Performance in Takeover and Characteristics of Non-driving Related Tasks during Highly Automated Driving in Younger and Older Drivers

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This paper aims to examine the effect of age and various characteristics of non-driving related activities during highly automated driving on subsequent performance in notified takeovers among younger and older drivers. The paper presents new analyses of data collected in our earlier study (Clark & Feng, 2016). Non-driving-related activities that participants voluntarily chose to engage in during automated driving were categorized according to their cognitive dimensions in information processing. Using hierarchical multiple regressions, we analyzed the effect of driver age, total duration and number of engagement in non-driving-related activities, the duration and cognitive dimensions of the last activity prior to takeover on average speed during takeover and the response time to a takeover notification. We found that older drivers speed was negatively predicted by age while their response time to a notification was not predicted by any factor. In contrast, younger drivers showed a trend of positive relationship between age and average speed and the characteristics of the last task engagement explained a significant portion of the variance of response time to a notification.

INTRODUCTION

Decades of research on driver distraction suggests detrimental effects of distraction on driving performance (for a review, see Young, Regan & Hammer, 2007). Involvement in conversation, mobile phone use (hand-held and hands-free), and electronic route guidance systems impairs attention (Mazzae et al., 2004; Spence et al., 2013; Strayer et al., 2003; Tijerina et al., 2000; for a review see Young & Regan, 2007) and subsequently lead to poorer driving performance (Al-Tarawneh et al., 2004; McKnight & McKnight, 1993). With higher levels of automation implemented in vehicles, drivers are less involved in the driving task (e.g., longitudinal and lateral controls), and thus may increase their engagement in non-driving-related tasks (Carsten, et al., 2012; Merat et al., 2014; Saxby et al., 2013). The research surrounding non-driving-related tasks on driving a highly automated vehicle varies, with some evidence suggesting that distracted driving has similar detrimental effects in controlling an automated vehicle as with present-day driving (Louw, Merat & Jamson, 2015; Merat et al., 2012; Zeeb et al., 2016), while other studies suggest the opposite. For example, Neubauer et al (2012) found that using a cell phone led to a quicker response to brake after a period of automated driving. Perhaps engagement in non-driving-related tasks supports the maintenance of vigilance by reducing boredom and drowsiness in highly automated vehicles. Indeed, Miller and his colleagues (2015) observed significant drowsiness when drivers operated a simulated automated vehicle. The level of drowsiness decreased when drivers were asked to engage in a non-driving-related task without impairing driver takeover performance. On a similar note, researchers have found that engaging in non-driving-related tasks alleviates alertness (Ma & Kaber, 2005; Young & Stanton, 2002).

With increased automation, it has been anticipated that drivers will engage more in non-driving related activities (Carsten et al., 2012; Merat et al., 2012). Studies have shown that drivers actively use strategies to reduce their crash risks when engaging in distraction such as slowing down, increasing the headway distance and controlling the pace of conversation (Young & Lenne, 2010; Zhou, 2014). Compared to younger drivers, older drivers tend to more regularly exercise compensatory driving strategies such as driving more slowly and keeping a longer headway distance (e.g., Clark & Feng, 2016; Dastrup et al., 2009; Körber et al., 2016; Miller et al., 2016), likely because older drivers are generally aware of slowed response and increased crash risks with age. As drivers can freely choose the non-driving related activities, when, and how to engage in these activities in highly automated driving, understanding how a driver's voluntary engagement in those activities during an automated driving phase impact the driver's performance in the subsequent takeover event needs to be examined. Our recent study (Clark & Feng, 2016) attempted to answer this question by observing younger and older drivers' voluntary engagement in non-driving-related activities during automated driving phases, and assessing their performance at notified takeovers. We found that both younger and older drivers showed significant individual variations in the level of engagement (as index by the total duration of activity engagement in the entire experiment). We performed a median split of each age group based on the level of engagement in non-driving related activities and compared the takeover performance among younger and older drivers with low and high engagement in activities. There was no group difference among the younger drivers in terms of speed, lane position, brake and throttle inputs, driving wheel angle, and response time to notification, while there was a trend of older drivers who engaged more in activities braked harder after a notification of takeover. In addition, younger and older drivers also demonstrated distinct preferences on the type of non-driving-related activities. More specifically, while younger drivers mostly used their smart phones during automated driving, older drivers tended to converse. Though these findings are interesting, the method (median split of participants for group comparison) to examine the effects of non-driving related activities on takeover performance may not have been particularly sensitive to such effects. It is possible to examine the characteristics of activity engagement before each takeover and

subsequent performance at the takeover. The current paper aimed to address the specific links.

