to the left-hand traffic system in Japan). Once the driver reaches the required speed, the simulator was programmed to fix its speed at 80 km/hr until the first brake application by the driver. However, the drivers were encouraged not to use the brake pedal unless it was necessary, such as to avoid an impending collision. With such speed, each scenario may last for 8 min on average. The instructed driving task was to initiate several overtaking maneuvers to avoid slower leading vehicles (70 km/hr) in order to maintain the required speed of the host vehicle (80 km/

Figure 1. Honda driving simulator showing the cockpit, driver's position, and driving scene.

hr). The participants were strongly instructed to start the overtaking maneuver when the headway distance to the leading vehicle is approximately 10 to 15 m (time headway = 3 s) and to return to the left-hand lane after each passing maneuver.

Experiment Protocol and Design

According to the instructions of this experiment, the required overtaking maneuvers comprised three sequential phases (Figure 2). The maneuver starts when the driver first changes lanes from the host lane to a destination lane with the same direction of travel. The second phase starts once the driver reaches the destination lane, and the host vehicle is driving straightforward to pass the slow vehicle. The third phase begins when the driver changes lanes from the destination lane to the initial lane. The overtaking maneuver ends once the host vehicle returns completely to the initial lane and starts driving straightforward again.

These overtaking maneuvers were labeled as hazardous and nonhazardous based on the approaching traffic in the adjacent lane area and distance between vehicles. The hazardous overtaking maneuvers arise when a vehicle (I) attempts to pass a slow-leading vehicle (III) and dangerously closes in on an adjacent vehicle (II) located in the critical adjacent lane area, in which the most common lane-change crashes occur, as shown in Figure 3. For the nonhazardous overtaking maneuvers, the drivers could perform the maneuver in the absence of any hazard in the critical adjacent lane area.

In this experiment, the critical adjacent lane area was divided into four potentially dangerous regions based on drivers' ability to perceive

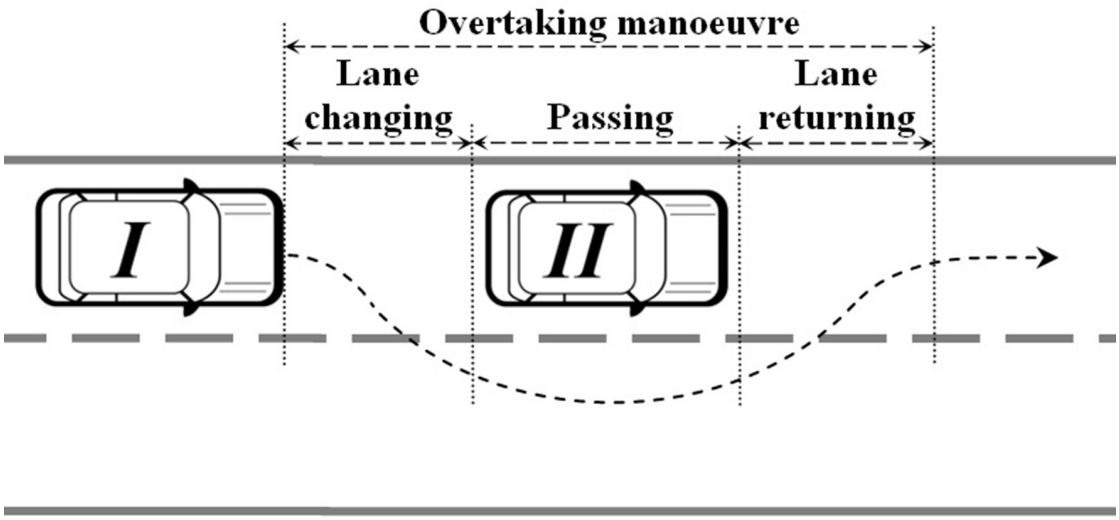

Figure 2. An overtaking maneuver: the host vehicle (I) approaches a slower leading vehicle (II), then changes lanes to pass vehicle (II), and then returns to the initial lane.

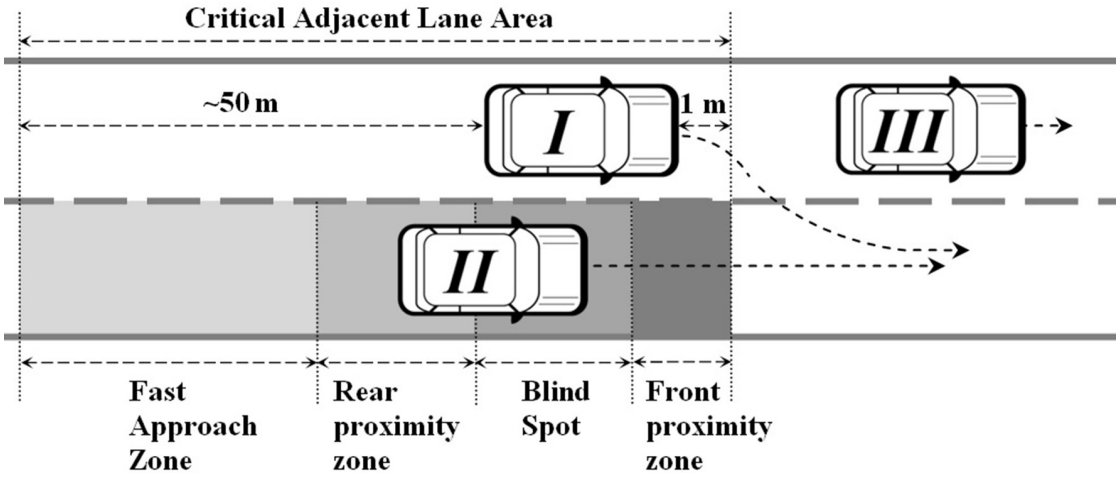

Figure 3. A potentially hazardous overtaking maneuver is showing the four potentially risky regions in the critical adjacent lane area that should be monitored by the overtaking driver.

the hazard in each region (Chovan et al., 1994; Lee et al., 2004). Accordingly, four hazardous scenarios were designed and considered for investigation as follows:

Front proximity zone. This region includes the area beside vehicle (I) that can be observed by looking through the left or right part of the front window and the side windows. The critical scenario was designed such that the front portion of vehicle (II) is in the front proximity zone of vehicle (I) while the rear portion of vehicle (*II*) is in the blind spot (defined below) of vehicle (I) during lane change initiation.

Blind spot. This region consists of the area beside vehicle (I) that cannot be directly observed by looking through the front window or side- and rear-view mirrors, but can be observed by looking out of either side window. To simulate the

blind spot, in this experiment, a specific area in the adjacent lane was defined so that it could not be perceived by the driver even when the driver attempted head movements to check the side window. The critical scenario was designed such that vehicle (II) is located entirely in the blind spot of vehicle (I) during lane change initiation.

