AGING AND AUTOMATION: NON-CHRONOLOGICAL AGE FACTORS AND TAKEOVER REQUEST MODALITY PREDICT TRANSITION TO MANUAL CONTROL PERFORMANCE DURING AUTOMATED DRIVING

by

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To my loved ones

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ABSTRACT

Adults aged 65 years and older have become the fastest-growing age group worldwide and are known to face perceptual, cognitive, and physical challenges in later stages of life. Automation may help to support these various age-related declines. However, many current automated systems often suffer from design limitations and occasionally require human intervention. To date, there is little guidance on how to design human-machine interfaces (HMIs) to help a wide range of users, especially older adults, transition to manual control. Multimodal interfaces, which present information in the visual, auditory, and/or tactile sensory channels, may be one viable option to communicate roles in human-automation systems, but insufficient empirical evidence is available for this approach. Also, the aging process is not homogenous across individuals, and physical and cognitive factors may better indicate one's aging trajectory. Yet, the benefits that such individual differences have on task performance in human-automation systems are not well understood. Thus, the purpose of this dissertation work was to examine the effects of 1) multimodal interfaces and 2) one particular non-chronological age factor, engagement in physical exercise, on transitioning from automated to manual control dynamic automated environments. Automated driving was used as the testbed. The work was completed in three phases.

The vehicle takeover process involves 1) the perception of takeover requests (TORs), 2) action selection from possible maneuvers that can be performed in response to the TOR, and 3) the execution of selected actions. The first phase focused on differences in the detection of multimodal TORs between younger and older drivers during the initial phase of the vehicle takeover process. Participants were asked to notice and respond to uni-, bi- and trimodal combinations of visual, auditory, and tactile TORs. Dependent measures were brake response time and maximum brake force. Overall, bi- and trimodal warnings were associated with faster responses for both age groups across driving conditions, but was more pronounced for older adults. Also, engaging in physical exercise was found to be correlated with smaller maximum brake force.

The second phase aimed to quantify the effects of age and physical exercise on takeover task performance as a function of modality type and lead time (i.e., the amount of time given to make decisions about which action to employ). However, due to COVID-19 restrictions, the study could not be completed, thus only pilot data was collected. Dependent measures included decision making time and maximum resulting jerk. Preliminary results indicated that older adults had a

higher maximum resulting jerk compared to younger adults. However, the differences in decision-making time and maximum resulting jerk were narrower for the exercise group (compared to the non-exercise group) between the two age groups.

Given COVID-19 restrictions, the objective of phase two shifted to focus on other (non-age-related) gaps in the multimodal literature. Specifically, the new phase examined the effects of signal direction, lead time, and modality on takeover performance. Dependent measures included pre-takeover metrics, e.g., takeover and information processing time, as well as a host of post-takeover variables, i.e., maximum resulting acceleration. Takeover requests with a tactile component were associated with the faster takeover and information processing times. The shorter lead time was correlated with poorer takeover quality.

The third, and final, phase used knowledge from phases one and two to investigate the effectiveness of meaningful tactile signal patterns to improve takeover performance. Structured and graded tactile signal patterns were embedded into the vehicle's seat pan and back. Dependent measures were response and information processing times, and maximum resulting acceleration. Overall, in only instructional signal group, meaningful tactile patterns (either in the seat back or seat pan) had worse takeover performance in terms of response time and maximum resulting acceleration compared to signals without patterns. Additionally, tactile information presented in the seat back was perceived as most useful and satisfying.

Findings from this research can inform the development of next-generation HMIs that account for differences in various demographic factors, as well as advance our knowledge of the aging process. In addition, this work may contribute to improved safety across many complex domains that contain different types and forms of automation, such as aviation, manufacturing, and healthcare.

1. INTRODUCTION

Adults aged 65 years and older have become the fastest-growing age group worldwide (United Nations, 2019). Declines in perceptual, cognitive, and physical abilities are common with age (Anstey et al., 2005; Czaja et al., 2019; Erber, 2012), which may make performing certain daily activities challenging. Automated systems, such as smart home technologies, automated speech recognition systems, automated vehicles, and service robots, are systems that are capable of performing operations without continuous input from human operators (Lee et al., 2017; Zhang et al., 2017). With respect to the aging population, these systems may augment various age-related changes, and help older adults to maintain independence, good health, mobility, or safety, all which contribute to a greater quality of life (e.g., Pak, McLaughlin, Leidheiser, & Rovira, 2017).

However, interacting with these intelligent systems, in many cases, often still requires considerable cognitive and physical effort, for example, to quickly perceive and process information from the systems, select an appropriate action, and execute that action, especially when they malfunction and need human intervention. In this case, age-related declines may hinder older adults from successfully completing their intended task. For instance, even though future autonomous vehicles are expected to bring a number of benefits to society, such as improving safety, decreasing drivers' workload, and reducing travel costs and time (e.g., Anderson et al., 2014; Bishop, 2000; Saffarian, de Winter, & Happee, 2012; Wan & Wu, 2018; Young & Stanton, 2007), several publications suggest that for at least the next 20-30 years, the majority of vehicles on highways will only have semi-autonomous capabilities (Litman, 2017; Niles, 2019). This means that in off-nominal situations, such as missing lane markers, road construction zones, and/or high traffic volume, automated vehicles may struggle to perform and will need help from drivers to take over, or resume, manual control (Eriksson & Stanton, 2017; Körber et al., 2018; Molnar et al., 2017). This takeover process requires drivers to 1) perceive and process a takeover alert, 2) preempt motor readiness (i.e., move eyes on the road, hands on steering wheel, and foot on gas/brake pedals), and 3) control the vehicle as in manual driving (McDonald et al., 2019; Zeeb et al., 2015). Yet, in general, age-related changes may limit the extent to which older drivers can effectively complete this complex takeover task.

While there are commonly-known physiological changes that occur with age, a large body of research suggests that chronological age alone (i.e., years a person has been living) may not be the best predictor of cognitive and physical functioning nor task performance. Rather, non-chronological age factors, such as continuous engagement in daily physical, cognitive, and social activities may mitigate age-related declines. Specifically, older adults who engage in physical exercise often benefit from improved/less declined executive function (e.g., Barnes, Yaffe, Satariano, & Tager, 2003), perceptual and processing speed (e.g., Marmeleira, Godinho, & Fernandes, 2009), attention (e.g., Pesce, Cereatti, Casella, Baldari, & Capranica, 2007), and motor learning abilities (e.g., Huebner, Godde, & Voelcker-Rehage, 2017). Similarly, cognitive and social activities (such as reading and conversing, respectively) are also known to lead to enhanced cognition (e.g., Ghisletta, Bickel, & Lövdén, 2006; Glei et al., 2005). However, the benefits of these non-chronological age factors are often reported for simple cognitive tests such as Mini-mental state (MMSE; Folstein, Folstein, & McHugh, 1975) exam (as used in Carlson et al., 2012) or simple physical exams such as walking speed or balance test/measures (e.g., Rogers, Larkey, & Keller, 2009). These effects have not been demonstrated for more complex tasks, such as taking over control from an automated system. Currently, **there is a lack of empirical data on the influence of non-chronological age factors on (takeover) task performance in complex environments in older adults (Gap 1).**

Additionally, with respect to interactions within human-autonomation systems, research has found that improving operators' performance can be achieved through the use of multimodal displays (i.e., interfaces that present information in visual (V), auditory (A), and/or tactile (T) sensory channels). This approach has been shown to increase alertness and response rate to critical information, as well as to aid humans in decision-making (Sarter, 2007; Sarter, 2006; Wickens, 2008). For example, in automated vehicles, studies have found that when multimodal signals (i.e., VA, VT, AT, and VAT) are used as takeover warning signals, they are often associated with faster response times compared to unimodal signals (i.e., single V, A, or T) (e.g., Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017; Politis, Brewster, & Pollick, 2017; Yoon, Kim, & Ji, 2019). However, **it is unclear to what extent multimodal displays can assist drivers, especially older adults, in recovering manual control from automated systems (Gap 2)**.

The purpose of this dissertation work was to fill the above gaps in the research literature and to examine the effects of 1) the non-chronological age factor, engagement in physical activity, and 2) multimodal interfaces on transitioning from automated to manual control in human-automation systems. This dissertation focuses on physical exercise (as a starting point into investigating non-chronological age factors) because engagement in physical activities has been found to slow down the rate of cognitive and physical decline in older adults – both of which are critical for vehicle takeover. Automated driving was used as the testbed. This dissertation was completed in three phases and three human-subject experiments, respectively.

The first phase focused on differences in the detection of multimodal TORs between younger and older drivers during the initial phase of the vehicle takeover process. Participants were asked to notice and respond to uni-, bi- and trimodal combinations of visual, auditory, and tactile TORs. Dependent measures were brake response time and maximum brake force.

The second phase aimed to quantify the effects of age and physical exercise on takeover task performance as a function of modality type and lead time (i.e., the amount of time given to make decisions about which action to employ). Dependent measures were decision-making time and maximum resulting jerk. However, due to COVID-19 restrictions, this study was not able to recruit a sufficient number of older participants, and thus only pilot data was collected. For the same reason, the objective of the phase two shifted to examine the effects of signal direction, lead time, and modality on takeover performance. Dependent measures included pre-takeover metrics, e.g., takeover and information processing time, as well as a host of post-takeover variables, i.e., maximum resulting acceleration.

The third, and final, phase used knowledge from phases 1 and 2 to investigate the effectiveness of meaningful tactile signal patterns to improve takeover performance. Structured and graded tactile signal patterns were embedded into the vehicle's seat pan and back. Dependent measures were response and information processing times, and maximum resulting acceleration.

The structure of this dissertation is organized as follows: Chapter 2: Literature Review discusses the current knowledge of older adults, automated systems, and multimodal interfaces. Chapters 3 to 6 present methodologies and findings from the four human-subject studies. Chapter 7: Conclusion summarizes key findings, highlights the broader implications of this dissertation work, and proposes future directions for research.

2. LITERATURE REVIEW

2.1 Worldwide Aging

2.1.1 Current status of older adults

As shown in Figure 2.1, older adults (aged 65 years old or over) have become the fastest-growing population globally. According to the United Nations, Department of Economic and Social Affairs (2019), in 2019, the proportion of older adults among all populations was 9%, which is projected to be at least 12% by the year 2030 and 16% in 2050. For countries in Europe and Northern America, older populations could account for 25% of the general population in 2050 (United Nations, 2019). Specifically, in the United States, this rapid increase may due to the baby boomer generation (i.e., individuals who were born between the years of 1946 to 1964), who began to turn 65 years of age in 2011. This trend is expected to continue and is coupled with increased of life expectancy for this generation (Czaja et al., 2019; Erber, 2012; Ortman et al., 2014).

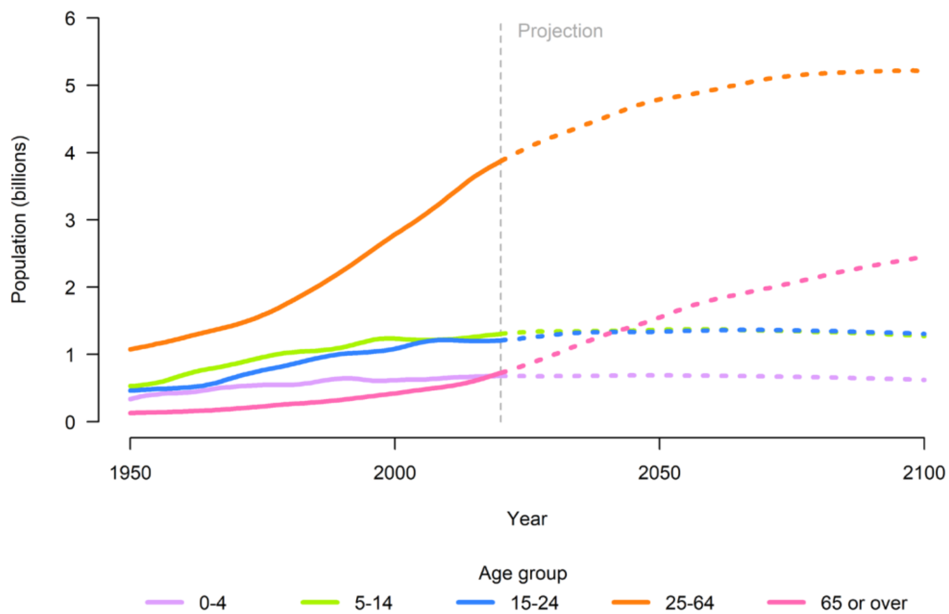


Figure 2.1. Projected global population by age groups (excluding Australia and New Zealand) (United Nations, 2019)

2.1.2 Age-related declines

One major concern with a rapidly growing aging population is that perceptual, cognitive, and psychomotor abilities are known to change with age, and most often decline (e.g., Eby & Molnar, 2012; Erber, 2012), which may make performing daily tasks difficult. For instance, a decline in vision can impair driving abilities, while decrements in psychomotor abilities may cause physical mobility issues. The following section will briefly introduce the most common declines found in the aging literature.

Perceptual decline

Visual acuity is an index of ability to discriminate objects such as letters or numbers at a given distance, while visual contrast sensitivity is the ability to distinguish between similar shades of light and dark (Monge & Madden, 2016). According to Monge and Madden (2016), visual contrast sensitivity is more associated with deteriorated daily task performance (such as driving and judging distances) compared to visual acuity. For useful field-of-view, the visual area that objects can be localized/recognized without eye/head movement (Kline & Scialfa, 1996), is also known to reduce as a function of age (Ball et al., 1988). Similarly, the sense of hearing is another perceptual system that experiences declines with age and is common in that at least 30% of older adults have apparent impairments (Czaja et al., 2019; Kausler et al., 2007). These may include declines in perceiving high-frequency sounds (i.e., presbycusis), hearing acuity which may lead to difficulties in distinguishing sounds in noisy environments (Tun & Wingfield, 1999), and sound localization (Dobreva et al., 2011). Finally, the sense of touch, also declines due to age, and manifests itself as reduced pressure sensitivity (resulting in difficulties perceiving and distinguishes absolute forces), tactile sensitivity, and spatial acuity (ability to distinguish between two points of touch) (Czaja et al., 2019; Tremblay & Master, 2016). Especially for the tactile sense, older adults have substantial declines of sensitivity in detecting high frequency (such as 250 Hz) vibrations (Verrillo, 1980).

Cognitive decline

In the human information processing framework, cognition is the step that involves collecting the products of perception and then providing interpretations for action execution (Czaja et al., 2019). Age-related declines in cognition have been observed in cognitive constructs, most notably processing speed, attention, memory, and executive function (Harada et al., 2013). Processing speed refers to the rate of processing the information, which may impair overall cognitive functioning if processing speed is slowed (Salthouse, 1996). Older adults typically have slower processing speed when performing a task, such as verbal fluency (Elgamal et al., 2011), speech comprehension (Wingfield et al., 1985), or spatial information (Jenkins et al., 2000). Attention represents the ability and capacity to concentrate and process information (Czaja et al., 2019; Harada et al., 2013). According to Harada et al. (2013), age-related declines in divided attention, i.e., the ability to timeshare tasks (Salthouse et al., 1995) and selective attention, the ability to ignore task-irrelevant information (Carlson et al., 1995), are more apparent in complex attention tasks, such as driving. Additionally, older adults have been shown to experience challenges in maintaining vigilance over an extended period of time (McAvinue et al., 2012). Age-related declines are also observed in memory, including working memory (Baddeley, 1992) that temporarily stores and manipulates information for cognitive activity (Cabeza et al., 2009; Salthouse & Babcock, 1991), and long-term memory, including episodic memory, prospective memory, and procedural memory (Luo & Craik, 2008). For instance, in driving, working memory is used to hold temporary information such as position and speed information of adjacent vehicles, while long-term memory helps to remember the daily routine of driving home as well as the regulations of traffic. Thus, declines in memory may cause safety issues. Finally, executive function relates to mental processes that are critical for cognitive control of abilities and behaviors, such as response inhibition control, attention management, action adaption, and working memory (Bryan & Luszcz, 2000; Diamond, 2013). Deterioration of executive function has been widely observed in the literature (e.g., Wecker et al., 2000, 2005) and may lead to difficulties in regulating emotions, staying focused, self-regulating behaviors, and organizing and planning.

Psychomotor decline

Age-related declines in psychomotor aspects include movement control and strength (Czaja et al., 2019). For movement control, declines mainly affect movement speed (Stelmach & Hömberg, 1993) and accuracy (Fraser et al., 2009), and balance and gait control (Tang & Woollacott, 2004). Specifically, older adults in general move are slower and with less precision than younger adults, and have a higher chance to fall due to poorer balance and gait control.

Reduction in strength is another type of physical decline with age, such as less muscle strength and reduced endurance (Czaja et al., 2019; Metter et al., 1997; Narici et al., 1991) and can result in difficulties of performing simple tasks, such as grasping and holding an item for a short period of time.

2.1.3 Individual differences and non-chronological age factors

While in general, the above perceptual, cognitive, and psychomotor abilities tend to decline with age, researchers understand that these declines are not homogeneous across individuals. In other words, these abilities change at different rates for different people (e.g., Franklin & Tate, 2009; Şoitu, 2015). As a result, chronological age (i.e., the number of years a person has lived) alone may not be the best predictor of task performance, given the many factors in one's life that influence how a person ages. These relate to physical, cognitive, and social aspects of one's lifestyle and are known as non-chronological age factors (Ballesteros, Kraft, Santana, & Tziraki, 2015; Baltes & Baltes, 1990; Franklin & Tate, 2009; Hertzog, Kramer, Wilson, & Lindenberger, 2008; Rowe & Kahn, 1997; Seeman & Chen, 2002; Stein & Moritz, 1999; Strawbridge, Cohen, Shema, & Kaplan, 1996; Vaillant & Mukamal, 2001).

