The Effects of Lead Time of Take-Over Request and Non-Driving Tasks on Taking-Over Control of Automated Vehicles

Jingyan Wan and Changxu Wu

***Abstract*— Automated vehicles have received great attention, since they offer the possibility of significantly increasing traffic safety, mobility and driver comfort. Current automation technology is still imperfect, therefore, there will still be situations in which the automation will not be able to handle and will request the driver to suspend non-driving tasks and take over control of the automated vehicle in a limited period of time. Accordingly, it is necessary to understand the effects of the lead time of take-over request as well as non-driving tasks on driver take-over. The present driving simulator experiment studied the effects of lead time and various realistic non-driving tasks on take-over behavior and driver acceptance to the automated vehicle. Results suggested optimal driver take-over performance when the lead time of the take-over request was 10-60s for general non-driving tasks. Specifically, take-over request with lead time at 10-60s led to lower crash rate, greater minimum time-to-collision (TTC), and lower lateral acceleration. However, a longer lead time (e.g., 15-60s) was necessary to achieve optimal driver acceptance even though drivers could successfully take over control with shorter lead time (e.g., 10s). In addition, driver take-over performance was significantly influenced by non-driving tasks. When more sensory modalities were occupied or when the cognitive load was very low, driver take-over performance was impaired, especially when the take-over request was too late (e.g., lead time was 3s). Potential applications of the results in designing of take-over request in automated vehicles were further discussed.**

***Index Terms*—Automated vehicles, Accident, Response time, Human-automation interaction**

I. INTRODUCTION

AUTOMATED vehicles, also known as self-driving vehicles, have received a great degree of attention in recent years, since an automated vehicle has the potential to sense its environment and navigate without human input, make driving decisions without intervention of a human and fulfill the transportation capabilities of a traditional car. Automated vehicle technology offers the possibility of significantly increasing traffic safety [1-6,8], mobility [1,2], and driver comfort [8,10,13], and reducing driver workload [7-13], congestion [1,2] and fuel emissions [1,2]. Google driverless vehicles have self-driven over 1 million miles [14] and car manufacturers such as Mercedes-Benz, General Motors, and BMW have proposed their concept automated vehicles. It is predicted that automated cars will account for up to 75 percent of vehicles on the road by the year 2040 [15].

In the latest federal automated vehicles policy, the National Highway Traffic Safety Administration has adopted the SAE International definitions for levels of automation [16]. Level 0 automation requires the driver to control everything. Level 1 automation can assist the driver conduct a part of driving task sometimes. Level 2 automation refers to automation of multiple control functions, however, drivers are still expected to continually monitor the driving scenario. At Level 3, automated vehicle enables the driver to cede full control in some instances but the driver must be available and ready to take over when the automated vehicle requests. Level 4 automated vehicle enables the driver to cede full control and thus s/he is able to engage in non-driving tasks under certain traffic conditions. At Level 5, the automated vehicle can perform all the driving tasks under all conditions. Level 4 and 5 automation no longer require the driver to be available for control. Since current automation technology is far from perfect, the automation is still unable to handle some situations (e.g., severe weather) and rare events which require more reliable and robust hardware and more real-world miles accumulation [17], and thus Level 3 automated vehicles are still the focus of current researchers and vehicle manufacturers. When the drivers have to switch their attention back from the non-driving task to the manual driving, “out-of-the-loop” issue emerges which may lead to overreliance, skill degradation, reduced situation awareness, etc. [7,18]. For example, Winter et al.’s review suggested that situation awareness (defined by Endsley as “the perception of the elements in the environment within a volume of time and space, the comprehension of their mearning, and the projection of their status in the near future” [70]) deteriorates in highly automated driving compared to manual driving if drivers are engaged in non-driving tasks [71].

It is critical that the driver is aware of the request of the control transition from the automation system to the driver early enough to avoid potentially dangerous situations and too ensure a comfortable take-over process [19]; However, NHTSA has

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not defined how early the automated vehicle should request the control transition. Existing research involving driver assistance systems showed that drivers provided sufficient lead time of the warning exhibited more gradual and stable response and higher trust to the systems. However, distraction, unnecessarily early response, and even trust issues were observed when the lead time was too long. When the lead time of the warning was too short, drivers may not have enough time to interpret the driving scenario or generate an appropriate response, which may lead to a higher probability of accident [20-28]. Therefore there should be an optimal range of lead time from the tradeoff between early and late warning messages, considering the issues of safety, response process and trust [29]. In the automated vehicle domain, there were only a few studies involving the timing of the take-over request and its effects on safe (presented by crash rate, maximum acceleration, and minimum time-to-collision (TTC)) and comfortable take-over performance (evaluated by subjective questionnaires). Damböck et al. suggested that a 6s lead time of the take-over request was sufficient for most visually distracted drivers. In [19], participants received take-over request with the lead time of 5s and 7s during Surrogate Reference Task (SURT) [31]. They found that with 7s lead time reactions were slower but better in quality compared with 5s [19]. Mok et al. distracted automated vehicle drivers with videos and found that the majority of drivers in the 5s or 8s conditions were able to safely negotiate the road hazard situation [32]. These research suggested that a lead time of the take-over request at 5s-6s could provide a safe response. However, a take-over request which generates "a safe response" does not necessarily result in positive experience. Even if no accident happens, a take-over request without sufficient time budget may increase driver workload, generate abrupt and erratic driver response, and harm driver trust and acceptance of the automated vehicle. Moreover, since the current automation technology is still under development, the current automated vehicle may not be capable to detect a system boundary 5s-6s in advance, especially under abnormal situations (e.g., automation failure, road blockage, severe weather conditions, and sudden maneuvers by another vehicle) [7]. Situations in which the driver needs to respond to emergent hazard still exist, but have not been addressed yet. On the other hand, safer and less critical situations in which the driver has enough time to respond in an unhurried and comfortable manner are still understudied [73]. With the fast development of intelligent transportation technology [33] and vehicle diagnostic technique, in the future, the automated vehicle should be able to detect system boundary very early. Therefore, wider range of lead time of the take-over request should be investigated to study driver response and subjective opinion under both emergent and non-emergent situations as well as to answer the much-asked question in automated vehicle domain "how long does it take drivers to get back in the loop?"