Rear proximity zone. This region includes the area behind vehicle (I) that can be observed by looking through the side-view mirrors. The critical scenario was designed such that the front portion of vehicle (II) is in the blind spot of vehicle (I) while the rear portion of vehicle (II) is in the rear proximity zone of vehicle (I) during lane change initiation.

Fast approach zone. This region is located in the adjacent lane area from 9 to 49 m behind the rear-end of vehicle (I). Although the fast approaching zone can be perceived by a driver looking through the side- and rear-view mirrors, the driver's misunderstanding of the adjacent vehicle's speed in this area increases the likelihood of an accident, particularly when the time gap between vehicles is critical (between 1.2 and 1.4 s). The critical scenario was designed such that when the host vehicle (I) approaches vehicle (III) and the host driver starts with lane change initiation, a fast vehicle (II) approaches at 100 km/hr in the passing lane. Although the host drivers may feel that the distance between vehicle (I) and vehicle (II) is safe for completing the overtaking maneuver, vehicle (II) may strike the host vehicle from behind during the passing phase.

By means of direct steering intervention, an adaptive collision avoidance system with a dynamic control allocation strategy depending on the situation is proposed to support drivers' avoidance of colliding with vehicles in the adjacent lane during hazardous overtaking maneuvers. The steering wheel function was automated based on the design of soft and hard automation philosophies, which were first proposed and developed in aviation automation domain (Hughes & Dornheim, 1995; Schneider et al., 2015; Stanton & Marsden, 1996; Young et al., 2007) and then discussed to be integrated into the design of driving automation systems (Young et al., 2007). The soft automation is implemented using a haptic steering control function in which the driver has the final authority over the vehicle directions. The hard automation is implemented using an automatic steering control function in which the system has the final authority over the vehicle directions. Parameters for designing the haptic and automatic steering control functions were determined based on previous studies (Cramer & Zadeh, 2011; Griffiths & Gillespie, 2005; Hesse et al., 2013, Hesse et al., 2013Itoh & Inagaki, 2014) and feeds from our previous experiments (Muslim & Itoh, 2017b, 2018a, 2018b, Muslim & Itoh, 2019b; Muslim, Itoh, Pacaux-Lemoine et al., 2016).

The system is designed to provide a steering intervention during the first phase of hazardous overtaking maneuvers (Figure 2). Specifically, when a driver inputs a steering angle of more than 0.088 rad toward an adjacent lane where a vehicle is located in the critical adjacent lane area, the system activates one of the following assistance functions:

Haptic steering control. Following the soft automation design philosophy, a haptic steering control assistance function manipulates the steering wheel torque required to steer the vehicle by providing different degrees of steering wheel stiffness (between 1 and 9.6 N/m) against the direction of lane-change maneuver. In association with the change in steering wheel torque, an auditory alarm to alert the driver about the hazard is provided to enhance the driver's understanding of the situation and reduce automation surprises. The driver can override the additional steering wheel torque by increasing the applied steering effort to proceed with the intended maneuver.

Automatic steering control. Following the hard automation design philosophy, an automatic steering control assistance function decouples the steering input from the driver and automatically controls the tire angle to avoid potentially hazardous overtaking maneuvers. Although there is no direct relation between the steering wheel angle and tire angle during the activation of the automatic steering control function (i.e., steer-by-wire), the drivers have to maintain the longitudinal vehicle motion control. The activation of the automatic steering control function is associated with haptic steering feedback to help the drivers align the steering wheel angle with the system-applied tire angle to reduce the yaw rate between the steering wheel and tire angles and avoid

TABLE 1: The Degree of Hazards and Types of Steering Automation Functions of the Adaptive Collision Avoidance System

Scenarios	Driver's Risk Perception	Degree of Hazard $\beta e^{\theta * \text{distance}}$ ($\beta = 1.0$, $\theta = 0.001$)	Steering Automation Function
Nonhazardous	No passing vehicle in the adjacent lane	0	No steering automation intervention
Front proximity zone	The front portion of the adjacent vehicle (80 km/hr) appears in the rightmost corner of the front screen	0.3	The system sets off a warning and increases the steering wheel torque from 1.5 to 5 N/m
Blind spot	The participants using the available field of view in this experiment could not observe the adjacent vehicle (80 km/hr)	1.0	The system decouples the driver's steering input and automatically drives the vehicle away from the hazard
Rear proximity zone	The rear portion of the adjacent vehicle (80 km/hr) appears on the right side-view display	0.5	The system sets off a warning and increases the steering wheel torque from 1.5 to 7 N/m
Fast approach zone	Although the adjacent vehicle appears far from the host vehicle and is difficult to be seen at first when the host driver initiates an overtaking maneuver, the adjacent vehicle's speed is 100 km/hr and the time headway between the host and adjacent vehicles would be between 0.9 and 1.2 s	0.7	The system sets off a warning, gradually increases the steering wheel torque from 1.5 to 9.6 N/m, and decreases the vehicle speed to 70 km/hr

rapid steering control by the drivers when they resume the manual control again. The activation and deactivation process of the function is also associated with a set of auditory alarms to make it known for the driver that lateral vehicle motion control has been transferred from the driver to the system. When the system detects that the risk has been avoided entirely, it provides an auditory alarm to inform the driver that the deactivation is starting within 3 s to prepare the driver to resume manual steering control smoothly.

The proposed system adaptively integrates both haptic and automatic steering control functions to provide a specific driver support function, haptic or automatic, depending on the degree of hazard. The degree of hazard was zero when the drivers initiate an overtaking, and no cars were passing in the adjacent lane (nonhazardous maneuver). When the drivers initiate an overtaking while there was a car passing in the adjacent (hazardous maneuver), the degree of hazard was calculated based on the exponential function of the relative distance between the host vehicle and the passing vehicle in the critical adjacent lane area (Price et al., 2017). Considering the four regions in the critical adjacent lane area, the system was designed to provide four types of assist functions equivalent to four degrees of hazard, as presented in Table 1.

Procedure

Upon arrival, the participants received an explanation about the experiment design, tasks,

and ethical rights information. For each participant, the experiment was conducted in four stages, once a week, in a month. In total, every participant had to perform approximately 40 training, testing, and demo drives that were distributed in a randomized order over the four stages. Although all participants received the same order of the experimental stages, the scenarios used for the training and testing drives were balanced among the participants using a Latin square method to reduce the learning and carry-on effects. For each stage, the experiment started with some familiarization drives using nonhazardous highway scenarios such that the participants could earn an adequate skill to drive and control the driving simulator smoothly. This was followed by training and testing drivers. The participants were unable to distinguish the start and end of the familiarization, training, and testing trials in each stage. The details of each stage were as follows:

Stage i—no automation support. There were two familiarization (nonhazardous) drives followed by two training and four testing drives comprised of several nonhazardous and hazardous overtaking maneuvers. The participants were exposed to these hazards without automation support (baseline).