Physical factor/activities

Researchers have found that engaging in physical activities can benefit physical body functioning and body health such as improving glucose metabolism, vital capacity, balance control, and body flexibility, as well as mitigate perceptual and cognitive related declines (Ballesteros et al., 2015). Evidence has been found in three different categories of physical activities: physical exercise, sportive activities (including meditative movement and martial arts), and complex activities (Ballesteros et al., 2015).

Physical exercise

Aerobic and non-aerobic exercises are types of physical exercises that can benefit physical and cognitive functioning. Example aerobic exercises are intense walking, jogging, swimming, or bicycling (Tomporowski & Ellis, 1986), and have been shown to be associated with better executive function (Barnes et al., 2003; Voelcker-Rehage, Godde, & Staudinger, 2010), perceptual and processing speed (Ballesteros et al., 2013; Marmeleira et al., 2009; Voelcker-Rehage et al., 2010), attention (Barnes et al., 2003; Marmeleira et al., 2009; Pesce, Cereatti, Casella, Baldari, & Capranica, 2007), memory (Cassilhas et al., 2012; Erickson et al., 2011), and motor learning (Huebner et al., 2017) in older adults. Non-aerobic exercise, on the other hand, according to Ballesteros et al. (2015), includes resistance (e.g., weight lifting), stretching (e.g., shoulder stretch), and coordination training (e.g., standing balance training). Studies have found that coordination training can also improve executive function (Niemann et al., 2014), but the effects were more salient when non-aerobic exercise was combined with aerobic exercise (e.g., Voelcker-Rehage, Godde, & Staudinger, 2011). Similarly, resistance training was observed to improve older adults' executive function (Liu-Ambrose et al., 2010) and memory (Cassilhas et al., 2012). However, evidence of the benefits of resistance training was more observed in combination with aerobic exercise, as reported by a meta-analysis (Colcombe & Kramer, 2003). For stretching training, no direct benefits on cognition but physical function (enhanced postural stability and balance, and improved joint of motion, e.g., Garber et al., 2011; Lee, Jackson, & Richardson, 2017) was found, and therefore, stretching training was usually used as a control group in exercise effect on older adults' cognition studies (e.g., Colcombe et al., 2006, 2004; Erickson et al., 2011; Niemann et al., 2014; Voelcker-Rehage et al., 2011). A recent review article on the benefits of physical activity states that aerobic and coordination training seemed to be most beneficial to cognition compared to other physical exercises (Muiños & Ballesteros, 2018). Combining these findings, aerobic exercise appears to be the most crucial physical exercise type that mitigates age-related declines in cognitive and physical functioning.

Sportive activities (meditative movement and martial arts)

Meditative movement (e.g., Tai Chi or Qi Gong) and martial arts (e.g., Judo, Kung Fu, or Taekwondo) also present benefits to older adults in terms of cognitive and physical functions (Ballesteros et al., 2015). Specifically, a meta-analysis compared 36 aging studies and found that Tai Chi and Qi Gong can reduce fall risk, increase grip strength and walking speed, reduce blood pressure, and reduce depression and anxiety (Rogers et al., 2009). Martial arts also showed benefits to older adults in both cognitive and physical aspects, such as visual attention and processing speed (Mónica Muiños & Ballesteros, 2014), dynamic visual acuity (the ability to discriminate critical details of an object when there is relative motion) (Mónica Muiños & Ballesteros, 2015), and postural control (Krampe et al., 2014).

Complex activities

Complex activities here refer to physical activities in which aerobic exercise is only one component of the activity – such as dance, which involves emotions, sensory simulation, motor coordination, and social interaction (Kattenstroth et al., 2010, 2013), were found to be associated with both cognitive and physical functions for older adults (Ballesteros et al., 2015), such as facilitating balance and posture (Alpert et al., 2009; Granacher et al., 2012; Kattenstroth et al., 2010; Keogh et al., 2009), executive function (Coubard et al., 2011), and perceptual speed (Kattenstroth et al., 2013).

Cognitive factor/activities

Engagement in intentional cognitive activities may also be correlated with better cognition (Bielak et al., 2012; Ghisletta et al., 2006; Hertzog et al., 2008; Wilson et al., 2012). Examples of cognitive activities including playing games (e.g., crossword puzzles, cards, chess), singing, reading, cooking, and watching TV (Ghisletta et al., 2006; Schinka et al., 2005). Carlson et al. (2012) divided these activities into three levels based on their cognitive demands: high (e.g., playing, singing, drawing, and reading), moderate (e.g., cooking, playing cards, or discussing politics), and low (watching TV/movies, or listening to music/radio) levels, based on nine psychologists' ratings, and found that engaging in a variety (or a large number) of cognitive activities predicted more variance in older adults' overall scores on cognitive functioning tests(i.e., the Mini-Mental State Exam; Folstein, Folstein, & McHugh, 1975) and memory tests (i.e., the Hopkins Verbal Learning Test-Revised; Benedict, Schretlen, Groninger, & Brandt, 1998), than the levels of cognitive demand or frequency of engaging in any single activity alone. Similar findings were reported in Baer et al. (2013) which found that a larger variety of cognitive activities positively correlated with higher cognitive test scores (measured by the Montreal Cognitive Assessment; Nasreddine et al., 2005). Yet, other studies have found that the frequency of engaging in cognitive activities may also be associated with global cognitive function, memory, perceptual speed, and executive function (e.g., Bielak et al., 2012; Wilson et al., 2012). In all, while the frequency of engaging in cognitive activities can benefit cognition, the number of activity types produces even more benefits. One possible explanation is that participating in multiple activities exercises several aspects cognitive of abilities such as task switching and flexibility (Carlson et al., 2012).

Social factor/activities

Research has also found engagement in social activities to contribute to positive cognitive functioning (Ballesteros et al., 2015; Bassuk et al., 1999; Glei et al., 2005; Kelly et al., 2017; Zunzunegui et al., 2003). According to these research studies, three categories were identified: social engagement, social network, and social support.

Social engagement

Social engagement involves interactions with people, attending social events/activities, maintaining and reinforcing social roles, and obtaining a sense of value and attachment (Berkman et al., 2000). A large body of research evidence has found that participating more in social activities can prevent or slow down cognitive declines, based on global cognitive tests (Glei et al., 2005; James et al., 2011; Kimura et al., 2017; Lee & Kim, 2016; Lee et al., 2009; Wang et al., 2013). For example, Wang et al. (2013) investigated the effects of cognitive, physical, and social activities on cognitive functioning, and found that higher levels of social engagement led to less decline in global cognition, and that engagement in all three types of activities actually improved global cognition score. However, no effects on specific cognitive domains, such as memory or executive function, were observed in this study. Conversely, James et al. (2011) found that social engagement not only reduced global cognitive declines, but also slowed declines in executive function, memory, and perceptual speed.

Social network

Social network consists of different types of social contacts (e.g., close friends, family members, or neighbors) (Wrzus et al., 2013), which may have different sizes, relationships, and frequency of interaction (Berkman et al., 2000; Kelly et al., 2017). Similar to social engagement, a larger social network, as well as a high frequency of contacts, positively correlated with better cognitive functions (e.g., Barnes et al., 2004; Béland, Zunzunegui, Alvarado, Otero, & Del Ser, 2005; Holtzman et al., 2004; Hughes, Andel, Small, Borenstein, & Mortimer, 2008; Zunzunegui et al., 2003).

Social support

Social support refers to perceived emotional, instrumental, and/or informative support from social network, to share feelings and experiences, and to get help with daily tasks and decision makings (Berkman et al., 2000). According to the literature, positive support generally leads to better global cognitive functions, especially with positive emotional support and greater satisfaction with the support (Ellwardt, Aartsen, Deeg, & Steverink, 2013; Holtzman et al., 2004; Seeman, Lusignolo, Albert, & Berkman, 2001; Windsor, Gerstorf, Pearson, Ryan, & Anstey, 2014; Yeh & Liu, 2003). One study investigated the effects of social support on specific domains of cognitive functions and found that social support was positively correlated with better perceptual speed, attention, and memory (Hughes et al., 2008). Given that instrumental (e.g., help with daily tasks) and informative support (e.g., advice/information about medical problems) mean that a person generally has poorer (cognitive) health (Hughes et al., 2008), studies that investigated healthy older adults did not find correlations between these types of social support and cognitive functioning (e.g., Ellwardt, Aartsen, Deeg, & Steverink, 2013; Hughes et al., 2008; Seeman, Lusignolo, Albert, & Berkman, 2001).

In conclusion, all three factors: physical, cognitive, and social have positive impacts on older adults' cognition. However, the physical factor has been widely examined and consistently reported to contribute to both improved cognitive and physical functions, whereas cognitive and social factors are more reported to benefit mainly (or just) cognition. As a result, physical activities (especially aerobic exercise) may be the more appropriate non-chronological age factor to better understand interactions with complex systems that require high demands of both cognitive and physical resources.

2.2 Automation

2.2.1 Complex automated systems

Automation is often developed to help humans perform tasks that are beyond their abilities and/or unpleasant to be performed, which contribute to improved safety (Scerbo, 2018; Wickens, Hollands, Banbury, & Parasuraman, 2015). Automated systems can be found in a wide range of environments, including transportation, manufacturing, construction, healthcare, retail services, and education (Mouloua & Hancock, 2019).

Automated systems provide a number of benefits (e.g., Davis, Curry, Wiener, & Harrison, 1983; Endsley & Kiris, 1995; Parasuraman, Molloy, Mouloua, & Hilburn, 2018; Scerbo, 2018; Wickens et al., 2015; Woods, 2018). First, they can reduce human operators' workload, making available both attentional and physical resources. Second, they are able to lessen sources of variability related to human performance. Finally, they can help to decrease the amount of time needed to complete tasks. Given the rapid rise of technological developments in today's society, designers and engineers have the responsibility of thinking about what aspects of tasks should be performed by the human and which can be carried out by automation (Raja Parasuraman et al., 2000). Parasuraman et al. (2000) proposed a 10-level automation framework for describing the roles of humans and machines in joint human-automation systems.

As presented in Figure 2.2, this common taxonomy for representing the different levels of automation is on a 10-point scale, where the lowest level (1) is no automation (or fully manual) and the highest level (10) is full automation. As the automation level increases, so does the role that the system plays in performing certain tasks, from no contribution at all (no automation), to assisting with decision making and execution (partial automation), and to completely performing tasks without human intervention (full automation). This general automation scheme is applicable for automated systems across a wide range of machines and devices. However, similar versions of such taxonomy have been developed for specific automated systems, such as vehicle driving systems.

HIGH 10. The computer decides everything, acts autonomously, ignoring the human.

9. informs the human only if it, the computer, decides to

8. informs the human only if asked, or

7. executes automatically, then necessarily informs the human, and

6. allows the human a restricted time to veto before automatic execution, or

5. executes that suggestion if the human approves, or

4. suggests one alternative

3. narrows the selection down to a few, or

2. The computer offers a complete set of decision/action alternatives, or

LOW 1. The computer offers no assistance: human must take all decisions and actions.

Figure 2.2. Levels of automation (based on decision and action selection) (Raja Parasuraman et al., 2000)

Problems with automation

While there are numerous potential benefits of automation, its design has also raised a variety of concerns regarding how humans interact with automation, given that these systems are not perfect. One concern is the chance for the loss or degradation of skills necessary for task operations (Endsley & Kiris, 1995; Scerbo, 2018). For example, a driver may lose the ability to proficiently control vehicle operations after extensive use of semi- and autonomous vehicle functions. Secondly, although automation aims to reduce workload, automation can sometimes increase mental workload in that additional planning, monitoring, and diagnosis may be required, which together can be more work for the human than pure manual input alone (Raja Parasuraman et al., 2018). For example, when automation failure occurs, an operator needs to first figure out the reasons, then make decisions regarding how to handle the situation, and finally execute appropriate actions. In addition, monitoring automation systems may require certain levels of vigilance, which is not a task that humans are particularly good at doing. Lower vigilance may lead to passive, as opposed to, active monitoring or may cause a person to shift their attention to other tasks (Raja Parasuraman, 1987). Relatedly, Endsley (2018) stated that automation might take operators out-of-the-loop, leading to a decreased awareness about the system and environment (i.e., their situation awareness). This would especially be a concern in the case of automated vehicle failures, which may require operators to spend a great deal of time to regain environment/situation awareness in order to intervene successfully. Furthermore, overreliance on automation has been cited as another potential issue (Raja Parasuraman & Manzey, 2010). This phenomenon happens when a person establishes a sense of complacency in automation as a result of high system reliability. This may result in the operator not paying attention to particular aspects of the automation behavior because of the built-up expectation that the system will perform as intended. Thus, the operator may not be ready to resume manual control when needed. In summary, these common problems in automaton suggest a gap in the literature regarding how best to support operators while using automation, such as the design of human-machine interfaces (HMIs).

2.2.2 Aging and automation

Even though there are some potential concerns related to human-automation interaction, certain characteristics of this technology may benefit particular demographics, e.g., older adults who are suffering from age-related declines. In this case, the assistance of automation can help maintain independence, good health (e.g., via automated health monitoring technologies), mobility (e.g., via autonomous vehicles), or safety (e.g., via automated fall detection systems) (e.g., Pak, McLaughlin, Leidheiser, & Rovira, 2017) – all which contribute to a greater quality of life.

Early research reported that new technologies (e.g., automated systems) were generally less accepted by older populations (Kantowitz et al., 1993). Initially, this was explained by older adults' lessened capacity to process information. However, more recent studies have found older adults to have more positive attitudes toward automated systems, such as smart home technologies (e.g., Demiris et al., 2004; Mann, Belchior, Tomita, & Kemp, 2007; Mitzner et al., 2010), once they sufficiently learn and feel comfortable using technologies. Many researchers cite this receptivity as older individuals perceiving particular technologies to be useful and easy to use (Mann et al., 2007; Mitzner et al., 2010; Zimmer & Chappell, 1999). For example, a systematic review on older adults' perceptions of Information and Communication Technologies (ICT) reported that they were more motivated to adopt automated systems that can maintain their independence and safety at home (such as fall prevention) (Hawley-Hague et al., 2014). Similarly, Arthanat et al. (2020) investigated older adults' smart home ownership and found that older adults had higher smart home ownership when the usability of ICT, and home safety and security levels were perceived higher. Furthermore, factors such as physical and cognitive functions, and social relationships, may also impact older adults' technology acceptance, as examined in the senior technology acceptance model (STAM) (Chen & Chan, 2014). Specifically, older adults with more cognitive and physical declines may influence the successful use of technologies, but better social relationships enable older adults to learn the benefits of technologies from their families and friends. Findings across studies suggest that to increase older adults' technology acceptance, it is necessary to increase the exposure of new technology to older adults and emphasize the benefits of technology.

The literature on aging and automation has shown more evidence that older adults are adopting using automated systems to maintain or improve task performance. Specifically, Sanchez et al. (2014) compared younger and older adults' detection task performance with and without automated decision aid while operating simulated agricultural vehicles, and found that both younger and older adults can adjust their reliance and behavior on automated systems when the reliability of the systems varied, even though older adults may take longer time to do so. In a different study, Sanchez et al. (2005) compared age-related differences in using automated aid for tracking the ingredients in a specific recipe, and found older adults to rely more on the automated aid when the workload was higher, and prefer real-time feedback from the system, while younger adults used the automated aid only for verification purposes. McBride et al. (2011, 2010) examined the effects of age on dual-task performance, where participants performed as a warehouse manager to receive packages into inventory and dispatch fully loaded trucks. An automated messaging system was used to provide real-time feedback to participants. The authors found that with more practice with automation, older adults relied more on the automation compared to younger adults, even when the automation failed. This finding is similar to the results in Ho et al. (2005) that older adults relied more on decision aids in dual-tasks compared to younger adults. One possible reason was that the declined cognitive ability, such as working memory, had diminished ability to detect automation failures, resulting in a relatively higher trust in the system. The results indicated that older adults who may particularly benefit from automated systems in complex task environments need more support to identify system failures.

Two studies compared younger and older adults' task performance in a luggage screening task in chromatic X-ray images with/without automated aids (McCarley et al., 2003; Wiegmann et al., 2006). Even though younger adults had better performance (as measured by sensitivity) with text cueing compared to older adults (McCarley et al., 2003), with more advanced automated features, e.g., spatial cueing, age-related differences were mitigated (Wiegmann et al., 2006). This finding suggests that with appropriate designs that consider the capabilities and limitations of older individuals, older adults' task performance can be improved. Thus, it is necessary to consider older adults' needs and identify features that may particularly benefit this population when designing automated support, which is the main gap to address in this dissertation.