Non-driving related tasks involved by the driver during automated driving also have influence on the take-over time and quality. During automated driving, drivers do not need to monitor the system and the traffic situation and are potentially free in occupying themselves with non-driving related tasks, such as reading, typing, and even sleeping. This can lead to a contingently serious deterioration of situation awareness caused by a shift in driver cognitive resources to the non-driving task without paying attention to the surrounding traffic situation and the vehicle status. If the automation system requires a take-over, lost situation awareness has to be regained in order to perform safely and comfortably. In addition, when being engaged into non-driving related tasks, the driver's hands and feet may also be occupied. Longer time may be needed for the driver to switch back to the driving tasks mentally and physically. For example, when a take-over request is prompted, the driver will need to put the phone down and put the hands back on the steering wheel if s/he is playing games with a cell phone. Gold et al. and Lorenz, Kerschbaum, and Schumann distracted drivers using the visual-motoric SURT as the only one non-driving task and presented the take-over requests with the lead time of 5s and 7s [19,34]. Radlmayr, et al. compared non driving tasks of SURT and a cognitive demanding task named 2-Back-Task and observed similar effects of the two non-driving related tasks on the take-over process when the lead time was 7s [35]. In Gold, Berisha, and Bengler's study, a cognitive-motoric task and a texting task were included besides the above two tasks [36]. Take-over requests with the lead time of 7.78s was used and results showed that take-over performance with a cognitive task was better compared with visual and motoric tasks in well-practiced and noncomplex situations. Realistic non-driving tasks were also adopted in existing work. Merat et al. used the verbal "20 Questions Task" to simulate a phone conversation and the drivers were pre-warned about critical approaching incident via a sign placed 1,5000 meters before the incident. It was found that impaired performance was observed when drivers were asked to regain control of driving during automated driving [37]. Neubauer et al. distracted drivers with cell-phone use (making phone call, texting message, free choice, or control) and found that phone use during automated driving was associated with a faster braking response following transition to manual control [38]. Neubauer, Matthews, and Saxby studied driver fatigue in automated vehicles by assigning drivers to one of three media device conditions (control, cell phone, or trivia). The media devices were found help minimize the loss of driving task engagement and elevated distress produced by vehicle automation [39]. Another commonly used non-driving task was video watching, which was used in [32] and [40]. Drivers were distracted by such non-driving task in both studies and it was suggested that proper transition times and multimodal take-over requests should be considered to prompt safe and comfortable takeovers. Blommer et al. adopted both video and radio tasks with visual+audio takeover requests and it was found that compared with video watchers, radio listeners responded faster, looked to the road scene more, and they were more often looking forward at event onset [41]. Miller et al. adopted both video and reading tasks with visual takeover requests but did not find significant difference in reaction time or minimum headway between video watchers and readers [42]. Reading task was also used to distract drivers in [43] and the authors found that drivers experiencing automation were slower to identify the potential collision, but once identified, the collision was evaded more erratically than when drivers were in manual control. Moreover, task involving interacting with in-vehicle information system including pressing buttons and typing were included in [44,45]. Auditory takeover requests were found beneficial for drivers to switch back to the driving task in both studies. Most of the studies mentioned above concentrate on one or two tasks within the same experiment, which make it difficult to compare the effects of different tasks. There were a few studies looking at the underlying processes of engaging in tasks that have a differential effect on how drivers engage with automation [74-76]. However, this is still an understudied area. Therefore, it is necessary to include more realistic non-driving tasks in one experiment in order to provide a broader perspective.

The objectives of this research were to investigate the effects of lead time of the take-over request as well as the non-driving tasks on driver taking over control behavior in automated vehicles and find out the optimal range of lead time which would generated the optimal take-over behavior and best acceptance.

II. Experimental design

A. Participants

Thirty-six participants (18 males, 18 females) ranging from age 18 to 44 (M=22.1, SD=5.0) years of age took part in this laboratory session. Their reported years of driving experience ranged from 2 years to 27 years (M=5.3, SD=5.0). All of them had normal or corrected-to-normal vision, valid driver licenses, and had driven within the past month. Participants were compensated with $10/hour. Written informed consent was obtained prior to the study.

B. Apparatus

In order to investigate how drivers interact with automated vehicles and their taking-over control behavior, a simulated automated vehicle platform was built using OpenDS driving simulator (see Fig. 1). OpenDS is an open source and platform-independent driving simulator software with high performance scene graph based graphics API [46]. The driving simulator was installed on a Dell Workstation (Precision T5810, Intel Xeon CPU E5-1607 v3 3.10GHz). The driving simulator includes an adjustable seat, wheel and pedal supports, Logitech Driving Force GT® steering wheel with force feedback (Logitech Inc, Fremont, CA), a throttle pedal, and a brake pedal. Driving scenario was presented on three LCD monitors with 3840 ×1024 pixel resolution.

Fig. 1. Simulated automated vehicle platform in the present study.

The implemented simulated automated driving system could take over longitudinal and lateral control for a specific period, during which the driver did not have to continuously monitor the system and/or the road. When system boundaries occurred, the system could send out a takeover request to the driver with sufficient time to take over control. Besides longitudinal and lateral control, the automated driving system was able to perform lane changes and overtaking vehicles which moved slower than the set speed of the subject vehicle. The automated driving system would turn off when the driver steer or pressed the brake pedal. Moreover, with a button on the steering wheel the driver could turn the automated driving system on and off.

Multimodal interfaces are able to provide larger information bandwidth to provide more effective support for time-sharing and attention management in complex scenarios, resulting in better task performance compared with unimodal displays [47-55]. In order to effectively draw the driver's attention back from various non-driving tasks under automated vehicle settings, multimodal interfaces were adopted in the current study. A LED strip in the green color was installed on the steering wheel, presenting visual information to the driver (see Fig. 1). Once the system boundary occurred, the LED would be turned off. A speaker in front of the participant provided auditory information as well as various sound effects. Auditory information was in the form of a digitized human female voice with a speech rate of ~150 words/min and loudness level of ~70dB and driving sound effects with a loudness level of ~55dB. Once the system boundary happened, a verbal takeover request would be sent out. Each warning message started with a signal word "Caution" and followed by the takeover request and the time available for the driver to regain complete control of the driving task and a safely executed response to the situation at hand [35]. The signal word was used for calling driver's attention to the warning message and the upcoming collision event. The length of the auditory take-over request was 3s. Moreover, four vibration motors were placed (2 x 2) in the seat and four were placed (2 x 2) in the back support. For each vibration motor, the duration of the vibration was 250ms and the duration of inter-vibration was 100ms. The vibration intensity setting followed the guidelines of [56]. Once the system boundary happened, the vibration motors would be activated in the order of back-left, back-right, seat-right, and seat-left.