In the current analyses, we used the multiple resource theory of attention (MRT; Wickens, 2002) as the framework to code the characteristics of the non-driving-related activities that occurred during our previous experiment. In addition, we included the duration and total number of activity engagements as additional characteristics of each automated driving phase (prior to each takeover). The MRT framework has been extensively used in research of dual-tasking and distraction, and characterizes tasks based on the modality, code and response dimensions of information processing in a task. If a non-driving-related activity competes for resources necessary for driving, it may be more likely to negatively impact the driving performance (Regan et al., 2009). Zhang and colleagues (2014) looked at distractors, categorized according to the multiple resource theory, and their impact on operational and tactical driving. They found that there was a larger speed variance and an increased steering entropy during the monitoring phase for both operational and tactical driving when paired with a visual-manual distractor. Additionally, there was an increased frequency and duration of off-road eye glance for both operational and tactical driving when paired with a visual-manual distractor. These results lead encouragement to using this same categorization of the multiple resource theory to understand the distractor impact on highly automated driving. Driving typically involves high resources from visual perception, spatial processing and manual manipulation (Liang, 2009), however attentional issues with highly automated driving may be more complex than assuming chunks of fixed multiple resources as a driver's overall alertness could be low after a period of automated driving.

The current paper presents a reanalysis of our data from Clark & Feng (2016). Building on our earlier analysis of driver behavior based on coding video recording of driving, we further extracted the duration and number of engagements in non-driving-related activities before each takeover, and characteristics of the engaged activity prior to a takeover. Guided by the multiple resource theory of attention, we coded the information processing characteristics of each non-driving related activity (modality and response dimensions). Hierarchical multiple regressions were conducted to examine the significance of each activity characteristic in predicting takeover performance.

METHOD

The method of the original study was described in detail in Clark & Feng (2016). In this paper, we provide a brief overview of information on participants, measures and procedure for context. Video data coding methods supporting the current analyses were elaborated in the Measures section.

Participants

The participants in this study included 17 older participants[1] (mean age = 70.2 years; 10 men, 7 women) and 17 younger participants (mean age = 19.9 years; 11 men, 6 women). All participants had normal or corrected-to-normal vision, had a valid driver's license, and drove at least once per week. Participants received either class credits or monetary compensation at a rate of $12/hour.

Measures

Simulated driving. Participants complete a drive using the STSIIM Drive 3 simulator, which provides a 180-degree field of view, three 42-inch television screens display the custom coded driving environment. This simulator is equipped with a steering wheel, driving pedals, a driver's seat, and input buttons for participant interaction.

The environmental scene was designed to provide logical justification for transfer of control in the form of a construction zone. The participants experienced several transitions between manual and automated driving, with the automated driving ranging from 1.5 to 2 minutes. Participants received an auditory notification prior to each takeover (transition from automated to manual driving). Their speed, lane position, brake and throttle input, and steering wheel angle were recorded by the simulator.

Non-driving-related activities. Throughout the drive, participants were video-recorded (Figure 1). Their frequency and duration of engagement in non-driving-related activities during automated phases were coded. These data was used in the current regression analysis to predict participants' takeover performance.

Using the MRT framework, each non-driving related activity that occurred in simulated automated driving was coded by modality and response dimension. Dimension of mental representation (codes) was not used to simplify the regression

Figure 1. A screen capture of one video recording of a participant's behavior in the experiment (image cited from Clark & Feng, 2016, Figure 3).

[1]Our original study included 18 older participants. Due to technical difficulties, video data from one older participant could not be accurately re-coded. Thus, this participant was excluded from the current analysis.

analysis. A list of non-driving-related activities and their categorizations was provided in Table 1. From the driving videos, we coded each participant's total number of activities in various non-driving-related activities, the total duration of non-driving-task engagement during each of the 12 automated driving phase, as well as the duration and type of their last engaged activity prior to the notification of takeover. If a participant first listened to music and then talked with the experimenter, this was coded as two distinct activities. The total duration of all non-driving-related activities and the duration of the last activity were both in units of seconds. The type of the last activity was coded using the MRT dimensions (e.g., visual-manual).