Stage ii—automation support with general information. After performing one familiarization (nonhazardous) drive, the participants were asked to read a general information manual (two pages of printed A4 papers consisting of approximately 500 words count with two pictures) explaining the system operation and properties. To avoid possible automation surprises, we provided graphical information about the critical events for which the adaptive collision avoidance system is triggered (similar to Figures 2 and 3). After reading the manual, the participants were given two opportunities to practice driving with the system and then they had to perform four testing drives during which they were exposed to hazardous situations with automation support.

Stage iii—automation support with driver training using graphical owner's manual. The experiment started with one (nonhazardous) familiarization drive followed by two owner's manual-based driver training drives before testing drives. The owner's manual was designed as PowerPoint slides with less textual and more graphical and auditory elements to provide drivers with the necessary knowledge and skills about the operating components. The training lasted 30 min per participant, focusing on improving drivers' understanding of the system functionalities and limitations. The participants, then, had to perform four testing drives during which they were exposed to hazardous scenarios with automation support.

Stage iv—automation support with interactive driver training. The experiment started with one familiarization drive followed by two practical training drives before the testing drives. The training lasted for 30 min and included comprehensive familiarization drives with additional descriptions by the experimenters. The objective was to improve drivers' understanding of and interaction with the system focusing on steering wheel behavior during the activation and deactivation of the system. The training was followed by four testing drives, during which the participants were exposed to hazardous scenarios with automation support.

All participants were asked to complete four questionnaire items to evaluate and compare the drivers' impression of the system after each experimental stage of driving with automation assistance. They had to mark their feeling by drawing a sign on a 10-cm line labeled from "0: not at all" to "10: absolutely." The questionnaires covered the following:

1. Understanding: To what extent do you think you could understand the system activities?
2. Effectiveness: To what extent do you think the system's support was effective at avoiding collisions?
3. Trust: To what extent do you think the system is trustworthy?
4. Acceptance: To what extent do you think you would like to use the system in real-world driving?

RESULTS

For all data analysis, only hazardous overtaking maneuvers were considered, and the significance level was set to .05. The experiment followed within-subjects design whereby all participants completed a four-stage experiment (independent variable) during which they had to

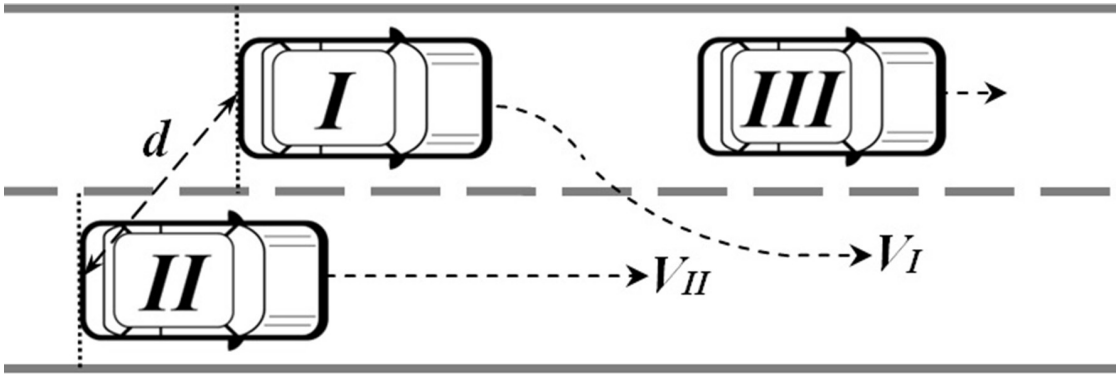

Figure 4. The minimum distance (*d*) between the host vehicle (I) and the adjacent vehicle (II). The time to collision (TTC) between vehicle (I) and vehicle (II) during lane change is calculated as TTC = $d/(V_{II} - V_I)$, where V_I and V_{II} are the velocity of vehicle (I) and vehicle (II), respectively.

perform hazardous and nonhazardous scenarios in a counterbalanced order. The effectiveness of driver training, system effectiveness, and human–automation interaction were evaluated in terms of three dependent variables: safety (number of crashes and near-crashes), driving performance (steering performance and braking reaction time), and questionnaires.

The first set of analyses examined the system's effectiveness in terms of the number of crashes and near-crashes during each type of scenario and experimental stage. No crashes or near-crashes occurred during the nonhazardous overtaking maneuvers; therefore, only hazardous overtaking maneuvers were considered in the evaluation. The total number of potentially hazardous overtaking maneuvers was 168 per stage for all participants (42 participants × 4 types of hazardous scenarios/participant = 168 hazardous maneuver/stage). This makes the total number of expected accidents during the entire experiment equal to 672 possible accidents. The number of crashes and near-crashes was calculated depending on the (TTC) between the host vehicle (I) and adjacent vehicle (II), as shown in Figure 4. The minimum distance (*d*) between vehicles was recorded during the first phase of an overtaking maneuver (see Figure 2). Because of the simulator constraint, the minimum TTC between the host and adjacent vehicles may not reach zero even when a physical contact occurred between vehicles. Therefore, a crash event is considered when the TTC is smaller than 1 s, and a near-crash event is considered when the TTC is smaller than 2 s and larger than 1 s. Accordingly, the crash rate (CR) and near-crash rate (NCR) are calculated as in equations 1 and 2.

$$\text{CR} = (\text{TTCs} < 1\text{ s}) / (\text{Total TTCs}) \quad (1)$$

$$\text{NCR} = (1\text{ s} < \text{TTCs} < 2\text{ s}) / (\text{TTCs} > 1\text{ s}) \quad (2)$$

Table 2 presents the breakdown of CR and NCR for each hazardous scenario and experimental stage. As can be seen from the table, results of CR and NCR indicate that the system was significantly effective in reducing collisions (CR) and maintaining safety (NCR) in the second stage compared to the unsupported driving in the first stage (χ^2 = 133.5 "CR" and 121.2 "NCR," $df = 1$, $p < .01$). Consistently, the chi-square test indicated significant differences in CR and NCR between the three supported driving stages (χ^2 = 119.8 "CR" and 129.1 "NCR," $df = 2$, $p < .01$). Results of the second stage are consistent with the collision data obtained in previous studies, during which the drivers have been exposed to hazardous situations with automation assistance in a single day (Itoh & Inagaki, 2014; Muslim & Itoh, 2018b; Schneider et al., 2015). Further reduction of collisions during the third and fourth stages compared to that of the second stage can, therefore, be attributed to the information conveyed to the drivers and driver training effectiveness.