C. Questionnaires

All participants were asked to complete a questionnaire before engaging in the driving task. The questionnaire was designed to capture participants' demographic situation (such as age, gender, etc.), driving history (such as estimated cumulative driving mileage, the year a driver license was first issued, etc.).

After each collision event, the simulation automatically paused and subject was asked to complete a subjective questionnaire regarding the driver's acceptance of the automated vehicle system, which included the loudness of the auditory warning, the intensity and the comfort levels of the vibration, the driver's workload when s/he took over control, how comfortable and how safe the subject felt about the automated vehicle, and the participant's acceptance of the automated vehicle system. After each reading task, the participant needed to complete questions regarding the content of the reading material. After each video watching task, the participant needed to rate the level of interesting of the video from 0 to 10. Before and after the taking a nap task, participants were instructed to complete the Stanford Sleepiness Scale [58].

D. Driving Scenarios

The Test Block was a simulated five-lane freeway environment. The subject vehicle was driving in the middle lane. There were running vehicles in the same direction. The take-over scenarios due to the system boundary were represented by 6 different common collision scenarios in the driver's lane (e.g., traffic accident, a suddenly stopped lead vehicle, an obstacle). To avoid the crash, the driver could either slow down and stop on his/her lane, or change to the left or right lane. Since the obstacle (e.g., a suddenly stopped lead vehicle) would not move or disappear after the take-over request occurred, the driver needed to change to the left or right lane to keep going if s/he slowed down and stopped the vehicle on his/her lane. To make lane changing possible, the adjacent left or right lane was not occupied by any other vehicles. After passing the hazard event, the driver needed to continue the manual driving for a further 1,000 meter. At the end of such 1,000 meter manual driving, the simulation automatically paused and the participant was instructed to complete the subjective questionnaire regarding the most recent takeover. Another 18 potential hazard events were designed that the automated vehicle can handle by itself.

E. Non-driving Tasks

In order to study a realistic case scenario in the automated vehicle setting, where the driver is out of the loop and not monitoring the automated vehicle system, six different non-driving tasks were provided. They were reading, typing, playing games, and video watching via a smart phone, sleeping, and monitoring. These non-driving tasks came from the most common observed passengers' tasks on public transportations [59-61] and a large scale opinion survey on what people would do instead of driving in a fully self-driving vehicle [62]. In the reading task, the participant was asked to read an article during automated driving and answer questions regarding the content of the reading material after taking over of the vehicle. In the typing task, the participant was instructed to type the same words as showed on the smart phone at the speed that they usually do during automated driving. In the video watching task, participants watched a video on the smart phone and answered questions regarding the content of the video after taking over. During automated driving, participants were asked to play a game using the smart phone in the task of playing game, relax and try to fall asleep in the task of taking a nap, and monitor the driving scenario as they were driving in the monitoring task. Participants were instructed to take over the driving task and be responsible for the safe driving when a takeover request occurred.

F. Experiment Design and Procedures

The current experiment used a two-factor experiment design with controlled lead time of the take-over request and non-driving task as independent variables. The controlled lead time had 6 levels (3s, 6s, 10s, 15s, 30s, and 60s) which was equivalent to the time to collision (TTC) at the moment of the take-over request. There were also 6 different non-driving tasks (reading, typing, watching videos, playing games, taking a nap, and monitoring). In total, each subject went through 6 hazard events in which they needed to take over control due to automated system boundary. The 6 collision scenarios were randomly assigned to the 6 hazard events. The 6 different lead times and 6 different non-driving tasks were also assigned to the above 6 hazard events using a balanced incomplete design so that 1) if the non-driving tasks are disregarded, the arrangement becomes 6 balanced Latin square design, 2) if lead times are disregarded, the arrangement becomes 6 balanced Latin square design, and 3) each pair of ($Leadtime_i$, $Task_j$) showed up in the *n*th event once [63].

In order to control the learning effects and prevent the driver to respond as soon as any auditory messages or traffic events occurred, auditory messages not relevant to any traffic events (e.g., ads, news) and normal traffic events (e.g., the emergence and departure of a lead vehicle, vehicles in other lanes, etc.) and potential hazard events which the automated vehicle could handle by itself were designed and randomly assigned between two adjacent hazard events. The time interval between two adjacent hazard events' locations were randomly assigned between 5 minutes and 15 minutes. In addition, hazard vehicle/object would not appear or were blocked by lead vehicles. As the take-over request occurred, the hazard vehicle/object would appear and the lead vehicle would change lane if any.

At first, participants were asked to sign an informed consent and fill out demographic, driving history, and personality questionnaires before engaging in the driving task. Next, participants were instructed on the operation of the driving simulator and how to turn on and off the automated driving system. Then, subjects were asked to complete a practice drive in order to get familiar with the driving simulator. They were instructed to drive in the middle lane unless they had to overtake a slow lead vehicle or an obstacle in the middle lane. The scenario in the practice drive was designed similarly with the one in the formal drive (no hazard events or warning included). In the 10-minute practice drive, 5 non-driving related messages occurred. After completing the practice drive, subjects completed the test drive which included 6 collision scenarios. All participants were informed that the automated driving system was able to handle the driving task all the time. Therefore, they did not need to monitor the system or the road.