Takeover performance. Takeover performance was measured in two ways: speed during takeover and notification response time. Average speed (km/h) of driving in the takeover zone starting from the point of transfer of vehicle control to the start of the construction area (for details, see Clark & Feng, 2016, Figure 2) was calculated for one of each 12 takeovers. We also measured notification response time which is the period from when the takeover notification was presented to the first relevant action of the driver (e.g., hands returned to the steering wheel or foot returned to a pedal) as shown in the video of driver behaviors.

Procedure

Participants experienced three experimental drives that included a total of 12 takeovers (transitions from automated to manual driving) and 12 releases of control (transitions from manual to automated driving). A particular auditory notification was provided to warn about upcoming takeover, and another auditory notification was given for upcoming release of control. Each participant completed the consent form, survey of opinions of vehicle automation, demographics questionnaire, practice and experimental drives.

RESULTS

We used hierarchical multiple regressions to examine the predictive value of various characteristics of participants' engagement in non-driving related activities of takeover performance in younger and older drivers. The response variables were the two measures of takeover performance, average speed and time to respond to a takeover notification. The predicting variables in general included: age of a participant, the total number of distinct engagements in non-driving-related activities in an automated driving phase, the total duration of activity engagement in an automated driving phase, the duration of the last engaged activity prior to takeover notification, and the type of the last engaged activity according to MRT dimensions (Table 1). For the purpose of multiple regression, the categorical variable – type of last activity – was dummy coded into four separate dichotomous variables: auditory modality (0 if visual in MRT dimension or no activity, 1 if auditory in MRT dimension), visual modality (0 if auditory or no activity, 1 if visual), vocal response (0 if manual or no activity, 1 if vocal in MRT dimension), and manual response (0 if vocal or no activity, 1 if manual). Within each age group, we performed three regression models on each takeover performance measure (speed during takeover, notification response time). The first model included only age as a predicting variable; the second model with age, the total number and duration of activity engagements as predicting variables; and the third model with age, the total number and duration of activity engagements, the duration of the last activity prior to a takeover notification, and the four dummy variables indicating the type of the last activity. We examined the significance of each model and the percentage of variance in the response measure that could be accounted by the predicting variable(s).

Average speed during a takeover

Younger drivers. A total of 204 takeovers were included in the analysis (12 takeovers from each of the 17 younger participants). The first model including only age as the predicting variable explained a small amount of the variance of average takeover speed, (R^2 = .017, F[1,202] = 3.44, p = .065). Additional predicting variables did not help much to explain more variance in speed in the second regression model (R^2 change = .012, F_{change}[2,200] = 1.26, p = .286), nor in the third model (R^2 change = .030, F_{change}[4,196] = 1.55, p = .189). In general no variable significantly predicted speed, except that the predictive value of age was approaching significance in all three models (model 1: β = .129, p = .065; model 2: β = .134, p = .067; model 2: β = .141, p = .056).

Table 1. MRT dimensions of non-driving related activities.

Non-Driving-Related Activity	*MRT Dimension*
Reaching for object	Visual- Manual
Grooming	Visual-Manual
Electronic Device Use	Visual-Manual
Horseplay	Auditory-Manual
Communicating with Experimenter	Auditory-Vocal
Communicating with Themselves	Auditory-Vocal
Listening to Music	Auditory-Manual

Older drivers. A total of 204 takeovers were included in the analysis (12 takeovers from each of the 17 older participants). The first model including only age as the predicting variable explained a small yet significant amount of the variance of average takeover speed, (R^2 = .027, F[1,202] = 5.52, p = .020). Age was a significant predictor of average speed, as increasing age among older participants predicted an overall lower speed during takeover (β = -.16, p = .020). Adding total number and duration of activity engagements in the second regression model explained some additional variance in speed (a trend of significance; R^2 change = .026, F_{change}[2,200] = 2.69, p = .070). Both age (β = -.163, p = .026) and the total number of activity engagements (β = - .158, p = .030) were significant predictors of speed, suggesting an association of older age and a greater number of distinct non-driving-related activities with an overall lower speed. Characteristics of the last activity prior to takeover notification did not improve overall predictability in the third regression model (R^2 change = .025, F_{change}[4,196] = 1.31, p = .267).