TABLE 2: Number of Crashes and Near-Crashes for Each Hazardous Scenario and Experimental Stage

Experimental Stages	Experiment Scenarios									
	Front Proximity Zone		Blind Spot		Rear Proximity Zone		Fast Approaching Zone		Total	
	CR	NCR	CR	NCR	CR	NCR	CR	NCR	CR	NCR
i	8/42	9/34	35/42	4/7	13/42	11/29	21/42	18/21	77/168	42/91
ii	0/42	3/42	9/42	28/33	1/42	5/41	16/42	18/26	26/168	54/142
iii	0/42	0/42	1/42	17/41	0/42	2/42	7/42	11/35	8/168	30/160
iv	0/42	0/42	0/42	18/42	0/42	0/42	0/42	3//42	0/168	21/168

Note. CR = crash rate; NCR = near-crash rate.

A Pearson correlation examined the relationship between drivers' behavioral adaptation as a function of experimental stages and system effectiveness as a function of CR and NCR. The relationship was negative, moderate in strength, and statistically significant ($r(40) = -.41$, $p < .01$), indicating that the number of CR and NCR decreased as driver exposure to hazards and automation assistance increased. For the blind spot scenarios in which the system would activate the automated steering assistance, crash and near-crashes in the supported stages may occur due to the driver's ability to control the longitudinal motion of the vehicle. For the other types of scenarios (front and rear proximity and fast approaching zones) in which the system would activate the haptic steering assistance, crashes and near-crashes may occur due to driver's ability to override the system. These emphasized the importance of human–automation cooperation to achieve optimum performance.

To evaluate the system effectiveness, collision reduction effectiveness (CRE) and collision avoidance effectiveness (CAE) were derived from CR and NCR as in equations 3 and 4, respectively. CRE is measured to evaluate to what extent the system's support was effective in reducing the number of collisions. CAE is measured to evaluate to what extent the system support has improved driving safety. The variables $CR_{supported}$ and $CR_{unsupported}$ and $NCR_{supported}$ and $NCR_{unsupported}$ in the equations are the crash rate and near-crash rate for supported and unsupported driving modes, respectively.

$$CAE = 1 - NCR_{supported} / NCR_{unsupported} \quad (3)$$

$$CRE = 1 - CR_{supported} / CR_{unsupported} \quad (4)$$

Figure 5 presents the percentage of CR, NCR, CRE, and CAE values for each experimental stage. The significant differences in CR and NCR percentages between the experimental stages ($\chi^2 = 88.5$ "CR" and 110.2 "NCR," $df = 3$, $p < .01$) yielded significant differences in CRE and CAE between the supported driving stages ($\chi^2 = 130.1$ "CRE" and 98.3 "CAE," $df = 2$, $p < .05$). What is interesting about the data in Figure 5 is that the CAE percentage is lower than that of CRE for all supported stages, indicating that reducing the number of collisions is not enough to improve the driving performance and safety. This is because CRE is more related to the design of the system, such as robustness and automation authority, while CAE is more related to human–automation cooperation, such as interference between human and automation, trust, and understanding of the automated action (Muslim & Itoh, 2019a). Although drivers could not override the automated steering control with a higher automation authority, the situation is still risky due to drivers' ability to control the longitudinal motion of the vehicle, and thus, driver–system cooperation and understanding were necessary to achieve a better safety.

However, the differences in CR, NCR, CRE, and CAE values between the experimental stages show that both measures are significantly affected by driver's adaptation to automation

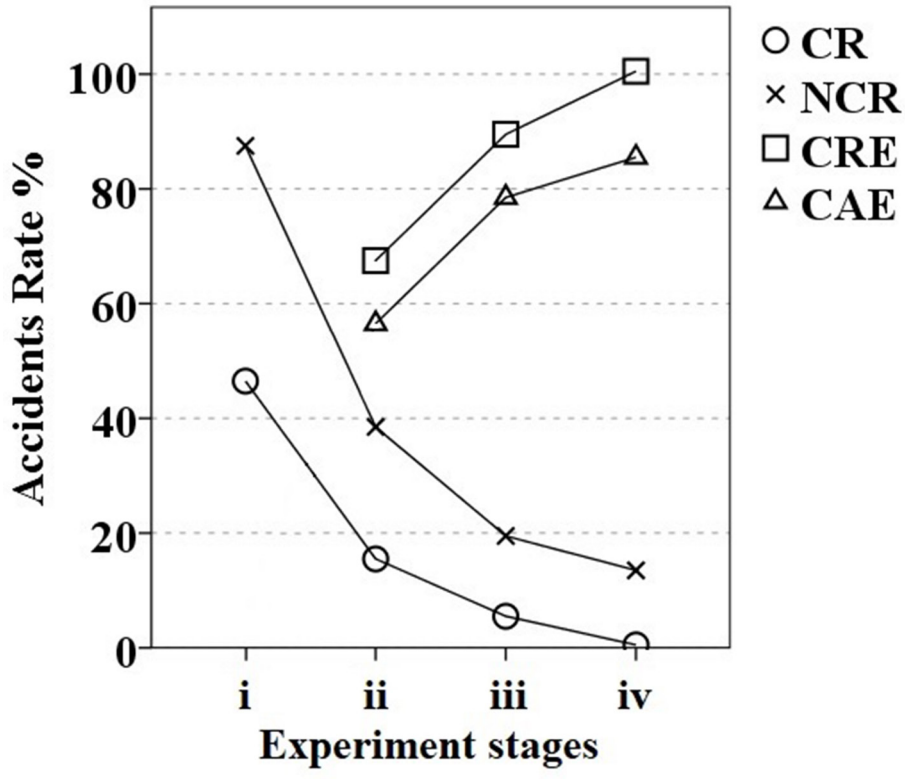

Figure 5. Accidents rate for each experimental stage. CR = crash rate; NCR = near-crash rate; CRE = collision-reduction effectiveness; CAE = collision-avoidance effectiveness.

assistance (i.e., the period of drivers' exposure to automation). The increase in CRE percentage from 67% to 100% reveals that further improvement is imposed by the long interaction and not due to the improved design of the system. Although it is difficult to specify how much interaction time versus training regime contributed to the increases in CRE or CAE, both factors are likely contributed to the result. On the one hand, the results of the second stage in the current experiment were similar to that of the previous experiment (Muslim & Itoh, 2019b). On the other hand, even though the training and long interaction raised the CAE percentage from 56% to 85%, the percentage did not reach 100%, indicating the importance of human–automation cooperation to handle critical situations.