2.3 Decision Support: Multimodal Information Presentation

One design approach that can facilitate communication between automated systems and human operators is multimodal information displays or multimodal information presentation, which integrate use the visual, auditory, and/or tactile sensory channels to display information (Giang et al., 2010; Ho & Spence, 2008; Ho, Nikolic, & Sarter, 2001; Sarter, 2007; Sarter, 2006; Spence & Ho, 2008). The idea is supported by research that resulted in the conceptualization of the Multiple-Resource Theory (MRT) (Wickens, 2008), which explains that humans can process information concurrently in multiple sensory channels, and that each channel is relatively independent. Also, each channel has limited capacity, and overloading one channel may result in poor task performance (Sarter, 2007; Wickens, 2008). For instance, it may be easier to miss the ringing of a phone in a noisy environment, whereas a phone vibration would instead be detected in the same (noisy) context. As such, multimodal displays can be very helpful in communicating to humans when automated systems have reached their limits by signifying to the operator the need for takeover. To successfully implement multimodal display designs, it is important to acknowledge that each sensory modality has its own characteristics and set of strengths for supporting various tasks/task environments (Sarter, 2006).

The attributes of visual displays, include color (frequency), size (pixels), or shape differentiation, contrast, or luminance differentiation (Chung & Byrne, 2004; Giang et al., 2010; Ho et al., 2001). For instance, a large flashing static color abstract (no associated meaning) cue may indicate the state of a system. On the other hand, a flashing visual icon (e.g., a steering wheel icon on the vehicle dashboard) implies a more meaningful visual cue, such as instructing drivers to put their hands on the steering wheel. Presenting information in the visual channel allows a large amount of information to be conveyed and at a high rate of information transfer (Sarter, 2006). However, the visual channel is often overloaded in many of today's data-rich environments, and therefore, the efficiency of visual displays may be degraded (e.g., as a visual alert) (Liu, 2001). In addition, visual displays require information to be presented in the operator's field-of-view and gaze direction (Hirst & Graham, 1997).

Auditory display parameters include frequency, loudness, tempo, and rhythm (Walker & Kramer, 2004). Changing these parameters can produce different types of auditory cues. For example, abstract auditory signals can be used for alerting, whereas meaningful auditory cues, via sonification, can be used to convey more complex messages to humans (Giang et al., 2010). Auditory cues are often used when the visual channel is occupied, are effective at quickly seeking a person's attention, and can be sent from any direction (Hirst & Graham, 1997; Sarter, 2006; Spence & Ho, 2008a). However, limitations of auditory displays can sometimes include 1) obtrusiveness, 2) difficultly in localizing (especially when surrounded by other auditory signals), and 3) the potential to cause pain when loudness threshold is reached (such as over 100 dB of loudness) (Eldridge, 2006; Neuhoff et al., 2002).

Tactile signal characteristics include frequency, rhythmic structure, spatial location, and amplitude (Brown, 2007; Giang et al., 2010; Spence & Ho, 2008a). Varying tactile parameters can also produce different abstract alerts or meaningful messages (Giang et al., 2010; Spence & Ho, 2008a, 2008b). Here, meaningful messages are generated by a single tactor (i.e., tacton) or a series of sequential activation of tactors (i.e., spatio-temporal tactile patterns) (Giang et al., 2010), which are encoded messages that can convey meaningful and complex concepts and information using the tactile modality. Common meaningful tactile patterns include informative (i.e., that communicate the status of systems) and instructional tactile signals (i.e., that command some action) (e.g., Cohen-Lazry et al., 2019; Meng et al., 2015). Tactile displays can be placed at different body locations, such as head, hands, wrists, and torso (Spence & Ho, 2008a). Also, similar to auditory displays, tactile displays are omnidirectional (Jones et al., 2006; Jones & Sarter, 2008). Finally, tactile displays offer communication to humans in a private manner (Petermeijer, De Winter, & Bengler, 2016). However, tactile displays, in general, convey less amount and complexity of information compared to visual and auditory displays (Lu et al., 2011).

When the same information that is presented at the same time using more than one of the above modalities, it is known as a redundant multimodal display (Sarter, 2006). This type of display has been shown to increase the bandwidth of information presented in complex environments (Jones & Sarter, 2008). Also, redundant multimodal displays may be particularly beneficial for older adults. Since information is presented in more than one sensory channel, it helps to compensate for deficits or losses experienced in any one modality. Research has found that performing tasks with the assistance of redundant multimodal displays can be associated with higher accuracy and faster response times in computer manual tasks (Emery et al., 2003; Jacko et al., 2004), touch screen interaction (Lee, Poliakoff, & Spence, 2009), and driving (Lundqvist & Eriksson, 2019; Pitts & Sarter, 2018).

2.4 Application in Automated Driving

This chapter has focused on the three main elements in human-automation interaction: the *human* (i.e., older adults), the *machine* (i.e., automated systems), and the *interface* (i.e., multimodal display). For the *human*, non-chronological age factors may be better predictors of task performance and capabilities than age alone; for the *machine*, automated systems may support age-related declines and help to maintain independence; and for the *interfaces*, multimodal displays seem to be a feasible approach to enable communication between humans and machines. This dissertation aims to use automated driving as the application domain to further investigate how older adults interact with partial automation, with the assistance of multimodal displays.

2.4.1 Aging and driving

As mentioned, older adults have become the fastest-growing population, which also means that there will be more older drivers. According to the Federal Highway Administration (2018), in 2017, about 20% of U.S. drivers were older adults. Driving is a complex task that requires the use of visual resources to monitor the road environment, cognitive resources, including processing speed in order to process driving information and make timely decisions, working memory used to temporarily store environmental information, executive function used to integrate information and manage attention quickly, and sustained attention to maintain alertness during driving; and physical resources to control the steering wheel, gas/brake pedals, and check side/rear mirrors (Anstey et al., 2005). In driving, to compensate for age-related declines, older adults may exercise self-regulatory driving strategies, such as reducing driving frequencies and distances, driving at lower speeds and with larger headway distances, and avoiding night time driving (Charlton et al., 2006; Gwyther & Holland, 2012; Meng & Siren, 2012; Molnar et al., 2015). Still, with age-related perceptual, cognitive, and physical declines, performing driving tasks may compromise safety.

However, older drivers take driving as a positive sign of maintaining mobility and independence (Hassan et al., 2015; Molnar et al., 2007), because driving cessation has been shown to lead to health/mental issues, such as depression (Chihuri et al., 2016; Ragland et al., 2005) or social isolation (Liddle et al., 2014; Molnar et al., 2007).

In this case, automated vehicles may help older drivers retain autonomy and ultimately achieve a higher quality of life. However, according to the literature regarding the older adults' perceptions of autonomous vehicles, they are less willing to use automated vehicles compared to younger adults (e.g., Abraham et al., 2017; Rovira et al., 2019). For example, about 40% of older adults expressed concerns about using automated vehicles as a transportation method even if it was the only option, compared to only approximately 20% of younger adults (Schoettle & Sivak, 2016). One reason for lower automated vehicle acceptance in older adults may be due to a lack of experience and knowledge on the operations of automated vehicles (Rovira et al., 2019). Specifically, studies have found that demographic factors, such as age, education, and living location, and common technology acceptance factors such as perceived usefulness and ease of use, were associated with automated vehicle acceptance (Acheampong & Cugurullo, 2019; Bansal & Kockelman, 2018; Czaja et al., 2006; Hudson et al., 2017, 2019; Hulse et al., 2018; Rovira et al., 2019). For instance, Haboucha et al. (2017) reported that older and lower educated individuals had lower automated vehicle acceptance due to a lack of knowledge and understanding of the benefits of these vehicles. Evidence showed that once being demonstrated with system capabilities, older adults' automated vehicle acceptance increased (Haghzare et al., 2021; Rahman et al., 2019). Alternatively, older adults' lower acceptance level may be because the self-regulatory behavior observed in manual driving is translated to the semi-autonomous driving context since automated vehicles still require takeover and perform manual driving. Thus, they may not find the need to use automated vehicles. Given these feelings of reservation, it is important that automated vehicles be designed in a way where the HMI clearly communicates to the driver the system status and decisions.

2.4.2 Automated driving

Automated vehicles are capable of controlling the dynamics of the vehicle without constant input from human drivers and are designed to reduce driver's workload and increase roadway safety (Anderson et al., 2014; Bishop, 2000; Litman, 2019; Saffarian, de Winter, & Happee, 2012;

Wan & Wu, 2018; Young & Stanton, 2007). In comparison to the 10 levels of automation framework discussed in Section 2.2 (Raja Parasuraman et al., 2000), the taxonomy for vehicle automation includes six levels (SAE International, 2018), as shown in Figure 2.3. Level 0 represents traditional manual driving; Level 1 means there is one automated system on the vehicle, such as adaptive cruise control or automated lane keeping; Level 2 (i.e., partial driving automation) indicates that two automated systems are activated on the vehicle. Levels 0-2 still require drivers to continuously monitor the driving task. Beginning with Level 3 (i.e., conditional driving automation), drivers are not expected to constantly monitor the driving environment, but are expected to be ready to resume manual control of the vehicle at any time. In Level 4 (i.e., high driving automation) automated vehicle systems will require human drivers for only very few and certain driving maneuvers. Finally, in Level 5 (i.e., full driving automation), drivers have no role as these vehicles have not steering wheel and foot pedals. As such, in Levels 3-5, drivers may choose to engage in non-driving related tasks (NDRTs), such as watching videos or sending emails. It is predicted that Level 5 automated vehicles may not be dominant on the public roadways for at least two decades, and therefore, Levels 2-4 will remain the main focus of research for the foreseeable future (Litman, 2018; Wan & Wu, 2018a). With system limitations of Levels 2-4, takeover requests will be sent by the vehicle to signify drivers to transition to manual driving when it encounters difficult or unusual conditions, such as in poor visibility or high traffic density, or the presence of construction (Eriksson & Stanton, 2017; Llaneras, Salinger, & Green, 2013; McDonald et al., 2019; Zhang, de Winter, Varotto, Happee, & Martens, 2019).

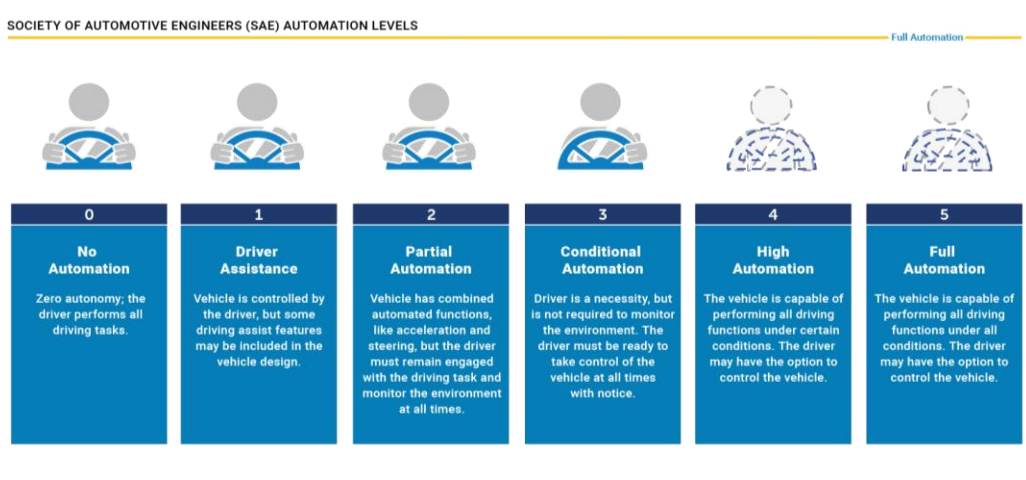


Figure 2.3. SAE levels of automation (NHTSA, 2018)

As presented in Figure 2.4, a takeover process is complex and consists of a: 1) Signal response phase, where drivers need to perceive and process takeover warning signals, and interpret the meaning of signals, and 2) Post-takeover phase, for which drivers need to be prepared ready to takeover (i.e., eyes on road, hands on steering wheel, and foot on pedal), analyze the driving environment, make a decision about how to execute the takeover as well as which post-takeover strategies to employ, and then execute the action (e.g., McDonald et al., 2019; Petermeijer, de Winter, & Bengler, 2016; Zeeb, Buchner, & Schrauf, 2015). The entire takeover process utilizes perceptual, cognitive, and motor resources, and can take anywhere from 3-21 seconds (Eriksson & Stanton, 2017), depending on many factors, such as age, NDRTs, the driving environment, and drivers' mental states (McDonald et al., 2019).

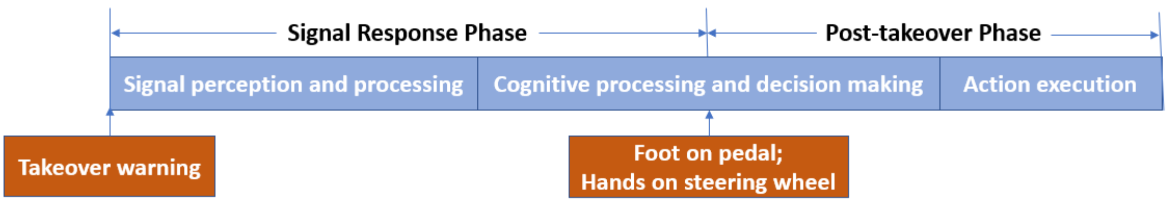


Figure 2.4. A vehicle takeover process (adapted from Petermeijer et al. (2016) and Zeeb et al. (2015))

In general, takeover performance is measured by both time- and driving-related metrics (see reviews: Eriksson & Stanton, 2017; McDonald et al., 2019; Zhang et al., 2019). For time-related measures, response time (the time between TORs and the initial brake/gas pedal or steering wheel contact) and takeover time (the time between TORs and the first conscious input to the vehicle) are most common. Here, conscious input is defined by a 2-degree change of the steering wheel or a 10% change of gas pedal inputs. Additionally, takeover quality, or post-takeover performance, is often measured using driving-related metrics, such as maximum/minimum/mean lateral and longitudinal accelerations, (maximum) brake force and input rate, minimum/mean time-to-collision (TTC), and maximum resulting acceleration. Currently, there is no consensus regarding which driving-related metrics are most representative of the overall takeover quality. Thus, more research is needed in the driving field to develop standards to regularize takeover performance measurements. One particular variable, maximum resulting acceleration, is seen as a good option because it encompasses a broader set of longitudinal and lateral aspects of vehicle handling, such as maximum longitudinal/lateral accelerations, steering wheel angle and velocity, and standard deviation of vehicle speed. It has been cited as an indicator of takeover quality and comfort in related literature (e.g., Gold et al., 2013; Hergeth et al., 2017; Wandtner et al., 2018).

2.4.3 Multimodal displays in automated vehicles

Multimodal displays have been largely used as warning signals in both manual driving studies (Biondi et al., 2017; Kramer et al., 2007; Lundqvist & Eriksson, 2019; Pitts & Sarter, 2018; Politis et al., 2014), and automated driving studies as takeover requests (TORs) (Huang, Steele, Zhang, & Pitts, 2019; Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017; Politis, Brewster, & Pollick, 2017; Yoon, Kim, & Ji, 2019).

Types and Forms of Takeover Requests

Currently, TORs are presented using the visual (V), auditory (A), and/or tactile (T) sensory modalities. Often, visual signals are presented either on the vehicle's windshield using a heads-up display (HUD) or an augmented reality (AR) interface (e.g., Lindemann, Muller, & Rigolll, 2019), or on the in-vehicle display (center) console (e.g., Petermeijer et al., 2017), represented as abstract icons or messages in text form. Auditory TORs are played through in-vehicle speakers as abstract sounds (e.g., a beep) and/or verbal messages (e.g., Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017). Finally, tactile alerts are generally presented using vibrotactile/haptic interfaces embedded into drivers' seats (e.g., Yoon, Kim, & Ji, 2019). In many cases, a single modality TOR may not be effective since drivers may engage in non-driving-related tasks (NDRTs), which may use the same perceptual resource that is needed to perceive the TOR (Naujoks et al., 2018; Roche et al., 2019; Yoon et al., 2019). For example, drivers may not notice an auditory TOR if they are listening to music or holding a phone conversation. Thus, researchers have investigated the benefits of multimodal TORs, which are combinations of visual, auditory, and/or tactile signals.

TORs can be used as alerts to inform drivers of the need to take over or as aids to guide them on how to takeover. For alerting purposes, studies have found that takeover performance is often better with multimodal signals than unimodal signals (e.g., Huang & Pitts, 2020; Huang, Steele, Zhang, & Pitts, 2019; Petermeijer et al., 2017; Politis, Brewster, & Pollick, 2017; Roche et al., 2019; Salminen, Farooq, Rantala, Surakka, & Raisamo, 2019; Yoon et al., 2019). For example, within the signal response phase, Yoon et al. (2019) compared all seven types of signals (single V, A, and T, combinations of two: VA, VT, and AT, and combination of all three: VAT), and found that multimodal signals (i.e., VT, VT, AT, and VAT) were associated with shorter takeover times compared to single modal stimuli (i.e., V, A, and T).

Directional Takeover Requests

In terms of using TORs to instruct drivers on how to take over, two commonly used HMIs have been employed: 1) Ipsilateral display: the interface presents a signal that is spatially compatible with the required action, based on the stimulus-response compatibility (SRC) (Proctor & Vu, 2006); and 2) contralateral display: the signal is incompatible with the required action (reversed SRC). For example, an ipsilateral signal shown on the left side of the vehicle's windshield instructs the driver to move into the left lane to avoid a possible collision with an adjacent vehicle in the right lane, while a contralateral signal shown on the left side informs the driver of a potential obstacle in the left lane, and thus the driver should instead steer away from the direction of the signal and move into the right lane.