G. Measurements

The OpenDS driving simulator automatically collected time elapsed (s), longitudinal and lateral speed (km/h), longitudinal and lateral acceleration (m/s^2), and distance (m). With such data, each participant's take-over reaction time, minimum time-to-collision (TTC), maximum lateral acceleration, and maximum longitudinal deceleration in each hazard event were calculated. The shorter one between the time to first steer (the time from when the take-over request occurred until the first steering input greater than 2 °was applied) and the time to first pedal pressing (the time from when the take-over request occurred until the first pedal input greater than 10% was applied) was used as the take-over reaction time [35]. If the collision happened, minimum TTC was calculated by dividing the collision velocity by the average deceleration during the whole response process and was given a negative sign. Its absolute value represented how long the time period was, before which the driver should have started braking [72]. Minimum TTC could be regarded as an indicator of the potential collision severity. Moreover, participants' levels of engagement were calculated in each non-driving tasks which equaled to the participant's performance of the non-driving task divided by the corresponding baseline performance (see Appendix I for the baseline performance). Specifically, after the reading task, the participant was asked to answers questions regarding the content of the reading material besides the subjective questionnaire when the simulation paused. The engagement of the reading task equaled to the accuracy of the driver's answers divided by the baseline accuracy of the reading task. After the typing task, the experimenter would calculate the driver's typing speed and the engagement of the typing task equaled to the driver's typing speed divided by the baseline typing speed. After the video watching task, the participant was asked to answers questions regarding the content of the video when the simulation paused. The engagement of the video watching task equaled to the accuracy of the driver's answers divided by the baseline accuracy of the video task. After the game task, the driver's highest score was recorded and the engagement of the game task equaled to the driver's highest score divided by the baseline highest score. After the taking a nap task, the driver's sleepiness level was collected using Stanford Sleepiness Scale [58] and the level of engagement equaled to his/her sleepiness level divided by the baseline sleepiness level. In order to make sure the participant was engaged into the non-driving tasks, the participant's behavior data would be included into the analysis only if his/her performance of the non-driving task was not lower than 50% of the baseline. In this study, all participants' actually performance of the non-driving tasks was included in the analysis.

In addition to objective data quantifying the drivers' vehicle control inputs, subjective measures were collected including the perceived loudness and perceived vibration intensity of the take-over request, the driver's workload during taking over control and acceptance of the automated vehicle.

H. Data Analysis

At first, a generalized linear model (GLM) (mixed ANOVA) was conducted using SPSS [57] with lead time and non-driving tasks as independent variables, objective measures (e.g., crash rate, response time, minimum TTC, and lateral acceleration) as well as the levels of engagement in non-driving tasks as dependent variables, and gender, age, driving experience, annual mileage, personality, subject's alertness at the start of the automated driving, and order as covariates. Next, a GLM analysis (mixed ANOVA) was conducted using subjective measures (perceived loudness, perceived vibration intensity, workload of taking over control, and the acceptance of the automated vehicle) as dependent variables, and gender, age, driving experience, annual mileage, personality, subject's alertness at the start of the automated driving, and order as covariates to examine the effects of lead time of the take-over request and non-driving tasks on participants' subjective opinions on the automated vehicle.

III. RESULTS

A. Objective Measures

1) Crash rate: Results indicated significant effect of lead time on crash rate ($F(5,175)=25.817$, $p<.001$, partial $\eta^2=.425$) (see Fig. 2). Tukey multiple comparison test suggested that early take-over request resulted in fewer crashes than did late take-over request. As shown in Fig. 2, an abrupt decrease of crash rate appeared with the lead time getting longer when the take-over request was late. The trend of such substantial change slowed down when the take-over request was early. Specifically, the crash rate was significantly higher at 3s than 6s ($p<.001$), 10s ($p<.001$), 15s ($p<.001$), 30s ($p<.001$), and 60s ($p<.001$); significantly higher at 6s than 10s ($p=.01$), 15s (p=.03), 30s (p=.01), and 60s (p=.03). In addition, main effect of task was not significant on crash rate.

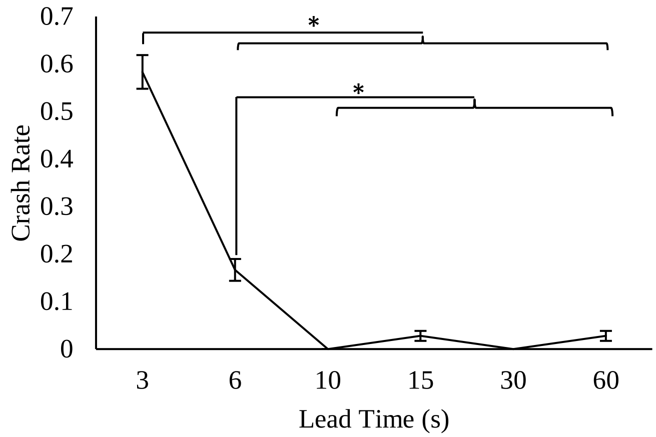

Fig. 2. Main effect of lead time on crash rate.

2) Response time: Main effect of task was significant on response time ($F(5,175)=3.349$, $p=.006$, partial $\eta^2=.087$). Multiple comparison test showed that response time under monitoring task was significantly shorter than any other tasks which required mental resources invested into non-driving tasks (see Fig. 3). Specifically, monitoring task generated faster response time than reading (p=.002), typing (p=.005), video watching (p<.001), playing games (p=.012), and taking a nap (p=.045). In addition, there was no main effect of lead time on response time.

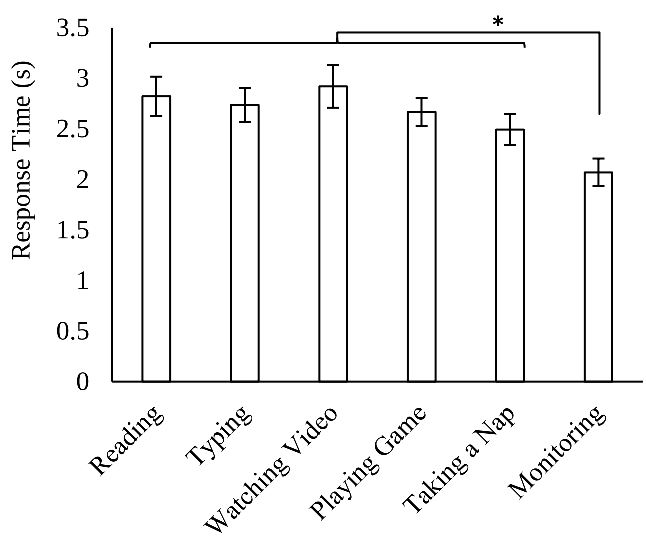

Fig. 3. Main effect of non-driving tasks on response time.