The next part of the analyses examined the impact of driving automation and training on drivers' lateral and longitudinal driving behavior during hazardous maneuvers based on drivers' steering and braking performance during hazardous overtaking. When the system detects a potentially hazardous situation, that is, a driver initiates an overtaking maneuver and closes in on a vehicle located in the critical adjacent lane area, the system provides automated assistance to support the driver in avoiding the hazard encountered. However, the driver needs to cooperate with the system by maintaining an appropriate steering angle, in the case of haptic steering assistance, and vehicle speed to control the lateral and longitudinal vehicle motion smoothly. The driver's steering and braking behavior monitoring starts after the system activation point during the first phase of an overtaking maneuver (see Figure 2). The maximum steering wheel angle was recorded during the period from the system activation point to the

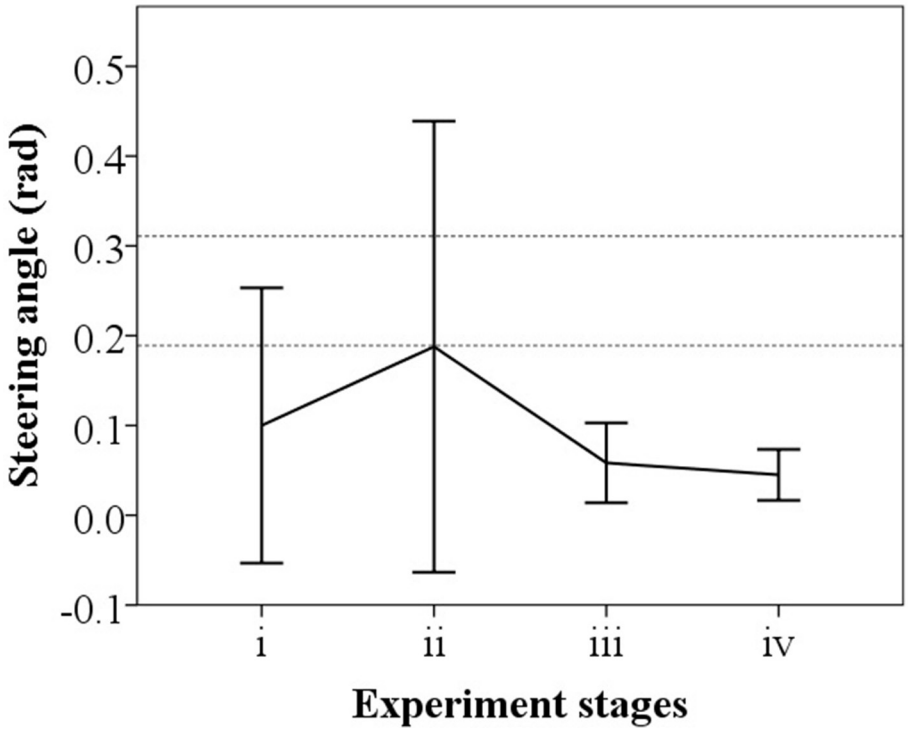

Figure 6. Steering wheel behavior during hazardous lane-change maneuvers. Error bars represent standard deviations. The reference dotted lines in the *Y*-axis represent the maximum and minimum values of the steering angle during nonhazardous overtaking maneuvers. For each experimental stage, the mean and standard deviation were calculated from the data of 42 participants.

point where the host vehicle returns entirely to the initial lane to avoid a side collision with the adjacent vehicle. The braking reaction time was calculated as the amount of time that elapses between the first steering input by either agent, driver, or system, to avoid a side collision with the adjacent vehicle and the first application of the brake by the driver to avoid a rear-end collision with a slower vehicle ahead when returning to the initial lane.

Figure 6 presents the mean and standard deviation of the maximum steering wheel angle for each experimental stage. The hypothesis was that the more the drivers reduce their steering angle during hazardous overtaking compared to nonhazardous overtaking, the more they understand the system. The drivers were able to perform smooth nonhazardous overtaking maneuvers on straight and curved road sections with an average steering wheel angle between 0.2 and 0.3 rad. For the second experimental stage, the maximum steering wheel angle was used to evaluate the driver's understanding of the automation assistance, compared to the first stage. For the third and fourth stages, the steering angle was used to assess the effectiveness of driver oral and practical training in reducing the conflict between drivers' intention and automation intervention compared to the second stage. A one-way ANOVA showed a significant effect of experimental stages, $F(3, 164) = 7.79$, $p < .01$; therefore, further data analysis is required to compare means and standard deviation of the steering wheel angle under each stage.

Table 3 provides summary statistics for the means and standard deviations of the maximum steering wheel angle. Multiple comparisons with LSD and Bonferroni revealed a significant

TABLE 3: Descriptive Statistics of the Maximum Steering Wheel Angle for Each Experimental Stage

Experimental Stages	*N*	Mean	Standard Deviation	Standard Error	95% Confidence Interval for Mean		Min	Max
					Lower Bound	Upper Bound		
i	42	0.10	.15	.02	0.05	0.14	0.02	0.71
ii	42	0.18	.25	.03	0.11	0.26	0.03	0.99
iii	42	0.05	.04	.01	0.04	0.07	0.01	0.20
iv	42	0.04	.03	.01	0.03	0.05	0.01	0.16
Total	168	0.09	.15	.01	0.07	0.12	0.01	0.99

difference in the steering wheel angle was detected between the first and second stages ($p < .05$). The comparisons reported that the mean steering angle was significantly reduced under the third and fourth stages compared to the second stage ($p < .01$), but the differences between the first, third, and fourth stages were not significant ($p = .57$, .28, and .33, respectively). The comparison of these results during the hazardous overtaking maneuvers in the first, third, and fourth stages with that of the nonhazardous overtaking maneuvers may lead to the conclusion that the training was efficient at improving driver interaction with the system. However, the reduced standard deviations in the third and fourth stages compared to the first stage may also indicate further improvement in steering behavior, which could also be attributed to the long-term interaction with the system as it has been previously highlighted by Abbink and Mulder (2009).

The maximum steering angle recorded during the second stage was larger than that of other stages. A possible explanation for this would be that the drivers could not form an appropriate mental model of the system when they first experienced the system in the second stage. Therefore, the steering wheel control of the drivers was not smooth during the activation and deactivation of the system. The driver training in the third and fourth stages was effective in reducing the steering wheel angle compared to that of the second stage and the nonhazardous overtaking, indicating an improvement in drivers' understanding of the system. However, these results should be interpreted with care. In this experiment, the participants were unable to see or feel the accidents when they occurred. Thus, the participants proceeded with the driving trials even when they were involved in accidents. This was mainly to avoid the negative influence of the accidents on participants' behavior during the subsequent drives. For this reason, the maximum steering wheel angle during the first stage, in which CR value (Figure 5) was high, was less than that of the second stage.