The effectiveness of ipsi- and contralateral approaches have been explored in both manual (e.g., Ho, Tan, & Spence, 2005; Müsseler, Aschersleben, Arning, & Proctor, 2009; Straughn, Gray, & Tan, 2009; Wang, Pick, Proctor, & Ye, 2007) and automated driving (e.g., Chen, Šabić, Mishler, Parker, & Yamaguchi, 2020; Cohen-Lazry, Katzman, Borowsky, & Oron-Gilad, 2019; Petermeijer et al., 2017) contexts. These studies often compare time-related metrics, such as response times to signals between the two directional signals, without measuring actual driving performance such as maximum lateral acceleration. Table 2.1 summarizes these studies and highlights the variability in findings among them.

Specifically, in manual driving, Ho et al. (2005) and Müsseler et al. (2009) found that people responded faster to ipsilateral signals compared to contralateral signals, while Wang et al. (2007) reported that an opposite finding, i.e., contralateral had shorter response times than ipsilateral signals. Furthermore, Straughn et al. (2009) compared two lead times: 2 and 4 seconds, which represented the timing before a collision would occur. In the 2-second lead time condition, participants reacted faster to ipsilateral signals compared to contralateral signals. This trend was the same, but slower, with the 4-second lead time. The authors propose that this difference may have been driven by whether drivers had enough time to evaluate the driving situation and make timely decisions. Findings are also conflicting in recent automated driving studies. For example, Cohen-Lazry et al. (2019) reported that drivers responded faster to ipsilateral signals, while Chen et al. (2020) found contralateral signals to be associated with shorter responses. No differences between these signal directions were found in Petermeijer et al. (2017). Two possible factors may explain these conflicting findings, namely the warning lead time and signaling modality, which are discussed in Chapter 5.

Table 2.1. Summary of studies that compared directional cues

Studies	Signal modality	Lead time/TTC	Participants' reaction times
Automated driving:			
(Cohen-Lazry et al., 2019)	T	4 seconds	Ipsilateral < Contralateral
(J. Chen et al., 2020)	A	2 – 4 seconds	Ipsilateral > Contralateral
(Petermeijer et al., 2017)	A, V, and AV	7 seconds	No difference
Manual driving:			
(Ho et al., 2005)	T	1.8 seconds	Ipsilateral < Contralateral
(Müsseler et al., 2009)	V	–	Ipsilateral > Contralateral
(Straughn et al., 2009)	A and T	2 and 4 seconds	For 2-second lead time: Ipsilateral < Contralateral For 4-second lead time: Ipsilateral > Contralateral
(Wang et al., 2007)	A	1 second	Ipsilateral > Contralateral

2.5 Summary

Overall, non-chronological age factors may be better predictors of cognition and task performance in older adults. However, the benefits of non-chronological age factors reported in the literature have not been evaluated in the context of complex task environments. Additionally, multimodal displays can be used to better facilitate communication between humans and automation. However, the extent to which these displays can assist humans, especially older adults, in function allocation with automation in complex environments is not known. This dissertation aimed to contribute to filling these gaps through four studies. As described in Chapters 1 and 2, the goals of the dissertation work aim to address the following questions:

Q1: Does engagement in physical exercise (a non-chronological age factor) affect takeover task performance in human-automation systems?

Q2: To what extent can multimodal displays assist humans in transitioning from automated to manual control during semi-autonomous operations?

The two research questions were addressed in four separate studies. Study 1 investigated the effects of engagement in physical exercise on the detection of multimodal takeover signals during the signal response phase. Study 2 focused on the impacts of age, physical exercise, and signal modality on the post-takeover phase. However, due to COVID 19 restrictions, Study 2 served only as a pilot study. Study 3 investigated the effects of signal direction, lead time, and modality on takeover performance in the entire automated vehicle takeover process. Finally, based on findings from studies 1, 2, and 3, study 4 examined the ability of meaningful tactile displays to improve performance in the takeover process.

The most common non-chronological age factors relate to physical, cognitive, and social aspects of a person's life. However, to date, there is comparatively more evidence suggesting that physical exercise improves both cognitive and physical functioning in older adults. Given that a vehicle takeover process demands the use of cognitive and physical resources, this dissertation first investigated engagement in physical exercise on interactions with automation in a complex environment (automated driving). Furthermore, three categories of physical activities were described in Chapter 2: physical exercise, sportive activities (meditative movement and martial arts), and complex activities. Compared to the other two physical activities, physical exercise has more varieties, e.g., intense walking, running, jogging, swimming, ball games, and bicycling. A recent study compared the types of physical activities that U.S. adults regularly participated in among a sample of 22,545, and found that 34% participated in walking, followed by bicycling (12%). As a complex activity, dance was found to have 8% participation (Dai et al., 2015). I assumed that engagement in physical exercise (especially aerobic exercise) is the most common physical activities and has demonstrated numerous benefits in terms of slowing down declines in physical and cognitive domains. Therefore, engagement in physical exercise was studied as the first non-chronological age factor in the experiment.

3. QUANTIFYING AGE-RELATED TIME DIFFERENCES IN NOTICING MULTIMODAL TRANSITION REQUESTS

A version of this chapter has been accepted by the *Applied Ergonomics* journal for publication.

3.1 Introduction

Given the complexity of a takeover event (as described in Section 2.4.2), it is necessary to delineate performance at different stages along the takeover continuum, i.e., signal response and post-takeover phase, in order to compare age-related differences and signal modalities. To date, very few studies have compared performance in the takeover signal response phase between older and younger drivers, and the results are somewhat conflicting (Clark & Feng, 2017; Körber et al., 2016; Li, Blythe, Guo, & Namdeo, 2018, 2019; Miller et al., 2016; Molnar et al., 2017). For instance, Clark and Feng (2017) and Körber et al. (2016) found no age differences in hands-on/feet-on/takeover times, which is equivalent to signal response time, while Li et al. (2018, 2019) found that older adults took longer to move their hands to the steering wheel and put feet on pedals compared to the younger group. A few possible explanations exist for the lack of consensus across these studies.

First, all of these studies used different types of sensory signals. Takeover warning signals are generally presented in single visual, auditory, or tactile, or in any combination of these three (see reviews in Eriksson & Stanton, 2017; McDonald et al., 2019). Specifically, Clark and Feng (2017) and Körber et al. (2016) used a single auditory alert, while Li et al. (2018) used a combined visual-auditory signal and Molnar et al. (2017) employed combined visual-verbal-haptic cues. However, research on multimodal signal detection and age has reported that compared to single visual (V), auditory (A), or tactile (T) signals, multimodal signals (i.e., redundant bi- or trimodal combinations of V, A, and T: VA, VT, AT, and VAT) often leads to faster response times, and higher detection and response accuracies in simple and complex environments, such as psychology experiments and manual driving tasks, respectively, regardless of age (e.g., Gottlob, 2007; Laurienti, Burdette, Maldjian, & Wallace, 2006; Liu, 2001; Lundqvist & Eriksson, 2019; Pitts & Sarter, 2018).

With respect to age, older adults generally have longer response times compared to younger adults, but the difference is relatively small (e.g., 130 – 270 msec in Gottlob (2007); 42 – 91 msec in Laurienti et al. (2006); and 200 msec in Lundqvist and Eriksson (2019)). In some cases, multimodal (compared to unimodal) signals were associated with larger response time reductions for older adults than for their younger counterparts (e.g., Laurienti et al., 2006). To date, no study has directly compared the effects of age and the 7 signal types on response times in the automated driving context to determine whether these results hold true across tasks and environments. This knowledge will be especially important given that in the automated driving environment, the attention allocation of the driver will be different as he/she becomes disengaged from the driving task (Politis et al., 2017; Yoon et al., 2019). For instance, in SAE Level 3, drivers may shift their attention away from the driving task and engage in non-driving related tasks (NDRTs; such as texting, watching a movie, or eating) (Naujoks et al., 2018), and differences may exist in how younger and older drivers allocate their attention. A recent study that focused on age differences in NDRTs selection and takeover (Clark & Feng, 2017) found that younger adults preferred engaging with electronic devices, while older adults enjoyed conversing with others during Level 3 automated driving. Engaging in NDRTs may negatively affect signal response performance. For example, Yoon et al. (2019) varied NDRT type (i.e., phone conversation, phone interaction, and video watching) and occasionally asked participants to takeover after receiving all 7 types of warning signals. They found that response times to takeover alerts varied based on the type of engagement and the sensory modalities occupied by the NDRT. But age was not a factor in their study and, thus, it is unclear how age and attention allocation interact to affect response times to the 7 signals.

A second reason for the inconsistent findings among the few studies that measured age differences in responses within the takeover signal response could be that even though the mean age of older adult participants were all between 65-75 years, which is often referred to as “young old” (Binstock, 1985), the age ranges in their studies were different (e.g., 60-81 years of age in Li et al, 2016; 70-81 years of age in Miller et al., 2016). While there are basic biological changes that occur with age, in general, as mentioned in Chapter 2, aging is a heterogeneous process in that perceptual, cognitive, and physical abilities deteriorate at varying rates for different people (e.g., Baldock, Mathias, McLean, & Berndt, 2007; Czaja et al., 2019). Thus, the findings from these studies may be influenced by co-variates and/or non-chronological age factors (such as physical and cognitive activities or lifestyle) that might have not been accounted for (e.g., Adrian, Postal, Moessinger, Rascle, & Charles, 2011; Lemke, 2009; National Research Council, 2004; Ravichander, Steve, & Joe, 2010).

The goal of this study was to fill the above research gaps in the aging literature by examining whether the non-chronological age factor, engagement in physical exercise, is associated with performance differences in multimodal signal perception (under different attention allocation conditions) between younger and older drivers. Physical exercise and multimodal warning signals (compared to unimodal) were expected to be associated with shorter response times for all ages, but with a larger reduction in response time for older adults. Given the nature of the task, which more closely resembled a response time task, we also expected any age- and/or exercise-related differences to be relatively small (Ballesteros, Mayas, & Reales, 2013; Huang, Steele, Zhang, & Pitts, 2019; Laurienti et al., 2006; Muiños & Ballesteros, 2018; Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017; Yoon et al., 2019).

3.2 Method

3.2.1 Participants

Forty-eight participants took part in this study. All participants were evenly recruited into four groups: 12 in a younger exercise group, 12 in a younger non-exercise group, 12 in an older exercise group, and 12 in an older non-exercise group. Younger participants were recruited from Purdue University, while all older participants were healthy residents recruited through Purdue's Center on Aging and the Life Course (CALC), and independent-living communities and senior activity centers in Lafayette/West Lafayette, Indiana area. For the physical exercise groups, volunteers were required to perform aerobic exercise at least 3 times per week and 45 minutes per time during the past five years, based on criteria used in previous research on related topics (e.g., Ballesteros, Mayas, & Reales, 2013; Gauchard, Gangloff, Jeandel, & Perrin, 2003; Marmeleira, Godinho, & Fernandes, 2009; Voelcker-Rehage, Godde, & Staudinger, 2011; Voss et al., 2010). As shown in Table 3.1, walking/jogging was the most common aerobic exercise type for both age groups. Both non-exercise groups were individuals who had not exercised regularly during the past 5 years. All participants were required to possess a valid driver's license, have a normal or corrected-to-normal vision, and have no impairments to hearing nor the sense of touch. All volunteers were paid $25 for their time. This study was approved by the Purdue University

Institutional Review Board (IRB Protocol ID: 1802020214). Demographic information for each group is presented in Table 3.2.

Table 3.1. Distribution of aerobic exercises performed by type and age group

	Walking/Jogging	Ball sports	Swimming	Biking	Other
Younger adults	9 (75%)	5 (42%)	1 (8%)	2 (17%)	4 (33%)
Older adults	7 (58%)	2 (17%)	5 (42%)	3 (25%)	5 (42%)

Note: the number outside of the parenthesis represents the number of participants who reported performing that activity (out of a total of 12); the percentage inside of the parenthesis is the proportion of people in each group who conducted the respective activity. Also, some participants performed more than one type of exercise. The 'Other' category includes, but is not limited to, exercises such as dancing, high-intensity interval training (HIIT), and trampoline jumping.

Table 3.2. Demographic information for each age group

Factor	Younger adults		Older adults	
	Exercise	Non-exercise	Exercise	Non-exercise
Mean age in years (SD)	21.25	22.58 (1.73)	72.50 (5.71)	70.83 (4.26)
Age range	20 – 22	20 – 26	66 – 84	66 – 77
Male	8	5	4	4
Female	4	7	8	8
Mean years of driving	5.33 (1.07)	5.08 (3.12)	54.17 (5.31)	54.09 (4.64)
Mean years of exercise	5.42 (3.13)	–	18.67 (15.66)	–
Miles driven per year (SD)	8,115.86 (7,221.66)	7,301.00 (7,206.90)	6,860.91 (4,280.07)	7,046.36 (5,225.77)

3.2.2 Apparatus/Stimulus

Driving Simulator

A medium-fidelity fixed-base National Advanced Driving Simulator (NADS), miniSim, with 138-degree horizontal field-of-view was used for this experiment. This system consists of three 48-inch TV monitors, one LED monitor as the dashboard, control panel, life-size seat, steering wheel, and foot pedals (Figure 3.1). All driving-related metrics were collected at 60 Hz.

Figure 3.1. Experimental setup and devices (featured: NADS driving simulator, Fovio eye tracker, and C-2 Tactors)

Warning Signals

The visual signal was a red circle (200 × 200 pixels) displayed on the center main monitor (presented in Figure 3.1). Auditory signals were 6-burst, 400 Hz beeps with a loudness range from 0-100 dB. Tactile signals were presented by two 1’’ × 0.5’’ × 0.25’’ piezo-buzzers (called C-2 Tactors developed by Engineering Acoustics, Inc.) at a frequency of 250 Hz with an intensity range of 1-255 gain units. Both Tactors were attached to the lower back center region (e.g., Eriksson et al., 2019; Pitts & Sarter, 2018). The duration of all signals was 1 second. Given the range of ages represented in this study, the intensities of the auditory and tactile signals were chosen by participants through the use of a crossmodal matching procedure (see details in Pitts, Riggs, & Sarter, 2016) conducted prior to the experiment.

3.2.3 Experimental Design

This study employed a 2 (age group: younger and older) × 2 (exercise type: exercise and non-exercise) × 7 (takeover request signal type: V, A, T, VA, VT, AT, and VAT) × 4 (task condition) full factorial design. For signal type, V = visual, A = auditory, and T = tactile. For task condition, participants completed four separate driving sessions/tasks: 1) no task, 2) a video watching task, 3) a headway estimation task, and 4) a video watching and headway estimation (combination) task. Each session consisted of 28 warning signals (i.e., each of the 7 signal types repeated four times in four similar blocks) that were presented randomly throughout each drive.

The driving task was designed to represent Level 3 automated driving, where speed and lane position were both controlled by the automation, on a four-lane highway (two adjacent lanes in each traveling direction) with random, and occasional traffic appearing in the two opposite lanes. The average time between warning signals was 20 seconds (e.g., Lundqvist and Eriksson, 2019; Pitts and Sarter, 2018; Politis et al., 2017), and the order of the four conditions and signals was counterbalanced.

In the 1) no task (or baseline) condition, participants responded to the 7 warning signals by pressing the brake pedal (with their right foot) as soon as they saw/heard/felt any of the multimodal signals (e.g, Dogan et al., 2017). In the 2) video watching task condition (a non-driving related secondary task that has been used in previous studies (e.g., Carsten, Lai, Barnard, Jamson, & Merat, 2012; Clark & Feng, 2017; Mok et al., 2015; Yoon et al., 2019), participants were asked to watch a TED talk video related to intelligent technologies, and also respond to the 7 warning signals as soon as they appeared. This video played on the windshield in the lower right-hand corner of the main display. Here, participants were informed that a video knowledge assessment (or quiz), that contained questions that required recalling of facts spoken by the speaker in the video, would be administered after the driving session. This assessment was used to encourage drivers to focus on the video and disengage from the driving task. In the 3) headway estimation task condition (a driving-related secondary task), the experimenter randomly asked the driver, 12 separate times, "how many seconds to a collision are you behind the car in front of you?" Here, headway was defined as the timing between the leading vehicle and the current/subject vehicle (Yanko & Spalek, 2014). These queries were made in-between, and least 5 seconds before or after, the presentation of the warning signals to avoid interference with the signal detection task. Participants' options were: 3, 5, or 7 seconds (i.e., the time to collision), corresponding to a close, medium, and far distance, respectively (see Figure 3.2). This condition was created to emulate drivers attending to the forward roadway as they would if automated functions – most notably, Adaptive Cruise Control (ACC) – are deactivated during real-world situations that require takeover. Finally, in the 4) video watching and headway estimation (combination) task condition, participants watched a similar type of video (as in condition 2) while, at the same time, being asked to make headway judgments (as in condition 3) and respond to all warning signals. The goal was to simulate a more complex situation that could occur in real-life and that requires greater cognitive demands (i.e., video watching, headway judgments, and signal perception) than those in task conditions 2) and 3).