3) Minimum TTC: Results indicated significant effect of lead time ($F(5,175)=24.090$, $p<.001$, partial $\eta^2=.408$) as well as non-driving tasks ($F(5,175)=2.896$, $p=.015$, partial $\eta^2=.077$) on minimum TTC (see Fig. 4 and Fig. 5), which suggested significantly different potential collision severity between the lead time conditions and non-driving tasks. Tukey test showed that minimum TTC was significantly lower when the lead time was 3s than 6s (p<.001), 10s (p<.001), 15s (p<.001), 30s (p<.001), and 60s (p<.001), which indicated significantly higher collision potential when the take-over request was too late. Also, minimum TTC under watching video task was significantly lower compared with reading (p=.005), playing game (p=.029), and monitoring tasks (p=.007); minimum TTC under taking a nap task was significantly lower compared with reading (p=.015) and monitoring tasks (p=.018). This indicated better take-over behavior when the participants conducted reading, playing game, as well as monitoring.

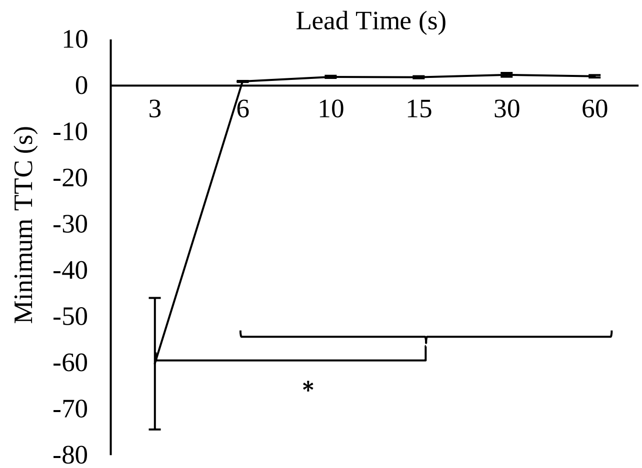

Fig. 4. Main effect of lead time on minimum TTC.

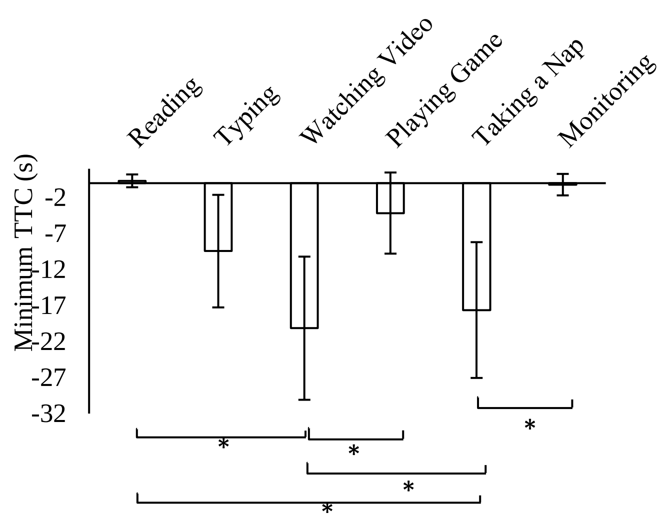

Fig. 5 Main effect of non-driving tasks on minimum TTC.

Moreover, the interaction between lead time and task had significant effect on minimum TTC ($F(25,175)=2.738$, $p<.001$, partial $\eta^2=.281$) (see Fig. 6). Simple effect analysis showed that non-driving tasks had significant effect on minimum TTC when the lead time was 3s ($F(5,175)=16.357$, $p<.001$). When the lead time was 3s, minimum TTC was significantly higher under reading compared with typing (p=.002), watching video (p<.001), and taking a nap (p<.001); minimum TTC was significantly higher under monitoring task compared with typing (p=.001), watching video (p<.001), and taking a nap (p<.001); minimum TTC was significantly higher under typing compared with watching video (p=.001), and taking a nap (p=.011); minimum TTC was significantly higher under playing game compared with watching video (p<.001) and taking a nap (p<.001). This made the results in Fig. 4 even clearer, which was, the significantly greater collision potential only appeared when the take-over request was too late. However, this effect did not appear when the take-over was relatively early and the drivers had more sufficient time to respond.

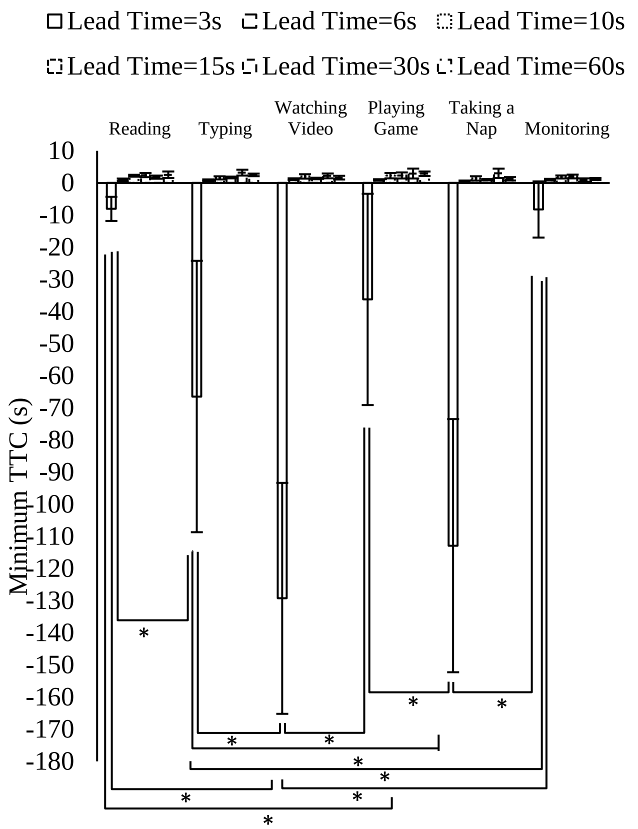

Fig. 6. Effects of lead time and non-driving tasks on minimum TTC.

4) Maximum lateral acceleration: Results also indicated significant effect of lead time on maximum lateral acceleration ($F(5,175)=7.575$, $p<.001$, partial $\eta^2=.178$). As shown in Fig. 7, a decrease of the maximum lateral acceleration appeared with the lead time getting longer when the take-over request was late. The trend of such substantial change slowed down when the take-over request was early. Specifically, the maximum lateral acceleration was significantly greater when the lead time was 3s compared with 10s ($p=.004$), 15s ($p<.001$), 30s ($p<.001$), and 60s ($p<.001$); significantly greater when the lead time was 6s compared with 15s ($p=.007$), 30s ($p=.003$), and 60s ($p<.001$); significantly greater at 10s compared with 60s ($p=.034$). In addition, there was no main effect of task on maximum lateral acceleration.