Response time to a takeover notification

Younger drivers. A total of 181 takeovers were included in the analysis. Twenty-three out of 204 takeovers were not included in this analysis as a participant had hand(s) on the wheel and/or foot on the pedal before a notification. When a participant had hand(s) on the driving wheel and foot on a pedal prior to or at the time of takeover notifications, response time could not be calculated for these cases. Therefore, the number of takeovers in the current analysis was fewer than the total number of takeovers that took place. The first model including only age as the predicting variable explained a very small and insignificant amount of the variance of average speed during takeover, (R^2 = .006, F[1,179] = 1.08, p = .300). In the second regression model, adding the total number and duration of activity engagements as predicting variables did not improve model prediction (R^2 change = .019, F_{change}[2,177] = 1.14, p = .324). However, characteristics of the last activity explained a significant amount of the variance of average speed in the third model (R^2 change = .065, F_{change}[4,173] = 3.07, p = .018). In this model, many predicting variables became significant. More total numbers of activity engagement (β = -.318, p = .015) predicted a faster response to takeover notifications. Longer total durations of activity engagements (β =.374, p = .051) were marginally associated with slower responses. Both engagements in an auditory activity and a visual activity was associated with faster responses than no activity (auditory modality, β = .471, p = .028; visual modality, β = .329, p = .006). In contrast, when the last activity involved vocal response, the younger participants were slower in responding to a takeover notification than engaging in no activity (vocal response, β = -.390, p = .048).

Older drivers. A total of 189 takeovers were included in the analysis. Similar to younger drivers, some older drivers already had hand(s) on the wheel and a foot on a pedal at the time of takeover notification, thus fifteen out of 204 takeover events were included in this analysis. The first model including only age did not explain much variance of average takeover speed, (R^2 = .001, F[1,187] = .19, p = .666). Additional predicting variables did not help to explain more variance in speed in the second regression model (R^2 change = .017, F_{change}[2,185] = 1.62, p = .201), nor in the third model (R^2 change = .009, F_{change}[4,181] = .43, p = .789). None of the variables predicted older drivers' response time to takeover notifications.

DISCUSSION

The current reanalysis of driver behavior video recording provided much insightful findings in addition to our previous results (Clark & Feng, 2016). Among younger drivers, speed was not significantly predicted by any of the variables, age in fact showed a positive association with speed, maybe reflecting overall better vehicular control with more driving experience. In contrast, speed has a negative association with age among older drivers, suggesting that speed decreases as age increases, consistent with the general literature on slower driving speed among older drivers.

Among younger drivers, the response time to a takeover notification was predicted by many variables. Younger participants responded to the takeover faster when they had a higher number of activity engagements (measured by sum of occurrence of distractor variables within automated driving). Constant switching among non-driving related tasks may be associated with a more flexible state of attention, allowing a faster reengagement of attention with the driving task. In contrast, a longer overall time of engagement in non-driving marginally related activities was related to a slower response to takeover notifications, reflecting the importance to consider duration of secondary activities during automated driving as a factor to infer time-to-takeover. However, it should be noted that further analysis should be done on how time of disengagement impact on performance, as with more time performance decreases. Another interesting finding is that engagement in either a visual or auditory activity led to faster rather than slower responses to takeover notifications, suggesting a potential "engagement" effect of non-driving related activities helping to maintain alertness of drivers in automated driving (Miller et al., 2015). In addition, among older drivers, no factor predicted their response time to a takeover notification. Perhaps due to a much stronger prevalence and effects of compensatory behaviors among older drivers. Indeed, as we allowed participants to freely choose their engagements in non-driving related activities, impact of these activities on takeover performance in the study has accounted for active planning and compensatory strategies to minimize crash risks (also participants could not have accurately anticipated when a takeover would happen).

Limitations

While the reanalysis revealed interesting findings, there are certain limitations which should be addressed. First, participants' free choices on their engagement in non-driving related activities had resulted in high uneven frequencies of various activities. The sample size was relatively small to accommodate this data characteristic. Analyses would benefit from an increased sample size. More data could result in a more accurate representation of performance under each condition, for further validation of the current findings.

Second, the notification lacked a visual element, which would potentially interfere with the attentional resources being absorbed by some of the non-driving-related tasks. Liu (2001) suggests that visual displays result in poorer driving performance, likely due to the attentional resources required for appropriate interpretation of the display. This is notable, considering many of the new vehicle technologies involving advanced in-vehicle visual display systems.

CONCLUSION

In conclusion, the results of this reanalysis lead promise to the prediction of performance at the takeover of control of a highly automated vehicle, based on engagement in non-driving-related activities for younger adults. However, it

should be noted that further analysis should be done on time of disengagement impact on performance, as with more time performance decreases. Additionally, older drivers do not see the same affects as younger within the context of this study.

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