(a) (b) (c)

Figure 3.2. Sample scenes for headway estimation and combination (of video watching and headway estimation) task conditions: (a) 3-second, (b) 5-second, and (c) 7-second headway

3.2.4 Procedure

The experiment lasted 90 minutes. Participants first signed the experimental consent form and then completed a pre-experiment questionnaire that asked about demographic information, driving experiences, and physical exercises. Then, the Montreal Cognitive Assessment (MoCA) was administered to assess capabilities for participating in our study (e.g., Nasreddine et al., 2005). Next, participants were introduced to the experimental setup and asked to perform crossmodal matching. After, a 10-minute training session, similar to the actual experiment, was performed. During the actual experiment, since Level 3 automation does not require constant manual control of the vehicle, participants were asked to place their hands in their laps and their feet on the floor (base) of the driving simulator. They were informed that the vehicle can fail due to operational limits and that the study was designed to mimic the moment when a failure occurs. The 7 types of warning signals would be presented to signify when the system was failing. They were instructed to respond to the warning signals as quickly as possible after receiving an alert by pressing the brake pedal as to avoid a collision, which deactivated the automated driving mode (e.g, Dogan et al., 2017). However, since a takeover event was not required, no actual collision would occur if participants missed a signal. This approach was employed to avoid inducing anxiety (especially in older participants) from a vehicle collision. Immediately afterwards, participants needed to reactivate the automation by pressing a button on the steering wheel and then prepare for the next signal(s). A 5-minute break was given between each of the four driving conditions. After the experiment, participants filled out a post-experiment questionnaire that asked about their performance and strategies they employed throughout the experiment.

3.2.5 Dependent Measures

Dependent measures were classified into three categories: a) driving-related, b) eye movements, and c) secondary task performance.

Driving-related measures

Driving-related measures included brake response time and maximum brake force (Winkler et al., 2018). Brake response time (in milliseconds (msec)) was defined in SAE J2944 as the time between the presentation of any warning signal and the initial contact of the brake pedal (Society of Automotive Engineers, 2015). Maximum brake force (Newtons; N) was defined as the maximum force applied to the brake pedal within the time period between the presentation of a takeover warning signal and the releasing of brake pedal (Winkler et al., 2018), with range of 0-180 N. Here, a smaller value indicates a better brake control (Roche & Brandenburg, 2020).

Secondary task performance

For task conditions 2 (video watching) and 4 (combination), the video knowledge accuracy was calculated as the percentage of correct answers out of the total number of questions asked after the video. In total, 6 questions (after each of the two task conditions) were evaluated based on the length of the video and the information extracted from the video. For task conditions 3 (headway estimation) and 4 (combination), headway estimation accuracy was defined as the percentage of correct responses to the total number of inquiries made during the experiment.

3.2.6 Data Analysis

For driving-related measures, Pearson correlation did not reveal a significant correlation between the brake response time and maximum brake force ($r = -.099$) and thus, two separate 4-way mixed-model Analysis of Variance (ANOVA) tests were conducted for measures, where age and exercise type were between-subject (quasi-independent) factors, and signal type and task condition were both within-subject factors.

For secondary task performance, a 3-way mixed-model ANOVA was performed. Signal type was not included in the model because for secondary tasks, performance was not necessarily assessed near a signal presentation. Thus, age and exercise type were between-subject factors, and task condition was a within-subject factor.

For all statistical tests, post-hoc comparisons with Bonferroni corrections were performed to identify significant differences and interactions between means. Also, Greenhouse-Geisser corrections were applied for violations of the assumption of sphericity. Significance level was set at $p < 0.05$.

3.3 Results

3.3.1 Driving-related measures

There was a significant main effect of age ($F(1, 44) = 4.503, p = .040, \eta_p^2 = .093$), signal type($F(4.0, 177.7) = 517.384, p < .001, \eta_p^2 = .922$), and task condition ($F(2.5, 109.8) = 21.267, p < .001, \eta_p^2 = .326$) on brake response time. For age, post-hoc comparisons revealed that older adults (mean = 1014 msec, standard error of the mean (SEM) = 30) had longer brake response times compared to the younger group (mean = 923 msec, SEM = 30). For signal type, the VAT (mean = 834 msec, SEM = 24) and VT (mean = 837 msec, SEM = 23) signals, were correlated with the shortest brake response time, followed by AT (mean = 883 msec, SEM = 23) and T (mean = 877 msec, SEM = 26) (see Figure 3.3). Finally, for task condition, the headway estimation (mean = 1008 msec, SEM = 24) and combination (mean = 986 msec, SEM = 21) tasks had longer brake response times than the baseline (mean = 926 msec, SEM = 23) and the video watching (mean = 955 msec, SEM = 21) conditions. No main effect of exercise was found ($F(1, 44) = 0.854, p = .360, \eta_p^2 = .019$).

There was a significant age × signal type interaction ($F(4.0, 177.7) = 7.260$, $p < .001$, $\eta_p^2 = .142$) on brake response time. Specifically, for single V and A signals, younger adults had shorter response times (for V: mean = 1003 msec, SEM = 28; for A: mean = 1186 msec, SEM = 31) than older adults (for V: mean = 1092 msec, SEM = 28; for A: mean = 1354 msec, SEM = 31).

However, no age differences were found between multimodal signals (see Table 3.3 for summary statistics).

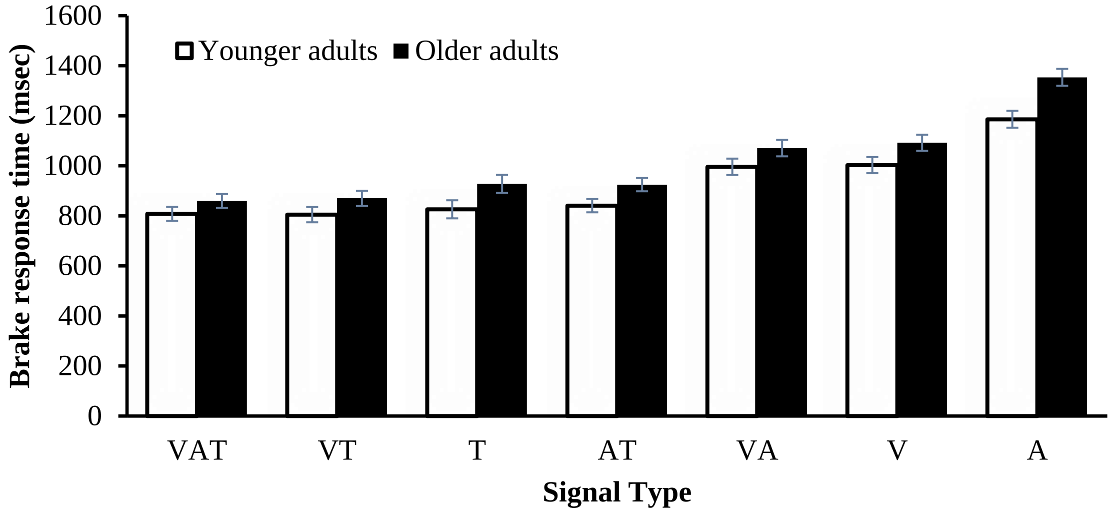


Figure 3.3. Brake response time as a function of age and signal type

Maximum brake force was significantly affected by age ($F(1,36) = 4.121$, $p = .050, \eta_p^2 = .103$) and exercise type ($F(1,36) = 4.316, p = .045, \eta_p^2 = .107$). Older adults (mean = 19.359 N, SEM = 1.443) had a larger maximum brake force compared to younger adults (mean = 15.217 N, SEM = 1.443). Also, the non-exercise group (mean = 19.407 N, SEM = 1.443) had a larger maximum brake force compared to the exercise group (mean = 15.168 N, SEM = 1.443). In addition, there was a significant age × exercise type interaction ($F(1,36) = 6.535, p = .015, \eta_p^2 = .154$) such that for younger adults, the maximum brake force in the exercise group (mean = 10.489 N, SEM = 2.040) was significantly less than the non-exercise group (mean = 19.944 N, SEM = 2.040), see Figure 3.4.

Maximum brake force was not affected by signal type ($F(4.5, 161.7) = 1.385, p = .237$, $\eta_p^2 = .037$) nor task condition ($F(3, 108) = 1.781, p = .155, \eta_p^2 = .047$), and there were no interaction effects between the two factors.

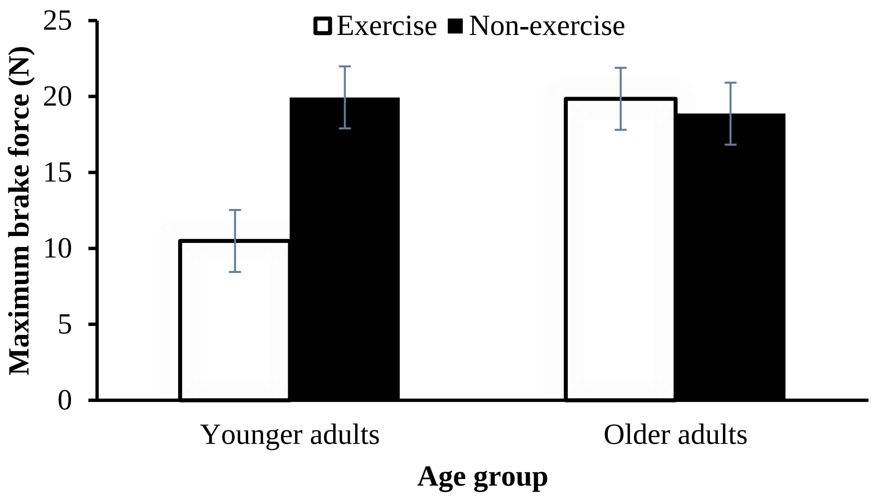


Figure 3.4. Maximum brake force as a function of age and exercise type

3.3.2 Secondary task performance

For headway estimation accuracy, there was a significant main effect of age ($F(1, 44) = 8.167, p = .006, \eta_p^2 = .157$) on headway judgements. Specifically, older adults (mean = 72.7%, SEM = 3.2) had a lower headway estimation accuracy than younger drivers (mean = 85.5%, SEM = 3.2).

For performance on the video knowledge assessment, a significant age × task condition interaction ($F(1, 44) = 4.474,\ p = .040, \eta_p^2 = .092$) was observed. In particular, in the video watching task condition, the difference in accuracy percentage (difference = 0.0%, $p = 1.000$) between the older (mean = 61.8%, SEM = 3.1) and younger groups (mean = 61.8%, SEM = 3.1) was smaller than in the combined (video watching and headway estimation) task condition (difference = 15.3%, $p = .027$) between older (mean = 52.8%, SEM = 4.7) and younger adults (mean = 68.1%, SEM = 4.7).

Table 3.3. Summary statistics of the dependent measures for all independent variables

	Age		Exercise		Signal Type							Task Condition				Interactions
	YA	**OA**	**E**	**NE**	**V**	**A**	**T**	**VA**	**VT**	**AT**	**VAT**	**T1**	**T2**	**T3**	**T4**	
BRT (msec)	923 (30)	1014 (30)	949 (30)	988 (30)	1047 (20)	1270 (22)	877 (26)	1033 (19)	837 (23)	883 (23)	834 (24)	926 (23)	955 (21)	1008 (24)	986 (21)	Age × Signal: F (4.0, 177.7) = 7.260 ***p* < .001*** η_p^2 = .142
	F (1, 44) = 4.503 ***p* = .040*** η_p^2 = .093		F (1, 44) = 0.854 *p* = .360 η_p^2 = .019		F (4.0, 177.7) = 517.384 ***p* < .001*** η_p^2 = .922							F (2.5, 109.8) = 21.267 ***p* < .001*** η_p^2 = .326				
MBF (N)	15.22 (1.443)	19.36 (1.44)	15.17 (1.44)	19.41 (1.44)	17.03 (1.05)	17.80 (1.14)	17.25 (.96)	17.04 (1.09)	17.49 (1.01)	16.85 (1.05)	17.56 (1.08)	16.28 (1.04)	18.08 (1.16)	17.20 (1.26)	17.59 (1.07)	Age × Exercise: F (1, 36) = 6.535 ***p* = .015*** η_p^2 = .154
	F (1, 36) = 4.121 ***p* = .050** η_p^2 = .103		F (1, 36) = 4.316 ***p* = .045** η_p^2 = .107		F (4.5, 161.7) = 1.385 *p* = .237 η_p^2 = .037							F (3, 108) = 1.781 *p* = .155 η_p^2 = .047				
HEA (%)	85.5 (3.2)	72.7 (3.2)	82.2 (3.2)	76.0 (3.2)	–							–	79.6 (2.4)	–	78.6 (2.6)	–
	F (1, 44) = 8.167 ***p* = .006*** η_p^2 = .157		F (1, 44) = 1.903 *p* = .175 η_p^2 = .041		–							F (1, 44) = .189 *p* = .666 η_p^2 = .004				
VKA (%)	64.9 (3.1)	57.3 (3.1)	64.2 (3.1)	58.0 (3.1)	–							–	61.8 (2.2)	–	60.4 (3.3)	Age × Task: F (1, 44) = 4.474 ***p* = .040*** η_p^2 = .092
	F (1, 44) = 3.113 *p* = .085 η_p^2 = .066		F (1, 44) = 2.084 *p* = .156 η_p^2 = .045		–							F (1, 44) = .148 *p* = .702 η_p^2 = .003				

Note: YA = younger adults; OA = older adults; T1 = baseline task condition; T2 = video watching task condition; T3 = headway estimation task condition; T4 = combination task condition; BRT = brake response time; MBF = maximum brake force; HEA = headway estimation accuracy; and VKA = video knowledge accuracy

3.4 Discussion

The goal of this study was to investigate the effects of age and physical exercise on performance differences in multimodal signal responses under different attention allocation conditions. Overall, bi- and trimodal signals were associated with faster brake response times for both age groups, but older adults responded more slowly and also had a higher brake force compared to younger adults. Additionally, physical exercise was associated with a smaller maximum braking force for younger drivers only.

3.4.1 Driving-related measures

Brake response time

Somewhat contrary to our expectations, aerobic exercise, did not produce a significant main effect on brake response time. Since the response time difference between the younger and older groups is already relatively small (i.e., 91 milliseconds), the effects of physical exercise may not be apparent for response time. The time differences reported in previous studies that found physical exercise to be associated with faster response speeds in older adults were also very small (e.g., 65 – 78 milliseconds between exercise and non-exercise group in Ballesteros et al. (2013); and 12 - 69 milliseconds in Marmeleira et al. (2009)) and these effects may be masked by the age effects. However, these studies did not generate data on the gains associated with exercise for younger adults, thus it is difficult to know whether the results are attributable only to exercise. Also, in this study, the signal response phase of a takeover process only included perception, processing, and movement (i.e., contact with the brake pedal). It did not contain significant decision-making components, such as planning for how to deactivate the automation, regaining environment and situation awareness, selecting courses of action (i.e., deciding the dynamic state of the vehicle after resuming control), nor executing actions (deciding how to maneuver). Thus, the benefits of physical exercise might reveal themselves in later, more involved, phases of the vehicle takeover process, such as decision-making regarding space availability in adjacent lanes and/or manual control of longitudinal and lateral accelerations and positions during post-takeover.

With respect to chronological age, older adults had longer brake response times to warning signals than younger adults across the four driving conditions. This finding is consistent with previous studies mostly in manual driving (e.g., Lundqvist & Eriksson, 2019; Pitts & Sarter, 2018) and only a few in automated driving (Li et al., 2018, 2019), and potentially points to biological changes in perception, cognition, and physical abilities observed with age (Anstey et al., 2005). We also found both age groups to respond faster to trimodal signals, followed by bimodal alerts, then single modality signals (Huang et al., 2019; Petermeijer et al., 2017; Politis et al., 2017; Yoon et al., 2019). In addition, any signal type that included a tactile component (i.e., T, AT, VT, and VAT) was associated with shorter brake response times for all ages (compared to those that did not; V, A, and VA, as shown in Figure 3.3). Lundqvist and Eriksson (2019) explained that the benefits of trimodal warning signals are still debated, but Pitts and Sarter (2018) proposed that the inclusion of the tactile modality (with fastest conduction velocity) is what ultimately dictates the response time to multimodal signals. An additional, and alternative, explanation for why the signals that included the tactile modality were associated with a faster response time compared to signals without a tactile cue may relate to the driving environment. It consisted of constant auditory input (i.e., sounds of the tires-on-road, the vehicle engine, and the video) as well as continuous visual information (i.e., monitoring the road in baseline condition, video watching and headway estimation in other conditions). Here, the tactile channel was most available (free) for detecting vibration information compared to the already occupied visual and auditory channels (Meng & Spence, 2015; Wickens, 2008).

The advantages of tactile signaling were also found for both age groups. Specifically, older adults were only slower than younger adults in responding to single visual and auditory signals, but no differences were found between the two age groups for all other signals. This implies that older adults may benefit from multimodal signals, especially if the signal combination includes tactile information. In other words, age-related declines, resulting in delayed responses to warning signals, may be mitigated by multisensory integration (Laurienti et al., 2006; Peiffer et al., 2007).

For task condition, response times in the headway estimation and combination (of video watching and headway estimation) task conditions were longer compared to the baseline and video watching conditions. One possible explanation for this finding is that a higher level of precision was needed to accurately estimate headway in these conditions. Here, participants might have been performing a complex spatial mental calculation, and when the signals were presented, it took them slightly longer to task switch and recognized the warning signals.

Maximum brake force

Maximum brake force has been used as an indicator of collision risk (Aries, 2019; Dziuk, 2015). In our study, physical exercise and age both affected maximum brake force. Participants who did not perform aerobic exercises had a higher maximum brake force. This finding may be attributed to the fact that aerobic exercise makes use of repetitive leg movement and muscle activation. In this case, those who engage in activity of their legs more frequently may benefit from better motor control. This hypothesis may be confirmed by comparing data collected from tasks that utilize arm movements, such as steering while driving, since aerobic exercise also makes use of upper body movements. However, steering metrics were not collected as part of this study.