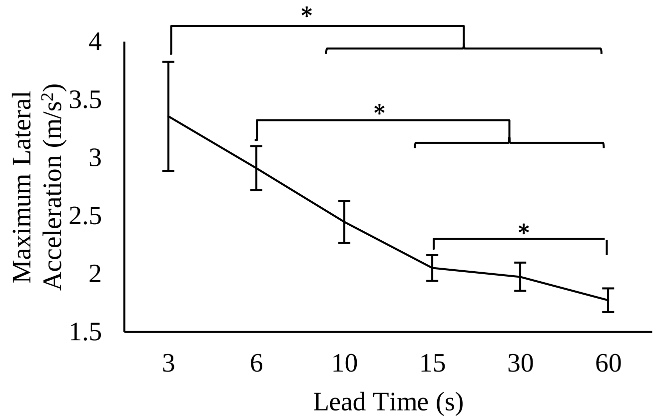

Fig. 7. Main effect of lead time on lateral acceleration.

5) Maximum longitudinal deceleration: Significant effect of lead time on maximum longitudinal deceleration ($F(5,175)=5.126$, $p<.001$, partial $\eta^2=.128$). As shown in Fig. 8, an increase of the maximum longitudinal deceleration was observed with the lead time getting longer except that a pit appeared when the lead time was 15s. Specifically, the maximum longitudinal deceleration was significantly greater when the lead time was 3s compared with 6s ($p=.012$), 10s ($p=.001$), 30s ($p<.001$), and 60s ($p=.001$); significantly greater when the lead time was 6s ($p=.039$) and 15s ($p=.003$) compared with 30s. In addition, there was no main effect of task on maximum longitudinal deceleration.

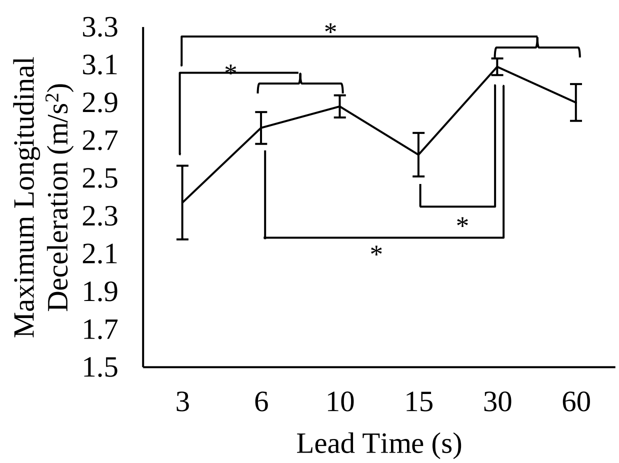

Fig. 8. Main effect of lead time on lateral acceleration.

6) Engagement in the non-driving tasks: Main effect of lead time was not observed on participants' level of engagement in the non-driving tasks. Non-driving tasks exhibited significant main effect on the levels of engagement of non-driving tasks ($F(5,175)=24.265$, $p<.001$, partial $\eta^2=.409$) (see Fig. 9). Pairwise comparison showed that the level of engagement in reading was significantly lower than video watching ($p<.001$) and playing game ($p<.001$) tasks. Similarly, the level of engagement in typing task was significantly lower than video watching ($p<.001$) and playing game ($p=.004$). Participants' engagement level in taking a nap was significantly lower than tasks of video watching ($p<.001$) and playing game ($p<.001$). Also, the level of engagement in monitoring was significantly higher than any other non-driving tasks ($p<.001$ for each pair-wise comparison).

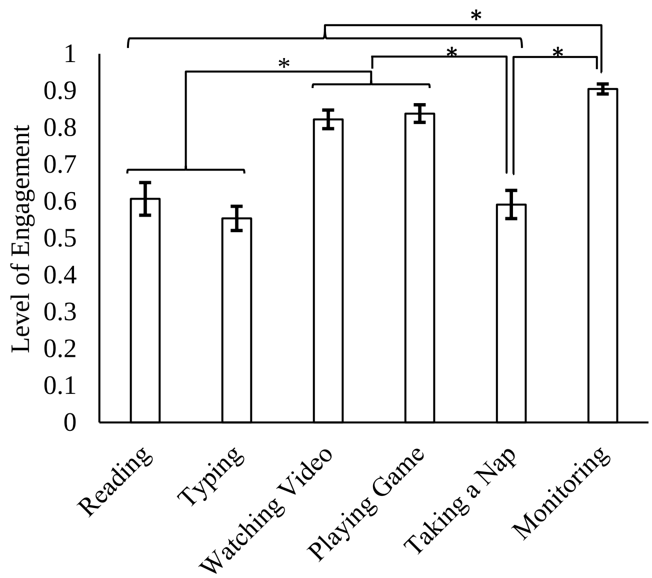

Fig. 9. Main effect of non-driving tasks on the levels of engagement in non-driving tasks.

B. Subjective Measures

1) Perceived Loudness of Warning Messages: Non-driving task had significant effect on perceived loudness ($F(5,175)=6.198$, $p<.001$, partial $\eta^2=.150$) (see Fig. 10). Specifically, the perceive loudness of the auditory take-over request was significantly lower under watching video task compared with other tasks ($p<.001$ for each pair-wise comparison). This made sense since the sound of the video weakened the loudness of the auditory warning.

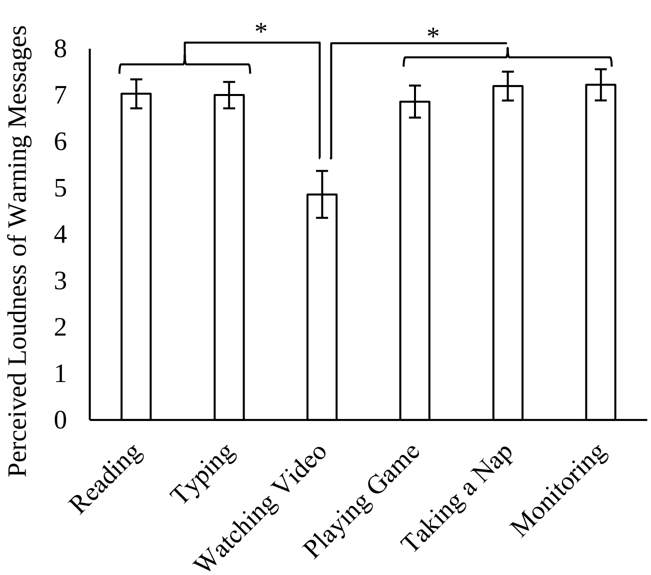

Fig. 10. Main effect of non-driving tasks on perceived loudness of the auditory take-over request.