In this experiment, all overtaking maneuvers were in response to a slower vehicle ahead. For each hazardous overtaking maneuver, if the maneuver is aborted, by the host driver and/or the system, to avoid colliding with a vehicle in the adjacent lane, the host drivers had to reduce the vehicle speed by applying a brake to avoid rear-end collisions with the slower vehicles ahead after returning to the initial lane. Figure 7 compares means and standard deviations of the braking reaction time among the four stages of the experiment. A one-way ANOVA revealed a significant difference between experimental stages, indicating a significant reduction in drivers' reaction time along with the progress in driver's experience of the system, $F(3, 167) = 83.22$, $p < .01$. Although a strong negative correlation was found between the braking reaction time and driver experience of the system ($r = -.51$, $p < .01$), such improvement in drivers' reaction time cannot be fully attributed to the effectiveness of the training due to the possibility of the learning effects that could be triggered by the redundant hazards and the long-term interaction.

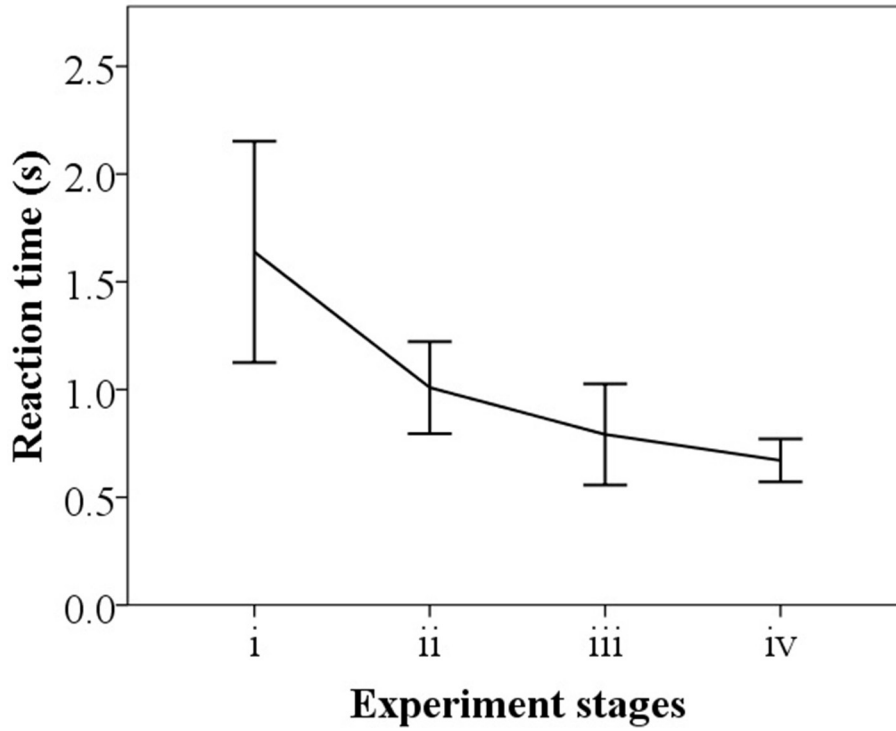

Figure 7. Driver reaction time. Error bars represent standard deviations. For each experimental stage, the mean and standard deviation were calculated from 168 potentially hazardous events.

TABLE 4: Descriptive Statistics of the Braking Reaction Time for Each Experimental Stage

Experimental Stages	*N*	Mean	Standard Deviation	Standard Error	95% Confidence Interval for Mean		Min	Max
					Lower Bound	Upper Bound		
i	42	1.63	.51	.08	1.47	1.79	0.91	2.89
ii	42	1.01	.21	.03	0.94	1.07	0.68	1.50
iii	42	0.79	.23	.03	0.71	0.86	0.10	1.37
iv	42	0.67	.09	.01	0.64	0.70	0.50	0.84
Total	168	1.02	.48	.03	0.95	1.10	0.10	2.89

Table 4 presents the descriptive statistics of the drivers' reaction time for each experimental stage. According to the multiple comparisons with LSD, there were significant differences in braking reaction time between experimental stages ($p < .01$) except between the third and fourth stages ($p = .07$). Although the drivers demonstrated a significantly shorter reaction time in the second stage compared to the first stage, the result should be translated with care as the drivers on the second stage became aware that they have to reduce their speed when they cancel the overtaking maneuver and return to the initial lane. Such learning effects can also

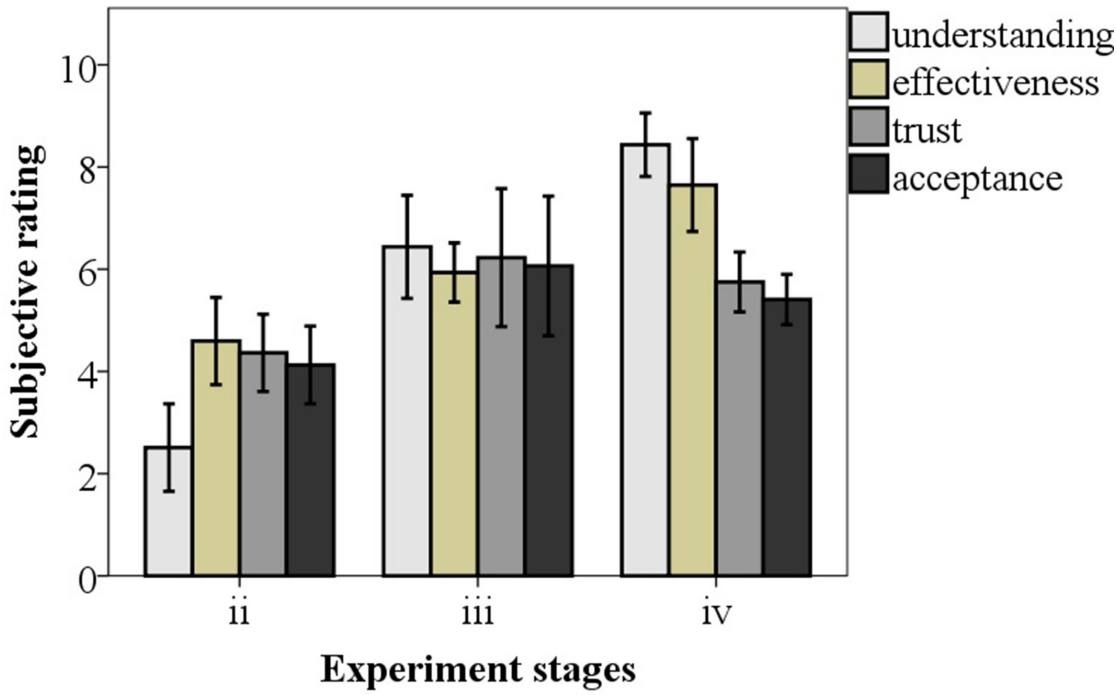

Figure 8. Subjective assessment of drivers' feelings of understanding, effectiveness, trust, and acceptance. For each experimental stage, each item represents the mean and standard deviation of 42 participants.

be applied to the differences between the first, third, and fourth stages. Therefore, the significant differences in braking reaction time between the second stage and that of the third and fourth stages can, partially, be attributed to the impact of the information conveyed to the driver and the training before interacting with the system.