For age, there was a tendency for older drivers to brake harder than younger adults. This supports the results of Clark and Feng (2017) and could highlight the uncertain feelings that older adults express about automated driving (Abraham et al., 2017). For example, to date, many older adults have not yet had the chance to experience intermediate levels of vehicle automation. It may take some time to accept the fact that they can divert their attention from forward driving, to some extent, and perform secondary tasks freely in the vehicle. Additionally, Marchese (2019) showed that older adults brake harder during manual driving while performing NDRTs to slow down in order to compensate for their slower responses and their attention lost due to the secondary tasks, and thus this behavior may simply be carrying over to automated driving.

Finally, there was an interaction effect between age and exercise on maximum brake force. Here, younger participants in the exercise group had a lower maximum brake force compared to older adults in the exercise group, while no difference was found between the two age groups in the non-exercise category. One possibility for this phenomenon is that the benefits of physical exercise, in terms of braking control, may not be determined only by aerobic exercise. In other words, in addition to aerobic exercises, many younger participants in this study are also likely performing anaerobic exercises (such as weightlifting), as well as other high-intensity workouts that make use of leg and overall body strength.

3.4.2 Secondary task performance

Older adults had worse performance on the headway estimation task, which is consistent with previous work (DeLucia et al., 2003) that reports lower accuracy in estimating time-to-collision in older adults. Boot, Stothart, and Charness (2014) and Czaja et al. (2019) explained that older drivers, in general, have difficulty judging headway distances, such as when turning across opposing traffic to make a left-hand turn. They explain that headway estimations require the use of visual resources, spatial processing, and working memory, and that age-related decrements in any of these abilities will limit such judgment abilities (Boot et al., 2014; Czaja et al., 2019; DeLucia et al., 2003; Scialfa et al., 1991; Sekuler et al., 1980).

For the video knowledge assessment, as expected, older adults recalled fewer facts about the video (compared to younger adults) when they had to watch the video and estimate headway at the same time (combination task condition). Also, consistent with previous studies, while no age-related performance difference was found in the video watching condition alone, this observation may further highlight the relative difficulty older adults experience when divided attention is required to complete multiple unrelated tasks – a phenomenon highlighted by several decades of research (e.g., Erber, 2012; Horberry, Anderson, Regan, Triggs, & Brown, 2006; Kemper, Schmalzried, Herman, & Mohankumar, 2011; McDowd & Craik, 1988; McKnight & McKnight, 1993; Somberg & Salthouse, 1982; Son, Lee, & Kim, 2011). In our study, older drivers performed worse on both the video knowledge assessment and the headway estimation task (in the combination task condition) when multiple tasks needed to be conducted simultaneously. Here, older adults seemed to prioritize the tasks related to safety, i.e., focusing more attention on the road and the warning signals (as indicated by eye-tracking data), which is in accordance with previous studies in terms of a safety prioritization strategy (e.g., Horberry et al., 2006; Son et al., 2011).

3.4.3 Limitations

One potential limitation of this study is the manner in which participants who exercise were recruited. Participants were grouped based on their self-reported exercising frequency. However, there was no upper limit (so some participants might have exercised daily), and engagement in particular types of physical activities (per person) might have changed within the 5 or more years. These factors could have caused variability even within the exercise groups. In addition, the MoCA was used to assess participants' cognitive capabilities for participating in the study. But, no actual cognitive abilities were measured to be considered as a potential co-variate. Thus, future follow-up studies may use additional cognitive tests, such as the Trial Making Test (Groth-Marnat, 2009), to quantify cognitive ability, e.g., processing speed and executive control, and include in analysis on the relationship between physical exercise and takeover performance.

In this experiment, baseline maximum brake force was not measured, which could have helped to support explanations of our findings regarding muscle control and braking intensity. Similarly, steering wheel-related measures were not collected, which may reflect the benefits of physical activities with respect to upper body functionality. Instead, the focus was on brake pedal behavior because deciphering when the signal response phase stops and the post-takeover phase starts can be difficult when using steering wheel activity.

3.5 Conclusion

The bi- and trimodal signals, especially those with a tactile component, were associated with shorter brake response times for both age groups, with a more pronounced effect for older adults. The non-chronological age factor, engagement in physical activity, was associated with better brake pedal control for younger adults, but did not help older adults as originally expected. However, chronological age differences were observed in that, compared to younger individuals, older adults had longer response times to warnings, larger maximum brake force, and poorer secondary task performance.

Nonetheless, this research fills gaps in the aging and (vehicle) automation literature by taking first steps to generate empirical data on the effects that signaling modality and physical activity have on performance in the signal response phase of the takeover process. Given the complexity of the task, the goal of Study 2 (in Chapter 4) was to examine the effects of age, physical exercise, and signal modality on the post-takeover phase.

4. DETERMINING THE EFFECTS OF AGE AND PHYSICAL EXERCISE ON TAKEOVER TASK PERFORMANCE AS A FUNCTION OF MODALITY TYPE AND LEAD TIME

A version of this chapter has been submitted for publication.

4.1 Introduction

As described in Chapters 1 – 3, the goal of this study (Study 2) was to extend the focus of Study 1 (the signal response phase) to the post-takeover phase, and quantify the effects of age, engagement in physical exercise, and takeover request alert modality on post-takeover driving performance. I expected that, while age-related differences may exist, engagement in physical exercise and multimodal warning signal (compared to unimodal) would be associated with better post-takeover quality (Clark & Feng, 2017; McDonald et al., 2019; Wan & Wu, 2018b).

4.2 Method

4.2.1 Participants

A total of 16 participants were recruited for this pilot study. Younger adults were students recruited from Purdue University, while older adults were healthy residents of the Lafayette/West Lafayette, Indiana area. Different from the criteria used in Study 1 to define the physical exercise group, this study used the score from the Godin Leisure-Time Exercise Questionnaire (Godin, 2011), which quantifies both frequencies and intensities of weekly aerobic exercises, to categorize participants into exercise and non-exercise groups. Specifically, to qualify for the exercise group, volunteers were required to have a score of 24 or more on this assessment (identified as the active group in Godin, 2011), while non-exercise group members only needed a score 14 or less (marked as the sedentary group). Additional eligibility requirements included: 1) possession a valid U.S. driver's license; 2) no sensory or cognitive impairments; and 3) normal or correct-to-normal vision. All participants were paid $30/hour for their time. The study was approved by Purdue University Institutional Review Board (IRB Protocol ID: 1802020214). Participants' demographic information is presented in Table 4.1.

Table 4.1. Demographic information for participants in the study

Factor	Younger adults		Older adults	
	Exercise	Non-exercise	Exercise	Non-exercise
Mean age	24.5 ± 2.1	26.0 ± 1.5	74.3 ± 2.6	72.0 ± 3.4
Number of participants	4	4	4	4

4.2.2 Apparatus/Stimulus

Driving simulator

A National Advanced Driving Simulator (NADS), simplified cab miniSim, was used to conduct this study. The driving simulator is equipped with three 48-inch monitors, which displays the main driving scene, and one 18.5-inch, which serves as the vehicle dashboard display. This system also includes, a steering wheel and associated driving foot pedals, an adjustable seat, and a control panel (see Figure 4.1). Driving data was collected at 60 Hz.

Takeover requests

Takeover requests (TOR) were presented as visual, auditory, and/or tactile stimuli. As shown in Figure 4.1, the visual cue (V) was a 200 × 200 pixels red dot presented on the center main display. The auditory cue (A) was a 0-100 dB 6-burst, 400 Hz beep. The tactile cue (T) was vibrations presented using two C-2 tactors developed by Engineering Acoustics, Inc, with an intensity range of 30-48 dB. Tactors were attached to a belt placed on participants' lower back center area (see Figure 4.1). The intensities of both the auditory and tactile cues were selected by participants through a crossmodal matching task (see details in Pitts, Riggs, & Sarter, 2016), using the visual cue as the reference stimulus. All takeover requests lasted for 1 second.

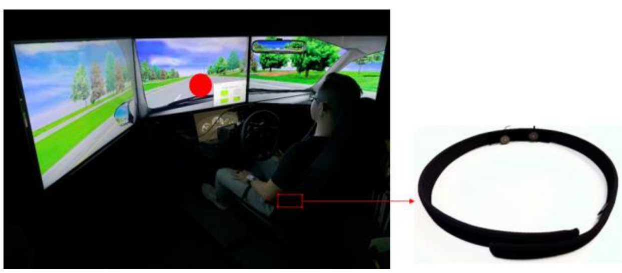


Figure 4.1. Experimental devices and setup (featured: miniSim (left) and C-2 Tactors (right))

4.2.3 Experimental Design

The study employed a 2 (age group: younger and older) × 2 (exercise type: exercise and non-exercise) × 7 (TOR signal type: V, A, T, VA, VT, AT, and VAT) full factorial design. During the experiment, participants rode in a simulated SAE Level 3 automated vehicle in the center lane of a three-lane highway. The traveling speed of the vehicle was 60 mph. The subject vehicle was followed by two fleets of vehicles in both left and right adjacent lanes with an equal distance from the subject vehicle. At the same time, a leading vehicle was randomly 4 and 7 seconds (or 352 and 616 feet, respectively) ahead of the subject vehicle. A construction zone occasionally appeared in the center lane, but its view was obstructed by the leading vehicle. In this case, the leading vehicle immediately stopped in front of the construction zone. The subject vehicle would then issue a takeover request. Once participants perceived and processed this TOR, they were instructed to first tap the brake pedal to deactivate the automation, then control the vehicle as they would in manual driving. During the time, the two fleets of vehicles in both adjacent lanes had then changed their headway and were at different distances with respect to the subject vehicle (see Figure 4.2 for example takeover scenario, where the left fleet was at 88 feet away from the subject vehicle and the right fleet was 264 feet away, representing a trailing headway of one second and three seconds, respectively). To avoid both a rear-end collision and a collision with the leading vehicle, drivers needed to determine which lane to move into by scanning the environment using the side-view and rear mirrors, and deciding which of the two adjacent lanes had the most available space. Once participants changed to an adjacent lane, they were asked to remain in that lane at a speed of 60 mph until they passed the construction zone, and then move back to the center lane and reactivate the automation. They were also informed that their handling of the vehicle during the takeover process was being monitored. Given that there were seven different types of TOR alerts, each participant completed a total 28 takeover events (e.g., Clark & Feng, 2017), separated by an average 2-minute time interval. Each TOR was randomly presented in four similar driving blocks (i.e., 7 takeovers per block). Participants were given 5-minute breaks between blocks.

Figure 4.2. Example of one takeover scenario

4.2.4 Procedure

Participants were first asked to sign the consent form, then fill out a pre-experiment questionnaire that queried demographic information and their engagement in daily activities (i.e., physical exercise and driving experience). Afterwards, they performed the crossmodal matching task and a 15-minute training session to become familiar with experiment equipment and takeover procedures. During the experiment, participants were required to place their hands in their laps and feet on the base of the driving simulator until they were presented with a takeover request. To divert participants' attention away from the road (to avoid being prepared for a takeover event in advance), they were also required to play a game located in the right-hand corner of the main screen. The game required participants to select, from multiple-choice options, the one item that was different from the other three, in terms of the color and locations of different shapes, and the spelling of words. This task was representative of drivers being engaged in a non-driving related task.

4.2.5 Dependent Measures

Decision-making time: Decision-making time (in milliseconds (ms)) was measured as the time between when participants deactivated the automation and the first steering input made towards an adjacent lane.

Maximum resulting jerk: Maximum resulting jerk (in m/s^3), the time rate of change of longitudinal and lateral accelerations, is an indicator of post-takeover quality, such as shift quality and ride comfort (Huang & Wang, 2004). It is calculated using the following formula:

$$Maximum\ resulting\ jerk = \sqrt{max\ longitudinal\ jerk^2 + max\ lateral\ jerk^2}$$

Here, a smaller maximum resulting jerk represents better vehicle control and higher takeover quality.

4.2.6 Data Analysis

A linear mixed-effects model was used to compare the effects of age and exercise type (between-subject factors), and TOR signal type (within-subject factor) on the two dependent measures. The significance level was set at $p < 0.05$.

4.3 Results

4.3.1 Decision-Making Time

Decision-making time was not significantly affected by age ($F(1, 260) = 2.220, p = .138, \eta_p^2 = .001$), exercise type ($F(1, 260) = 0.005, p = .942, \eta_p^2 < .001$), nor TOR signal type ($F(6, 260) = 1.977, p = .069, \eta_p^2 = .040$). However, there was a significant age × exercise type interaction effect ($F(1, 260) = 21.752, p < .001, \eta_p^2 = .080$). As shown in Figure 4.3, the mean differences in decision-making times between older (mean = 2088.03 ms, standard error of mean (SEM) = 256.68) and younger (mean = 1548.81, SEM = 266.55) adults was larger in the non-exercise group compared to the exercise group (older adults: mean = 1995.98 ms, SEM = 256.09; younger adults: mean = 1794.44 ms, SEM = 187.84).

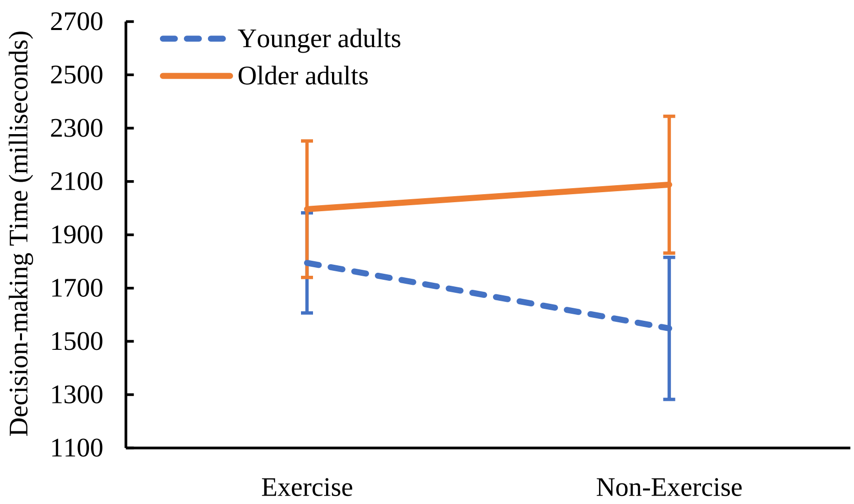


Figure 4.3. Interaction effect for age and exercise type on decision-making time

4.3.2 Maximum Resulting Jerk

Age had a significant main effect on maximum resulting jerk ($F(1, 260) = 40.792, p < .001, \eta_p^2 = .140$). Specifically, older adults had a higher maximum resulting jerk (mean = 72.44 m/s^3, SEM = 9.62) compared to younger adults (mean = 64.45 m/s^3, SEM = 8.95). There was also a significant interaction effect between age and exercise type ($F(1, 260) = 12.844, p < .001, \eta_p^2 = .050$) (see Figure 4.4). Here, older adults tended to have a higher maximum resulting jerk (mean = 77.65 m/s^3, SEM = 12.42) than younger adults (mean = 66.26 m/s^3, SEM = 10.01), but only in the non-exercise group. No significant main effect of TOR signal type on maximum resulting jerk ($F(6, 260) = .225, p = .968, \eta_p^2 = .001$) was found.

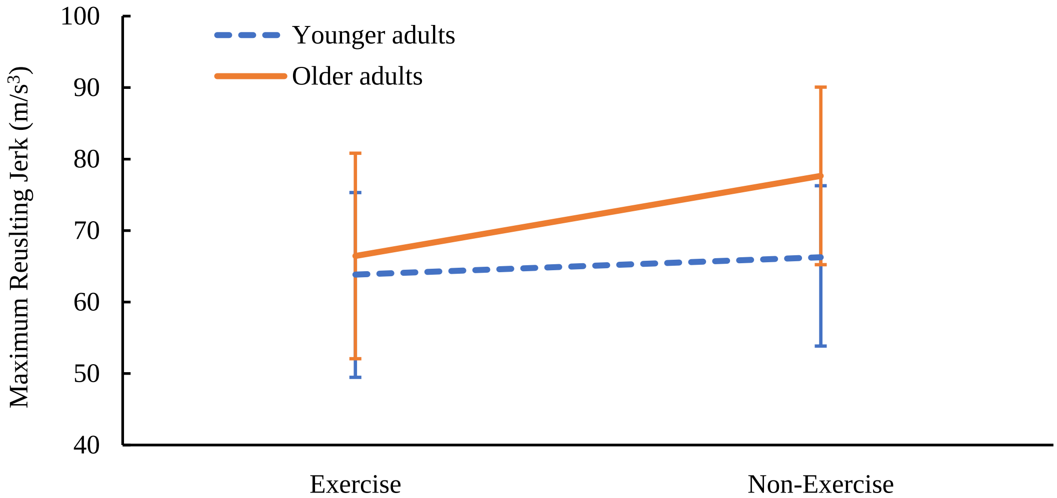


Figure 4.4. Interaction effect for age and exercise type on maximum resulting jerk

4.4 Discussion

This goal of this study was to collect pilot data regarding the effects of age, engagement in physical exercise, and takeover request signal type on task performance in the post-takeover phase. Preliminary results indicate that older adults had a higher maximum resulting jerk compared to younger adults. However, the differences in decision-making time and maximum resulting jerk were narrower for the exercise group (compared to the non-exercise group) between the younger and older groups. Finally, takeover request (TOR) signal type did not result in performance differences.