2) Acceptance: Lead time had significant effects on acceptance ($F(5,175)=12.976$, $p<.001$, partial $\eta^2=.270$) (see Fig. 11). Tukey test showed that subjects' acceptance was significantly lower at 3s than other levels of lead times ($p<.001$ for each pair-wise comparison); significantly lower at 6s than 15s ($p=.016$) and 60s ($p=.032$); significantly lower at 10s than 15s ($p=.036$). Results indicated that driver acceptance to the automated vehicle was low when they did not have enough time to respond to the take-over request. Their acceptance increased with the prolonging lead time and stabilized when the take-over request was very easy.

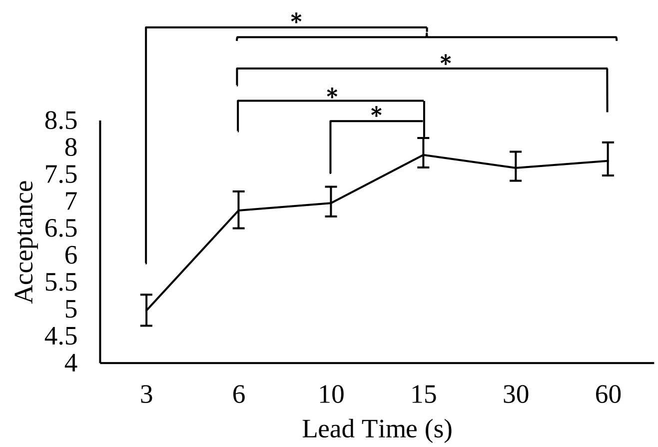

Fig. 11. Main effect of lead time on the acceptance of the automated vehicle.

3) Workload: There was not main effect of lead time or non-driving tasks nor the interaction effect between the two factors on driver workload.

IV. Discussion

This study investigated the effects of lead time of take-over request and non-driving tasks on driver take-over behavior and subjective opinion on automated vehicles. Compared with the existing works in automated vehicle domain, the range of the lead time in the present work was widely extended. Multiple realistic non-driving tasks were also addressed in the current study considering possible driver behavior in the future automated vehicles in order to provide a broader perspective. With the rapid development of intelligent transportation systems (ITSs), there will likely be a very low chance a system boundary of automated vehicles occur in reality. In order to control learning effects and generate realistic responses, auditory messages not associated with collision events and normal traffic events were designed and randomly assigned between two adjacent hazard events.

The results indicated that the lead time of take-over request would affect driver take-over behavior and subjective opinion on the automated vehicle. The optimal take-over behavior was observed when the lead time was equal or longer than 10s. Specifically, significant low crash rate was observed when it was equal or long than 10s and significantly greater minimum TTC was observed when it was equal or longer than 6s. In addition, lead time ranging from 10 to 60s led to more gradual maneuvering, which was revealed by the smoother lateral acceleration. Such results suggested that drivers would need sufficient lead time to better understand and respond to the takeover requests and the collision event, and, therefore, to generate better take-over behavior. Moreover, such gradual lateral maneuvering could reduce the risk of hitting road users in the adjacent lane. The optimal lead time in this work was longer than 4.5-6s which was obtained from [64] under connected vehicle settings and longer than 5-7s which was found from [19]. This was because drivers were engaged in realistic non-driving tasks during automated driving, and, therefore, they would need longer time to shift their attention from non-driving tasks to the driving task, put down the smart phone, put their hands and feet back onto the steering wheel and pedal, regain situation awareness, and take over control. Besides hazard ahead in the driver's lane, other vehicles could be driving in the adjacent lane (either left lane or right lane) at the onset of take-over requests in the current study. Therefore, drivers needed to spend more time on checking whether the adjacent lanes (left or right lane) were clear and making decisions of the direction of swerving. With too short lead time, at the onset of take-over requests, the driver may not have sufficient time to determine the direction in which s/he should swerve and collisions may occur with vehicles driving in the adjacent lane. Such collisions were observed in the current experiment.

Generally speaking, take-over requests given too late (the lead time was shorter than 10s) would do harm to the take-over behavior. The higher crash rate associated with too late takeover requests suggested that drivers did not have enough time to respond safely. Specifically, too short lead time generated lower minimum TTC and maximum longitudinal deceleration, which suggested inadequate brakes and greater potential collision severity. In addition, higher maximum lateral acceleration suggested that drivers swerved aggressively when the lead time was too short. However, due to the limitation of the technology under various conditions, takeover request with the lead time equal or longer than 10s may not be guaranteed. When the lead time is short, short auditory stimuli may be more effective than verbal takeover request in generating faster understanding and takeover response. Existing studies on driver assistance systems suggested that a warning provided too early without visual feedback may be treated as a false alarm or nuisance alarm, fail to assist the driver, and instead generate an inappropriate braking response [22-28]. It is of interested that such cases were not observed in the current study. The participant may understand that the system boundary of automated vehicle does not necessarily result from any hazard road users. The automation system can shut down simply because of the malfunction of sensors, cameras, etc. Moreover, after take-over requests occurred, some participants tried to switch the vehicle into automated driving but failed. Such cases also confirmed that the automation system was not functioning. Therefore, all subject did not treat any take-over requests including very early requests as false alarm. Although the crash rate was significantly lower when the lead time was equal or longer than 10s, the optimal acceptance to the automated vehicle did not reach the optimal and stable value until the lead time increased to 15s. This suggested that drivers expected sufficient time to complete take over control comfortably with high quality rather than just avoiding crash. The comfortable and high-quality take-over behavior coming with lead time at 15s or longer was also supported by the trend of maximum lateral acceleration. Besides the timing of the activation of the take-over requests, in the future the warning system should also be able to conduct real-time calculation of the "real" TTC and use such information in the verbal take-over requests. With the "real" TTC, the warning system would be able to deliver more accurate information and preserve driver acceptance to the system [69].