The final part of the results section evaluates drivers' experience of the system using four-questionnaire items, as shown in Figure 8. Repeated-measures ANOVAs were run on the scores of the driver's understanding of the system, system effectiveness, and driver's trust in and acceptance of the system, and Bonferroni post hoc tests were used to compare questionnaire individually between experimental stages. The analysis revealed a significant main effect of the experimental stages, $F(2, 40) = 714.10$, $p < .01$, and a significant interaction between questionnaire items and experimental stages, $F(6, 36) = 103.50$, $p < .01$. For each stage, the differences were also significant between questionnaires, $F(3, 39) = 27.57$, $p < .01$. Drivers' ratings of their understanding and the system effectiveness were gradually increasing as their experience of the system was improving with the progress of the experimental stages ($p < .01$). Compared to collision data (Figure 5), drivers' rating of the system effectiveness is in line with the actual system effectiveness. This is a rather important result outcome since it has been implied by previous research that users' evaluation of the system and their performance can usually be dissonance (Andre & Wickens, 1995; Bailey, 1993; Cummings et al., 2007).

The subjective scores of drivers' trust in and acceptance of the system were first increased in the third stage compared to the second stage ($p < .01$), and then noticeably decreased in the fourth stage compared to the third stage ($p = .0501$). A possible explanation for this unanticipated fluctuation can be related to the changing of drivers' understanding of the system with the progress of the experimental stages. In the second stage, the rating of drivers' understanding of

the system was low, and it was difficult for them to form their model of the system. Therefore, the trust and acceptance ratings were below the average. As the level of drivers' understanding of the system increased in the third stage, the drivers tend to put a higher trust in the system, and their level of acceptance increased accordingly. However, the standard deviations of trust and acceptance were diverging in the third stage compared to the second stage. When the level of drivers' understanding significantly increased in the fourth stage, the drivers rated their feeling of trust and acceptance slightly lower than that of the third stage but higher than that of the second stage. The convergence of the standard deviation in drivers' rating of trust and acceptance of the fourth stage can be used to conclude that the drivers were able to develop a more appropriate level of trust and acceptance compared to that of the second and third stages. This could be attributed to the individual variation of human skills and the ability to build a mental model of the system. Such variation has been narrowed in the fourth stage. These are rather significant results and can be used to confirm the association between humans' understanding of automation and the appropriate level of trust in automation (Itoh, 2012; Muslim & Itoh, 2018b).

DISCUSSION

While reported by several studies, the risk of automation-related human errors, as an inappropriate human–automation interaction that may or may not result in accidents and injuries, is still associated with automation implementation (National Transportation Safety Board, 2014; Parasuraman & Riley, 1997; Strauch, 2017). Automation implementation with inadequate consideration of human abilities and limitations can pose novel challenges for human operators. Focusing on system robustness and capabilities with little attention to the potential effects of humans' capabilities and limitations when interacting with the automated function may lead to lower the level of performance, system disruption, and fall short of expected benefits (Sullivan et al., 2016). It is necessary to understand how the potential users will interact with automation in the long term to recognize and resolve problems in the early designing stages. For this, the focus of the present study is to promote the role of humans to enhance their interaction with automation using a long-term simulation interactive training approach for supporting drivers' understanding, trust, and acceptance. The study also attempts to address some unexpected human behavior when introduced to new technologies. In the long view of human–automation interaction, such inappropriate behavior may be triggered by behavioral adaptation that may not be easily perceived in short-term studies. A multistage driving simulation experiment was designed to investigate the impact of long-term driver–system interaction. The study used staged training to address and enhance drivers' adaptation to the automated system during different degrees of hazardous situations.

In terms of safety, differences between experimental stages were significant both in the number of collisions and in safe driving performance. Drivers' rating of their understanding of the adaptive automated functions was significantly improved with the progress of drivers' experience of the system functionalities. The drivers evaluated the system effectiveness based on their level of understanding, which was nearer to the actual system effectiveness after completing the training course. Accordingly, the levels of drivers' trust and acceptance were significantly adjusted more appropriately in the final stages compared to the early stages. On closer examination of these findings, it seems that the further improvements in human–automation interaction are achieved due to the driver training. However, the long-term interaction between humans and automation might also account for such improvements.

The system's effectiveness was presented in two measures. One is related to the number of actual collisions (CR and CRE), and the other is related to safety enhancement (NCR and CAE). Because the drivers were able to avoid half of the accidents without automation support during the baseline stage (stage i), the system effectiveness in terms of accident reduction could only be speculated during the supported stages of the experiment. In other words, during the supported stages, it was not possible to

evidence the number of accidents the drivers could avoid without automation support versus number of accidents the drivers could avoid with automation support based on the crash rate only. However, the effectiveness of the system in maintaining a safe distance between vehicles can provide a better understanding of the impact of automation assistance on the lateral behavior of the vehicle during hazardous overtaking maneuvers. Keeping a safe distance between vehicles is mainly related to how the drivers interacted and cooperated with the automated functions to avoid the hazard encountered. The further improvements in collision avoidance effectiveness in the third and fourth stages compared to that of the second stage indicate enhancements in drivers' interaction and cooperation with the system. A comparison of the results from the third and fourth stages with results of our previous experiments (Muslim & Itoh, 2018a, Muslim & Itoh, 2019b) may lead to the conclusion that enhancing the design of the system is not enough to optimize the overall performance and safety. Enhancing human operator skills and information processing abilities is, therefore, an essential human factor for safe and practical application of driving automation.

Human–automation interaction was evaluated using the standard lateral (steering wheel) and longitudinal (brake pedal) controls during the activation of a distinct automated function during hazardous maneuvers. Although the driving demands during critical events triggering were highly related to the steering wheel control, the results indicate that the steering behavior of the drivers was stable, and their braking reaction time was slow in the first stage. A possible explanation for this might be that the drivers were focusing more on controlling the steering wheel to manage the lateral position of their vehicle during lane changing and returning maneuvers, affecting their attention to the longitudinal vehicle motion control (Rajalin et al., 1997). The steering wheel behavior of the drivers was significantly deteriorated, but their reaction time was reduced when the drivers first experienced the system in the second stage. The observed increase in the steering wheel angle could be attributed to experiencing the adaptive automated steering interventions without sufficient knowledge about the system properties and characteristics. In the third and fourth stages, both steering wheel angle and brake reaction time were significantly reduced compared to those of the second stage. It can, therefore, be suggested that the informational and practical training were effectual at bettering drivers' understanding of the system and the situation encountered. However, the observed differences between the results of the third and fourth stages were slight (not significant). On the one hand, these findings partially support the association between driver training and further improvements in driver performance and system effectiveness. On the other hand, all drivers have been exposed to the experimental stages in the same order; therefore, it would be difficult to indicate whether the training or the additional exposures achieved these improvements. Further research might be required to compare the impact of driver training and long-term driver–system interactions.