Even though age and engagement in physical exercise alone did not significantly affect the decision-making time, an interaction effect was found between age and engagement in physical exercise. Specifically, the difference in decision-making time between the two age groups was smaller for the exercise group compared to the non-exercise group. One possible explanation for this finding is that the benefits of physical exercise on decision-making may be more predominant in, and beneficial to, older populations. Decision-making in the takeover process requires significant utilization of many cognitive resources, e.g., information processing, working memory, and divided and sustained attention, within a short period of time (e.g., Knauff & Wolf, 2010; Prezenski, Brechmann, Wolff, & Russwinkel, 2017). As suggested by previous research, the decline of these cognitive components may be mitigated by continued engagement in physical exercise (e.g., Ballesteros, Mayas, & Reales, 2013; Barnes, Yaffe, Satariano, & Tager, 2003; Cassilhas et al., 2012) and these benefits appear to be manifesting in our study. In addition, these preliminary results indicate that the benefits of physical activity also apply to more complex tasks, not just to simple cognitive tests.

With respect to takeover quality, older adults had a higher maximum resulting jerk during the manual control of the vehicle compared to younger adults, indicating a poorer takeover quality. This finding is consistent with prior chronological age studies that report that older adults may experience declines in psychomotor abilities, such as hand-eye coordination and motor control (e.g., Fraser et al., 2009; Guan & Wade, 2000), due to biological changes that occur with age. However, similar to the results for decision-making time, there was also a significant interaction between age and engagement in physical exercise for maximum resulting jerk. In particular, the difference in maximum resulting jerk between the two age groups was larger for the non-exercise group than for the exercise group. This finding provides even more evidence that older adults who engage in active physical exercise may retain or improve their psychomotor abilities, which could be advantageous for the performance on both simple and complex tasks. Overall, the decision-making time and maximum resulting jerk findings further highlight the importance of considering non-chronological age factors in human-automation interaction research and could aid in developing theories regarding successful aging (Franklin & Tate, 2009).

Finally, in contrast to previous studies that examined the effects of signal type on response/takeover times in only the signal response phase (e.g., Politis, Brewster, & Pollick, 2017; Yoon, Kim, & Ji, 2019), the current study extended the measurement range to include the decision-making and manual driving stages. Contrary to our expectations, no significant main nor interaction effects of TOR signal type on decision-making time and maximum resulting jerk were found. One possible explanation could be that since the length of the warning signal was 1 second, its influence may have not lasted throughout the duration of post-takeover phase in order to affect decision-making and vehicle maneuver. However, more research is needed to confirm this hypothesis.

4.5 Conclusion

This pilot study quantified the effects of age, engagement in physical exercise, and takeover request signal type on decision-making time and maximum resulting jerk in the post-takeover phase of the takeover process. Preliminary findings suggest that for older adults, engaging in physical exercise may be beneficial to performing complex tasks in terms of both decision-making speed and physical control. Given that this is a pilot study, a larger sample size will be achieved in a future follow-up study and, thus results should be interpreted with caution. As mentioned, due to COVID 19 restrictions, the modified goal of the phase two (after this pilot study) was to address non-age-related gaps in the literature regarding multimodal information presentation. Specifically, the new goal was to examine the effects of signal direction, lead time, and modality on takeover performance, using timing between signals that is more representative of actual takeover events.

5. EXAMINING TAKEOVER PERFORMANCE AS A FUNCTION OF LEAD TIME AND SENSORY MODALITY/MODALITIES NOTIFICATION

A version of this chapter has been submitted to a journal for review.

5.1 Introduction

Study 1, in Chapter 3, quantified the effects of age and engagement in physical exercise on multimodal takeover warning signal response time. Study 2 in Chapter 4 quantified the effects of these same factors on post-takeover performance. However, due to COVID-19 restrictions, Study 2 was only served as a pilot study. To continue addressing the gaps identified in Chapter 1, the focus of this study (in Chapter 5) shifted to explore the effects of various characteristics of human-machine interfaces on takeover performance. However, findings are still expected to inform the design for a wide range of user groups.

As described in Section 2.4.2, the takeover process is comprised of multiple steps. Here, the takeover request (TOR) is presented only a few seconds prior to the event requiring the takeover (also known as the lead time or time-to-collision), and if the driver does not takeover within this timeframe, a collision may occur. Therefore, it is critical to develop effective human-machine interfaces (HMIs) that support drivers in successfully transitioning from automated to manual control of vehicles (e.g., Carsten & Martens, 2019; National Science and Technology Council and the United States Department of Transportation, 2020).

Section 2.4.3 introduced the applications of ipsi- and contralateral signals as an HMI option in automated vehicle. However, findings, in the very limited studies that examined the effects of this directional signal approach, were conflicting. Specifically, Cohen-Lazry et al. (2019) reported that drivers responded faster to ipsilateral TORs, while Chen et al. (2020) found contralateral signals to be associated with shorter response times. However, no differences between these signal directions were found in Petermeijer et al. (2017), where drivers could choose which action to make based on their own intuitive interpretation of the signals. Two possible factors may explain these conflicting findings, namely the warning lead time and signaling modality.

For warning lead time, Chen et al. (2020) evaluated five discrete lead times between 2 – 4 seconds, but did not find significant differences in response times between ipsilateral and contralateral signals. The lead times used in this study are considered to be short, based on a review that summarized findings from a series of takeover studies (Eriksson & Stanton, 2017) and classified times shorter than 4 seconds as short, whereas 7 seconds (or longer) were labeled as relatively longer takeover time budgets. With a longer lead time, the effects of the two directional signals on response times may be different. For example, Petermeijer et al. (2017) used 7 seconds and did not find significant differences between the signal types, while Cohen-Lazry et al. (2019) employed a 4-second lead time and reported that response times to ipsilateral (compared to contralateral) signals were shorter. A similar reversed effect of lead time was found in manual driving. Specifically, one study showed that drivers who were given a longer time allotment to make responses to auditory alerts, used to inform them about pedestrians walking across the road, responded faster to contralateral signals, but with a shorter time budget, they responded faster to ipsilateral signals (Straughn et al., 2009). The authors propose that with longer times, people had more time to evaluate the driving situation and make timely decisions. However, it is unclear whether longer vs. shorter lead times have this reversed effect on responding to directional signals during automated driving.

Secondly, signal modality can also impact drivers' responses to the two directional signals as they showed different effects on time-related metrics. For example, Cohen-Lazry et al. (2019) and Chen et al. (2020) employed single tactile and auditory signals, respectively, with a relatively short takeover lead time, and showed two opposite relationships between ipsi- and contralateral signals. Ipsilateral signals were associated with shorter reaction times in Cohen-Lazry et al. (2019), but with longer reaction times in Chen et al. (2020), compared to contralateral signal. Also, Petermeijer et al. (2017) compared V, A, and VA signals, but the interaction between signal type and direction was not reported. In order to resolve these contradicting findings, additional research is needed to more comprehensively examine the effects of signal modality/type on the responses to the two directional signals.

Therefore, this study aimed to examine the effects of signal directions, lead time, and signal modality on takeover performance. Particularly, participants rode in an SAE Level 3 simulated vehicle and took over control of the vehicle in response to TORs that varied in terms of direction (ipsilateral and contralateral), lead time (4 and 7 seconds), and modality (uni-, bi-, and trimodal combinations of visual, auditory, and tactile signals). Performance in both the signal response and post-takeover phases were measured. Our expectation was that with a shorter lead time, takeover performance would be better with ipsilateral compared to contralateral signals, but the benefits of ipsilateral signals would be dissipate as the lead time increased. We also expected that the benefits of multimodal signals would be observed in the post-takeover phase and would be associated with better vehicle takeover quality.

5.2 Method

5.2.1 Participants

Twenty-four volunteers ranging between the ages of 20 – 29 years (mean age = 24.0 years, standard deviation (SD) = 3.0) participated in this study. The average number of years of driving experience across participants was 4.9 years (SD = 3.2). All participants were students from Purdue University, West Lafayette, IN. Eligibility requirements included: 1) possession of a valid driver's license for at least one year; 2) regular driving at least once per week; 3) normal/correct-to-normal vision, and 4) no impairments to the senses of hearing and touch. Participants were compensated at a rate of $30 per hour. The study received approval from the Purdue University Institutional Review Board (IRB protocol #: 1802020214).

5.2.2 Apparatus/Stimuli

The experiment was conducted in a fixed-base driving simulator – miniSim, developed by National Advanced Driving Simulator (NADS). This system consists of three 42-inch monitors (which displays the main driving scene; resolution 1920 × 1080) and one 18.5-inch monitor (which serves as the vehicle dashboard display). Additional system accessories include driving foot pedals, a steering wheel, a control panel, and a driver seat (see Figure 5.1). Driving data was collected at 60 Hz.

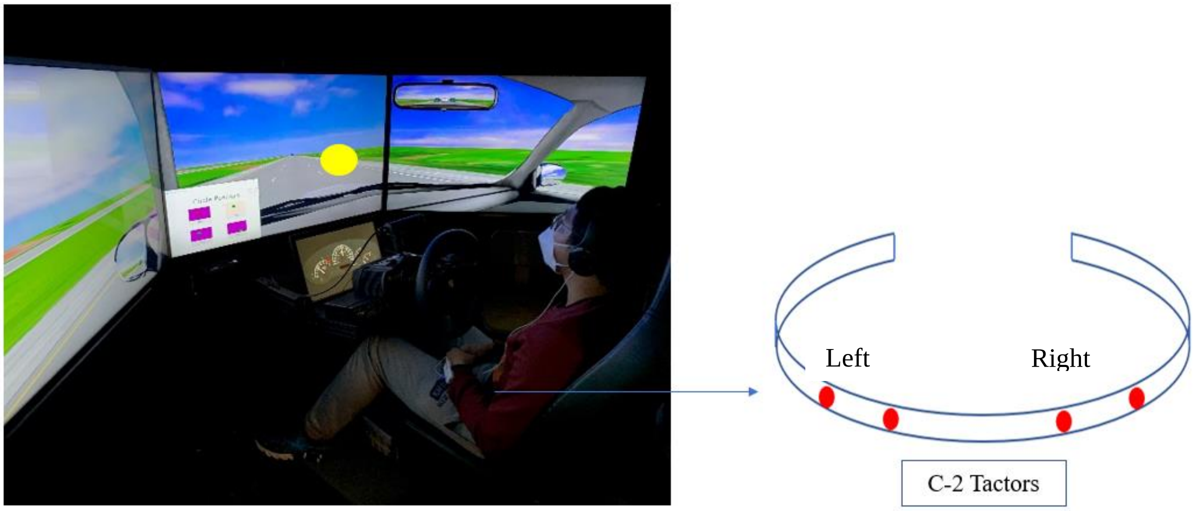
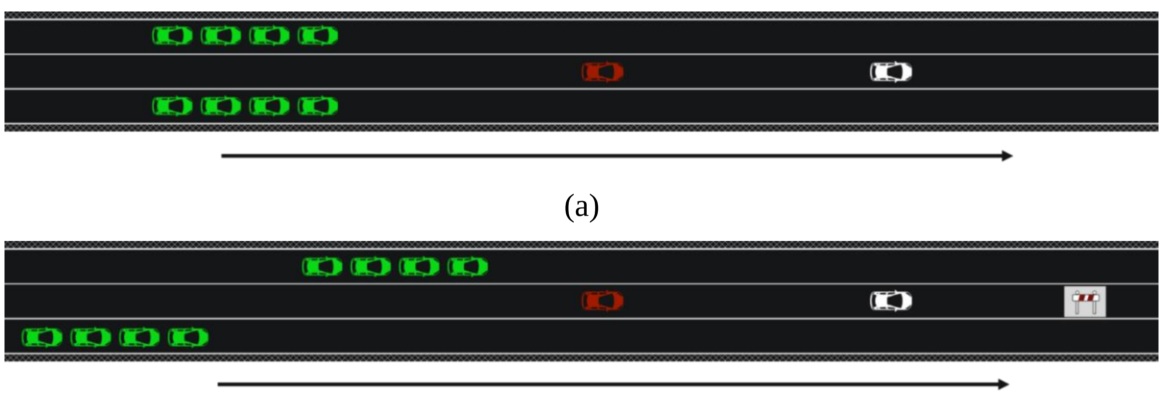


Figure 5.1. Experiment setup and apparatus/stimulus

The visual signal (V) was a 200 × 200 pixel yellow circle presented either on the left or right lane of the highway (e.g., visual signal on the left lane required drivers to move into the left lane for ipsilateral signals or the right lane for contralateral signals). Similarly, the auditory signal (A) was 400 Hz beeps presented via a headset, with an intensity range from 0 – 100 dB. The tactile signal (T) was presented using four C-2 tactors (by Engineering Acoustics, Inc.) attached to a belt and fastened around participants' upper waist. In particular, two tactors were placed on each side of the participant's lower back area (Figure 5.1). The intensity range of tactile signals was 30 – 48 dB. A crossmodal matching task was performed wherein each participant adjusted the intensities of the auditory and tactile signals to match that of a reference visual cue (Pitts et al., 2016). All visual, auditory, and tactile signals lasted for one second.

5.2.3 Driving Scenario

The driving scenario was similar to Study 2 in Chapter 4. Participants rode in a simulated SAE Level 3 automated vehicle, which automatically controlled lane position and speed. The automated vehicle traveled in the middle lane of a three-lane highway at a constant speed of 60 mph. A leading vehicle was continuously present either 4 or 7 seconds ahead of the subject vehicle. Also, two fleets of vehicles, also traveling at 60 mph in both left and right adjacent lanes, trailed the subject vehicle at a constant following distance of 176 feet, see Figure 5.2 (a). Occasionally, during the drive, a construction zone would appear in the center lane, which precipitated a sudden stop of the lead vehicle. When this happened, the subject vehicle detected the obstacle (road construction) 352 or 616 feet ahead (corresponding to a 4- or 7-second lead time, respectively) (Eriksson & Stanton, 2017), and initiated a takeover request (TOR) using one of the seven signal types. Simultaneously, the following distances of the two fleets of adjacent vehicles (with respect to the subject vehicle) randomly changed from 176 feet to either 88 or 264 feet away (correspondingly to 1- or 3-second headway, see Figure 5.2 (b) for an example). This was done to increase the complexity of driving task and environment. Here, in addition to avoiding the obstacle ahead, drivers also needed to avoid possible rear-end collisions with trailing vehicles. After receiving a TOR, participants were told to move into the lane with the most available space (in this case, the 264-feet distance). To do this, they needed to first deactivate the automation by stepping on the brake pedal, and then position their hands on the steering wheel and their foot on the accelerator pedal to maintain the speed. Directional TORs were used to guide drivers to the correct adjacent lane. After processing the TOR and information in the driving environment, participants needed to change lanes and manually control the vehicle at 60 mph, just as they would in real-life driving until they passed the construction zone. Once they were clear of this zone, they needed to move back into their original lane and reactivate the automation by pressing a button on the steering wheel.



(a)

(b)

Figure 5.2. Example bird's eye-view of the driving scenario: (a) absence of a takeover event: the subject vehicle (red) is following a leading vehicle (white), which is being followed by two fleets of vehicles (green) in both left and right adjacent lanes with equal distances; (b) during a takeover event: the subject vehicle (red) was expected to move into the right adjacent lane to avoid a collision with the leading vehicle (white), which was hindered by a construction zone in front, as well as with the approaching vehicles in the left lane (green)

5.2.4 Procedure

Upon arrival, participants first signed the study's consent form and completed a demographic data form. Then, each participant performed the crossmodal matching task and a 10-minute training session where they practiced takeover procedures and maneuvering the vehicle with all signal types and lead times, which was the same as those needed in the actual experiment. For the experiment, similar to Petermeijer et al. (2017), each participant completed a total of four driving blocks, with two blocks using the ipsilateral signals (i.e., ipsilateral condition) and two blocks employing contralateral signals (i.e., contralateral condition). With respect to Figure 5.2 (b), where the right lane had the most available space, in the ipsilateral condition, the visual signal was presented on the right side of drivers' screen (in the right lane), the auditory signal was presented only in the right side of the headset, and the tactile signal was presented as vibrations only of the two tactors on the right side, all of which indicated that the driver should move to the right lane after the TOR. In contrast, in the contralateral condition, all visual, auditory, and tactile signals were instead presented on the left side. For bi- and trimodal combinations, signals were presented concurrently. In each condition, 14 takeover requests with two lead times (i.e., 4 and 7 seconds) were presented, with each of the seven signal types randomly presented once in each block. The average interval between each takeover request was 2 minutes (Li et al., 2019; Petermeijer et al., 2017). To prevent potential order effects, the two ipsi- and contralateral conditions and the two lead times were counterbalanced. Additionally, 5-minute breaks were given to avoid task fatigue caused by the experiment.