Besides lead time, the effects of non-driving tasks were also analyzed. The shortest response time was observed when the driver took over control after monitoring the driving scenario. Greater minimum TTC was observed when the driver took over control after conducting monitoring and reading tasks. Video watching and taking a nap led to lower minimum TTC. When the take-over request was very late (e.g., 3s), greater minimum TTC was also observed with monitoring and reading tasks and lower minimum TTC with video watching and taking a nap tasks. These suggested that non-driving tasks such as monitoring and reading which consumed less mental and physical resource and took shorter time when the driver switching back to the driving task. Non-driving tasks similar with typing and playing game in the current study would increase complexity within the take-over situations since they occupy the driver's hands and require information processing and motor response to the information. Therefore, in addition to the conclusion of [36] that driving performance with cognitive demanding tasks were worse if following take-over control, physical demand of non-driving tasks should also be considered when designing take-over request. Taking a nap increased driver sleepiness, and, therefore, prolonged driver response time and undermined take-over behavior, which was in agreement with previous studies on the generalized-cognitive-slowing hypotheses [65]. Therefore, the automated vehicle may need to provide longer take-over time to the driver when sleepiness is detected. The reason that video watching led to the worse take-over behavior may be that the driver could not receive clear and complete verbal request. Another reason of the better takeover behavior reading, typing, and playing a game could be that they are self-paced tasks and they can more easily be stopped and resumed compared with video watching and taking a nap which run at their own course. While when the participant was watching a video, s/he may be reluctant to look away of disengage because s/he would miss something of the video.

Better take-over control behavior can be achieved by sending the take-over control request as early as possible. Rather than 5-6s lead time of take-over request recommended by existing works in automated vehicle settings, with realistic non-driving tasks considered, the present study suggested lead time at 10s or longer. What is more, to ensure a comfortable and high-quality take-over, longer lead time should be provided to the driver, especially if s/he is conducting cognitive and physical demanding non-driving tasks, non-driving tasks which run at their own course, his/her sensory channels are occupied by non-driving tasks, or his/her vigilance was very low. Such findings can be regarded as important recommendations to the design of automated vehicle and will drive the development of ITSs (e.g., LIDAR, cameras), infotaiment systems (e.g., pairing with the driver's cell phone and identifying the active app), and driver monitoring systems (DMSs) (e.g., cameras, gesture sensors, pressure sensors, and wireless non-contact EEG sensors [66-68]). The take-over behavior and driver safety will be further enhanced by collecting the driver's non-driving task information.

The limitations of the present study will be discussed. First, verbal takeover request requested the driver to take more time to understand and respond. Results suggested that when the takeover request was too late (e.g., the lead time shorter than 10s), short auditory stimuli such as tone should be adopted to generate faster takeover response. However, when the lead time was relatively long, verbal takeover requests are better to be adopted in order to deliver specific information. Second, this study only included the six most common non-driving tasks (reading, typing, watching video, playing game, taking a nap, and monitoring) from the most common observed passengers' tasks on public transportations [59-61] and a large scale opinion survey [62]. The optimal lead time obtained in this study should be applied to the automated driving involving of non-driving tasks, but not to all the non-driving tasks. Drivers involved in more demanding tasks, such as sleeping, will definitely need longer lead time to regain control safely and comfortably. In many existing studies, researchers have investigated take-over behavior under specific conditions (e.g., two or three non-driving tasks) and they have been trying to establish a gold standard performance in the take-over behavior in automated vehicle setting [19,34-45]. In the current study, similar measures of take-over behavior to those studies were used with extended, but still specific, use cases. More use-case specific standards should be developed before understanding what drivers' true capabilities and limitations are in such situations. Third, though the visual, auditory, and tactile take-over requests were activated at the same time, the length of the take-over requests in each modality was different. The LED was turned off until the end of the hazard event as the visual cue. The vibration motors were activated for 1.3s in order to call the driver's attention [56] in case that the driver's visual/auditory channel was occupied. Auditory take-over requests delivered the detailed take-over request information, therefore, they took the longest time. Fourth, there may be differences between real road driving and simulated driving and the subject may not perceive the real risk of driving in traffic or the aspects of drivers' dynamic vehicle control in a driving simulator. The main goal of the current study was to compare differences of driver take-over behavior between different levels of lead time and non-driving tasks. High fidelity driving simulator may be needed to extrapolate the results of the current study to the real driving. Also, the driver may exhibit different behavior in laboratory controlled experiment compared with real road driving. Therefore, real road test may also be needed to extrapolate the results of the current study.

In the future study, short auditory stimuli such as tone should be adopted to study driver take-over behavior under emergent situations. More non-driving tasks should also be taken into account to understand take-over behavior under different situations. In addition, high fidelity driving simulator and field study should be conducted to extrapolate the findings of the current study in the future. Besides, other factors of take-over such as loudness and the vibration pattern and different traffic situations such as traffic density will need to be addressed in the future work in order to study their influence on driver taka-over behavior in automated vehicles. Still, the present study constituted a first step towards a comprehensive understanding of lead time and non-driving tasks and their effects on human take-over behavior in automated vehicles.

Appendix I

In order to obtain the baseline of the non-driving task performance, before conducting the experiment, 5 participants with similar age (M=23.0, SD=3.5) and driving experience (M=5.0, SD=2.9) to the subjects in the formal task were recruited to complete the same non-driving tasks including reading, typing, video watching, playing games, and taking a nap without conducting the driving task. The average performance of those 5 participants was calculated as the baseline of the non-driving task performance. None of those 5 participants were included in the following formal automated driving experiment in order to prevent the learning effects of non-driving tasks.

Among those 5 participants, the average accuracy of the answers to the questions regarding the content of reading materials in the reading tasks was 88%. The average typing speed in the typing task was 29.6 words/minute. The average accuracy of the video materials description was 94%. The average highest score of the game was 10,000. The average sleepiness level was 3.6.

The level of engagement of the non-driving task (reading, typing, video watching, playing a game, and taking a nap) in the formal driving experiment equaled to the participant's performance of the non-driving task divided by the corresponding baseline performance. The level of engagement of the monitoring task equaled to the participant's eyes-on-screen time divided by the duration in which the vehicle was driving automatically. In order to make sure the participant was engaged into the non-driving tasks, the participant's behavior data would be included into the analysis only if his/her performance of the non-driving task was not lower than 50% of the baseline.

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