Another important finding was that the subjective assessments of drivers' trust in and acceptance of the system indicated comparable trends of increase and decrease over the experimental stages. The drivers reported that they have used their understanding of the situation and the type of automated function to rate their feeling of trust and acceptance. The results of the second stage showed that the trust and acceptance scores were low because the drivers could not fully understand the system when they experienced the adaptive automated functions for the first time. For example, although safety has been significantly improved in the second stage compared to the first stage, drivers' feeling of safety in the second stage was moderate. These findings may help us to understand the potential effects of users' understanding of a new system on their feelings and, therefore, their behavior toward that system.

With the progress of drivers' experience of the system during the third and fourth stages, their understanding and appreciation of the system were increasing, leading to more appropriate adjustments in the levels of trust and acceptance. Accordingly, the drivers were able to develop an appropriate level of trust in and

acceptance of the system in the fourth stage. The results of the fourth stage indicate that improving humans' understanding of an automation system may not necessarily lead to an increase in their trust in and acceptance of that system. The improvement in humans' understanding of automation may significantly lead to developing an appropriate level of trust and acceptance, which could be lower or higher than the initial evaluation of the system. For this, the levels of trust and acceptance may continue to increase and decrease based on drivers' adaptation to the system until they can form a complete and accurate mental model of the automated functions. This finding broadly supports the work of Inagaki and Itoh (2013), linking drivers' trust in driving systems with their understanding of the system.

When comparing the performance of the adaptive collision avoidance system of the current study with the results of our previous experiment (Muslim & Itoh, 2018a) in which the drivers were exposed to adaptive and non-adaptive collision avoidance systems in a single day, one can find differences and similarities. Although some system's design parameters were improved in the current experiment (e.g., the system's automatic deceleration during the fast approaching zone scenario), the results of system effectiveness in the second stage of the current experiment were comparable with that of the previous experiment. Thus far, the steering and braking behaviors of the drivers are also showing the same trends between the two experiments. Significant differences from the previous experiment could only be observed during the third and fourth stages of the current experiment, in which the drivers received more interactive informational and practical training on how to interact with the system appropriately.

Despite these promising results, a limitation of the current study related to the design of the adaptive collision avoidance system should be highlighted. The adaptive automation is usually designed to handle complex tasks, such as in air control and aviation (Kaber & Endsley, 2004), which require intensive training. However, the environment and tasks of the driving simulator experiments do not require a high level of skills because they are closely familiar to most people. Given that automating complex tasks can increase the possibility of human misunderstanding of the system, the set of assistances provided by the current system is considered low levels of automation with different levels of control authority, which makes it unclear how this intensive training could be presented to real drivers. This point has also been addressed by Casner and Hutchins (2019). This combination of findings, while preliminary, has important implications for developing adaptive driving automation systems in safety-critical situations not only during manual driving but also during automated driving when the system reaches a limitation and the drivers' ability to handle the situation varies depending on their workload and the situation.

CONCLUSIONS

The present study attempts to apply human factors attributes, which maintain the human as the main element of the system and make sure that the required physical and cognitive actions to engage in the automated function fall within human capabilities and limitations, for safe and effective implementation of driving automation. The objective was to perceive and address inappropriate human behavior when engaged in the automated process during dangerous conditions. The study conducted a four-stage driving experiment to assess how drivers supported by an adaptive collision avoidance system perform when exposed to various potentially hazardous situations while their level of understanding of the system was changing over time. A periodic and gradual simulation training approach was applied to support drivers' understanding of and interaction with automation in safety-critical situations. On the one hand, results indicate that training drivers on how to interact with the systems further improved the overall performance and safety. On the other hand, the long-term drivers' interaction with the system was efficient in recognizing and perceiving rarely occurring human actions that could be ignored or underrepresented in short-term experiments (Itoh & Inagaki, 2014; Muslim, Itoh, Pacaux-Lemoine et al., 2016; Muslim & Itoh, 2017a, 2018b, 2019a). Long-term studies may help to understand how humans act and

interact with automation and address drivers' behavioral adaptation issues related to trust and complacency.

Although safety in the second stage, during which the drivers exposed to the adaptive collision avoidance system for the first time, has been significantly improved compared to the baseline (no automation support), it was difficult for the drivers to anticipate the capabilities and functions of the support system based on the given information. Such incomplete drivers' understanding of the system during the second stage led to lower the drivers' steering performance while maneuvering between lanes and impacted the way they interact with the system. With the progress of the training during the third and fourth stages, drivers' understanding of the system and the situation encountered was significantly improved when drivers' expectations of the system and system capabilities were more aligned, leading to enhance drivers' trust and acceptance and system effectiveness. However, the system effectiveness was less than the expected as the system is assumed 100% reliable. These results confirmed that a proper balance of the dynamic control allocation between human and automation could be achieved based on the situation encountered and human's ability to handle the situation only when the human interacts appropriately with the system. The progress of driver training also leads to significant improvements in both driver performance and safety, concluding that how drivers adapt to automation is critical to their understanding of and interaction with the system as well as how they develop an appropriate trust in such a system.

Taken together, our previous and current findings suggest a role for applying human factors approaches in the early stages of system design to address inappropriate human–automation interaction. While designing systems that take into account human skills and abilities can go some way to improving their effectiveness, this alone is not sufficient. To maximize system performance and effectiveness, it is also important to ensure that the users understand its capabilities and limitations. For this, training is one essential and practical approach. The findings of this study have some important implications for the future application and practice of driving automation.

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KEY POINTS

- Drivers' behavioral adaptation to driving automation systems is critical to the efficacy of these systems.
- A multistage simulation training experiment was conducted to improve drivers' understanding of automation and better perceive and understand driving behavioral adaptation to an adaptive collision avoidance system.
- Results indicate significant improvements in drivers' adaptation to automation as their experience of the system was growing periodically with the type of information conveyed to them, providing a better understanding of drivers' interaction with and acceptance of the system.
- The study findings have important implications for effective and safe human–automation interaction design in which perceiving and understanding human is essential to avoid post human–automation interaction implications in real-world applications.

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