To control drivers' attention allocation and prevent them from preparing for a TOR in advance, participants were required to interact with a game - "Spot the Difference," located in the (right or left, counterbalanced) corner of the main display. This task was used to represent engagement in non-driving-related tasks during naturalistic automated driving. As shown in Figure 5.3, the game consists of four separate items, and participants needed to identify the one that was different from the other three based on the cue (i.e., color, location, shape, or spelling of words) presented at the top of the game interface. For example, in Figure 5.3 (b), the cue indicates that a "word" is different. Participants should identify the box containing the word "Late," which is different from the other boxes labeled "Mate" by simply telling the experimenter the location of the box. The experimenter selected the answer provided by participants. This approach aimed to minimize participants' physical demands during the driving session. Once the selection was made, a new trial will begin. The game was automatically paused during a takeover and automatically resumed once participants reactivated the automation.

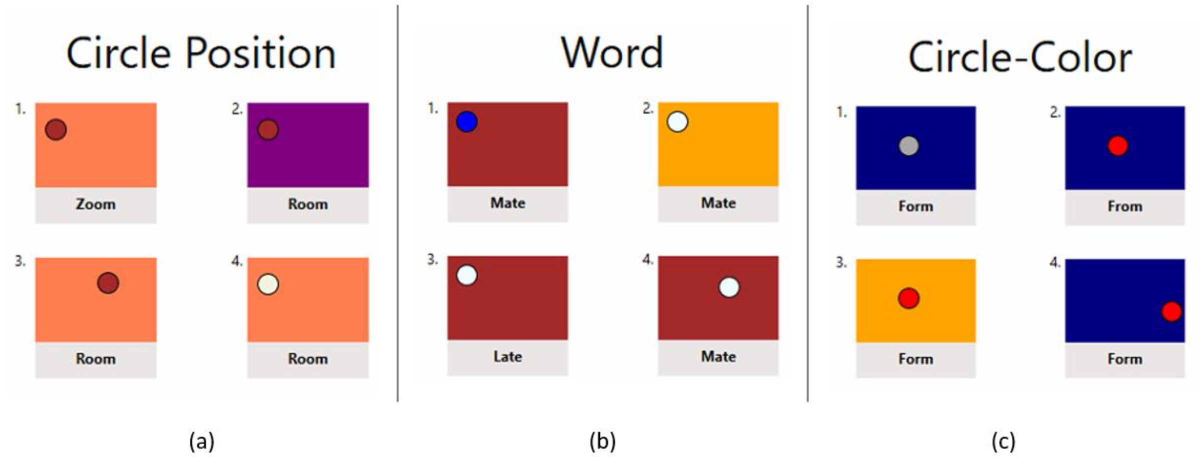


Figure 5.3. Three example trials of the game (circle position, the spelling of words, and circle color, respectively)

During each block, they were required to keep their feet on the base of the simulator and hands in their laps, and continuously interact with, and focus on, the game task until the onset of a TOR. After the four blocks, participants engaged in a 10-minute debriefing session where they completed a post-experiment questionnaire about their preferences of TOR signal type and directions. The experiments lasted around 75 minutes.

5.2.5 Dependent Measures

Post-takeover driving performance metrics included takeover time, information processing time, and maximum resulting acceleration. Also, perceived usefulness and satisfaction of each type of signal as well as preference for signal direction were assessed.

Takeover time: Takeover time (in seconds) measures the time between the presentation of a TOR and the first conscious input to the vehicle (McDonald et al., 2019). Here, conscious input is defined by a 2-degree change of the steering wheel or a 10% change of gas pedal inputs. This particular measure is used as an indicator of how quickly drivers prepare to control the vehicle.

Information processing time: Information processing time (in seconds) measures the time between the onset of a TOR and the initiation of a lane change (absolute deviation from the lane center larger than 6 feet, Petermeijer et al., 2017). It is used to determine how quickly drivers perceive and process takeover requests, and make appropriate decisions to avoid possible collisions.

Maximum resulting acceleration: Maximum resulting acceleration (in m/s^2) is calculated based on longitudinal and lateral accelerations during the post-takeover phase (see the equation below). This particular metric was used because it encompasses a broader set of longitudinal and lateral aspects of vehicle handling, such as maximum longitudinal/lateral accelerations, steering wheel angle and velocity, and standard deviation of vehicle speed. In general, it serves as an indicator of takeover quality and comfort (e.g., Hergeth, Lorenz, & Krems, 2017; Li et al., 2019), such that a smaller value represents better takeover quality.

$$Max\ resulting\ acceleration = \sqrt{max\ longitudinal\ acceleration^2 + max\ lateral\ acceleration^2}$$

Subjective measures: To examine the potential influence of drivers' perceptions of the TOR signals on takeover performance, a qualitative approach was employed that assessed subjective attitudes towards the signal types. Particularly, perceived usefulness and satisfaction of each signal type was measured using a 9-item technology acceptance questionnaire, where participants rate each item using a 5-point Likert scale that ranges from -2 to 2 (Petermeijer et al., 2017; Van Der Laan et al., 1997); see Table 5.1 in the Results section for a summary of the score of each signal type. The overall usefulness and satisfaction scores were computed based on the scores of the nine items. The preference of signal direction was assessed using a question in the post-experiment questionnaire: "What type of directional signal do you prefer?" The answer was either "ipsilateral signal" or "contralateral signal." The definition of the two terms was provided.

5.2.6 Data Analysis

A 2 (direction: ipsilateral and contralateral) × 2 (lead time: 4 and 7 seconds) × 7 (signal type; V, A, T, VA, VT, AT, and VAT) full factorial design was employed in this study. Performance variables were analyzed using a three-way repeated-measures analysis of variance (ANOVA) with signal direction, lead time, and signal type as factors. For violations of sphericity tests, degrees of freedom were corrected using Greenhouse–Geisser estimates. Bonferroni corrections were applied for multiple comparisons. For all statistical tests, results were considered significant at $p < 0.05$. Effect size was presented as partial eta squared (η_p^2).

5.3 Results

5.3.1 Takeover Time

There was a significant main effect of lead time ($F(1, 23) = 5.068, p = .034, \eta_p^2 = .181$) and signal type ($F(6, 138) = 24.838, p < .001, \eta_p^2 = .519$) on takeover times. For lead time, takeover times for the 4-second lead time (M = 1.749 s, standard error of mean (SEM) = .057) were shorter compared to the 7-second lead time (M = 1.789 s, SEM = .063; *p* = 0.034). For signal type (Figure 5.4), signals that included a tactile cue, i.e., T (M = 1.714 s, SEM = .069), VT (M = 1.625 s, SEM = .068), AT (M = 1.707 s, SEM = .067), and VAT (M = 1.632 s, SEM = .063), had shorter takeover times compared to those without a tactile signal, i.e., V (M = 1.899 s, SEM = .071), A (M = 1.995 s, SEM = .061), and VA (M = 1.810 s, SEM = .056). Also, takeover times were marginally affected by signal direction ($F(1, 23) = 3.200, p = .087, \eta_p^2 = .122$). Specifically, takeover times for ipsilateral signals (mean (M) = 1.746 seconds (s), standard error of mean (SEM) = .058) were marginally shorter compared to contralateral signals (M = 1.791 s, SEM = .064).

Figure 5.5 (a) shows the average takeover trajectories for each of the seven signal types, lasting for 20 seconds from the presentation of each takeover request. This 20-second time window was determined by the time needed to complete each takeover trial. The trajectories indicate that after receiving a TOR that included a tactile cue, drivers both initiated the lane change and centered themselves in the adjacent lanes faster than with TORs that did not contain a tactile signal.

There was also a significant direction × signal type interaction on takeover times ($F(3.5, 80.872) = 2.776, p = .038, \eta_p^2 = .108$). As shown in Figure 5.4, the difference between two takeover directions was present only for the V and AT signal types. For these two signal types, takeover times were faster with ipsilateral signals (for V: M = 1.804 s, SEM = .062; for AT: M = 1.658 s, SEM = .068) compared to contralateral signals (for V: M = 1.993 s, SEM = .093; for AT: M = 1.756 s, SEM = .072) (*p* = .010 and .024).

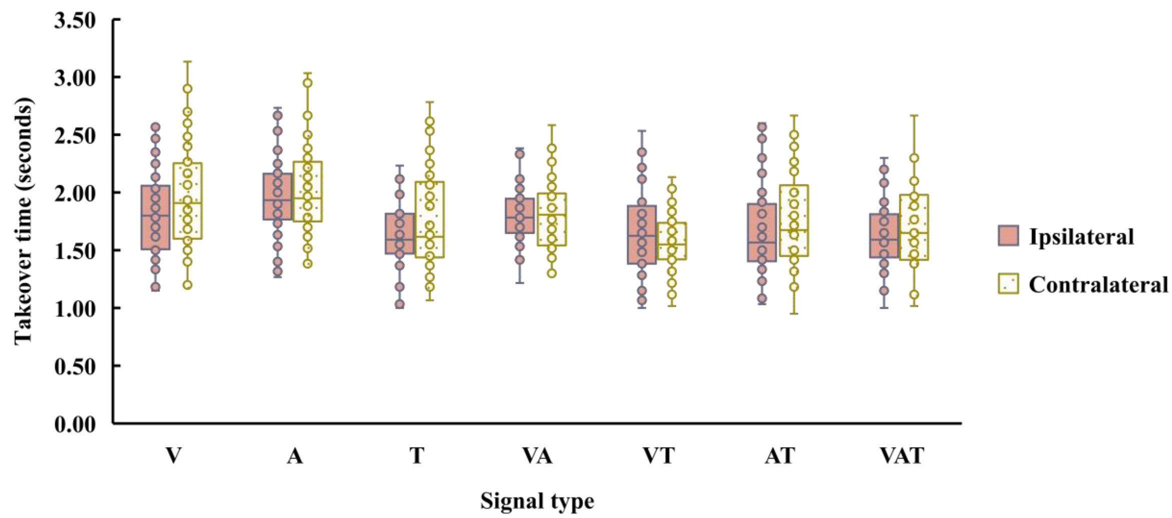
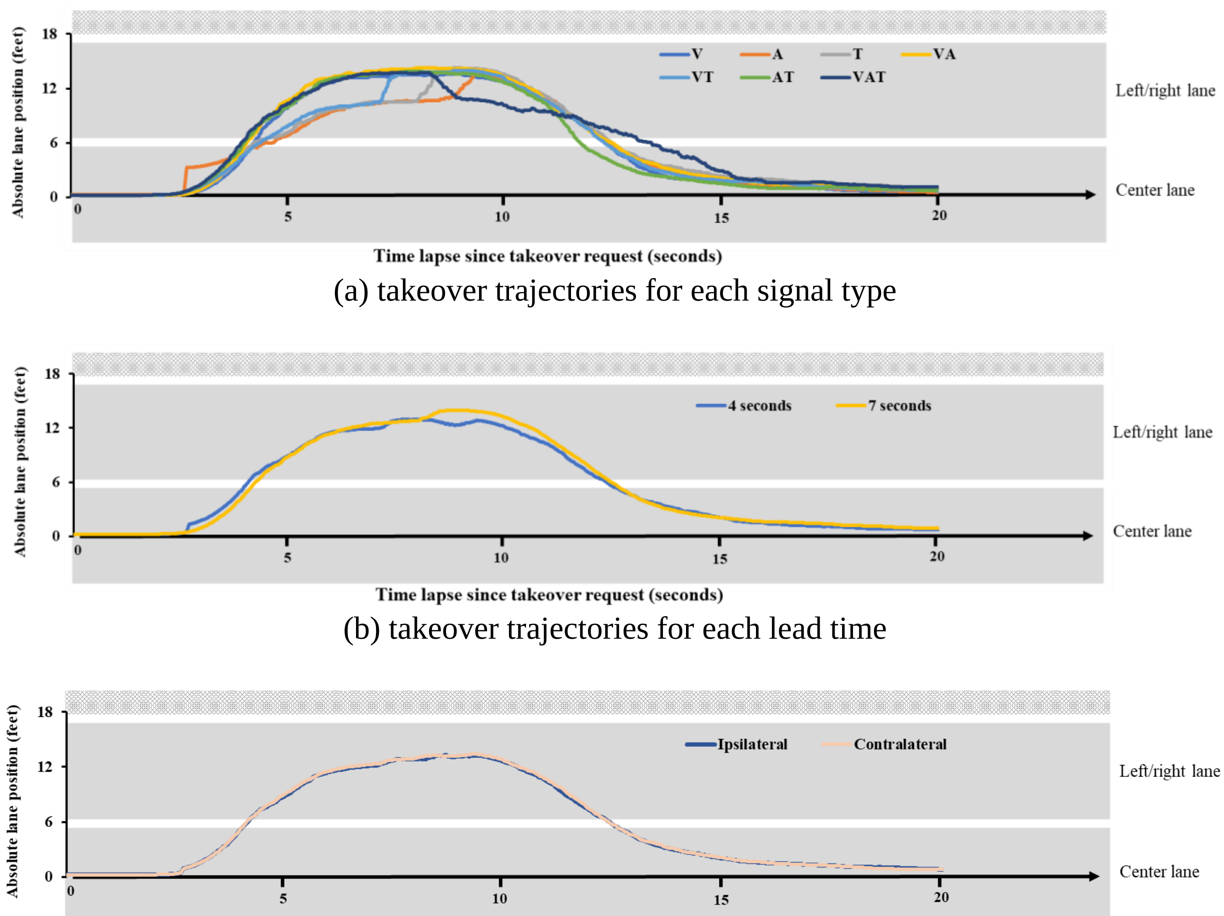


Figure 5.4. Takeover time as a function of signal direction and type



(a) takeover trajectories for each signal type

(b) takeover trajectories for each lead time

(c) takeover trajectories for each signal direction

Figure 5.5. Takeover trajectories 20 seconds within takeover request

5.3.2 Information Processing Time

There was a significant main effect of signal type ($F(6,138) = 21.528, p < .001, \eta_p^2 = .484$) on information processing time (Figure 5.6). Similar to takeover times, signals using the tactile modality, i.e., T (M = 2.880 s, SEM = .073), VT (M = 2.765 s, SEM = .072), AT (M = 2.802 s, SEM = .066), and VAT (M = 2.748 s, SEM = .062) had shorter information processing times compared to signals without a tactile cue, i.e., V (M = 3.080 s, SEM = .061), A (M = 3.092 s, SEM = .051), and VA (M = 2.955 s, SEM = .048). However, no significant main effect of signal direction ($F(1,23) = 2.260, p = .146, \eta_p^2 = .089$) nor lead time ($F(1,23) = .059, p = .810, \eta_p^2 = .003$) on information processing time was found.

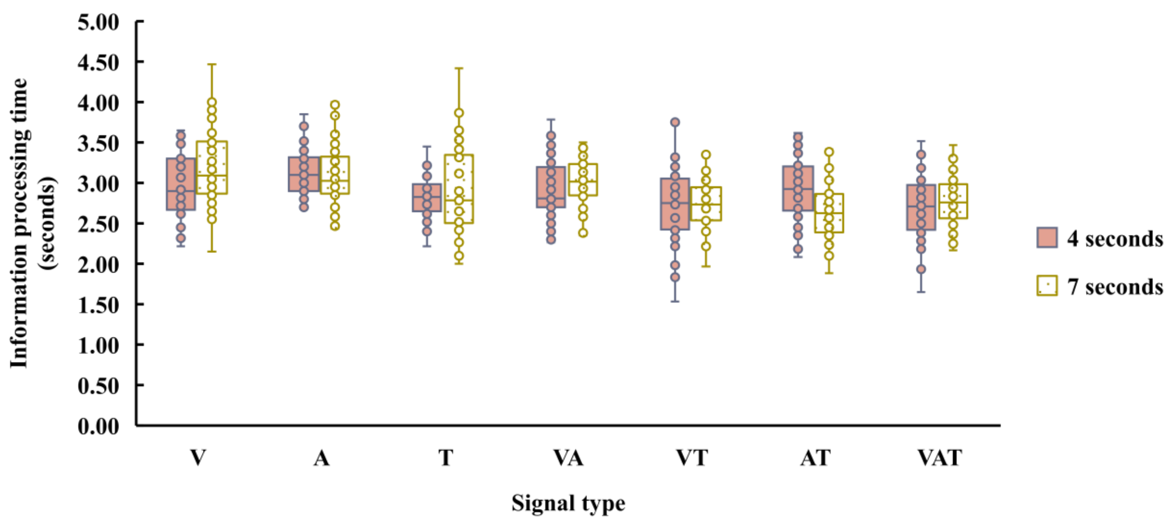


Figure 5.6. Information processing time as a function of lead time and signal type

5.3.3 Maximum Resulting Acceleration

Lead time had a significant main effect on maximum resulting acceleration ($F(1,23) = 8.601, p = .007, \eta_p^2 = .272$). Here, the 4-second lead time was associated with a larger maximum resulting acceleration (M = 11.23 m/s^2, SEM = .073) compared to the 7-second lead time (M = 10.67 m/s^2, SEM = .347). The average takeover trajectories for each lead time (Figure 5.5 (b)) suggest that with a longer lead time, the trajectory was smoother. No significant main effect of direction ($F(1,23) = 2.245, p = .148, \eta_p^2 = .089$) nor signal type ($F(6,138) = .453, p =$

$.842, \eta_p^2 = .019$) was observed. As shown in Figure 5.5 (c), the average takeover trajectories of ipsilateral and contralateral signals were overlapping.

5.3.4 Subjective measures

Table 5.1 summarizes the average scores for each of the nine items in the technology acceptance questionnaire, as well as the overall scores of usefulness and satisfaction. A one-way ANOVA was employed to compare the means of usefulness and satisfaction ratings between each signal type.

Table 5.1. Average usefulness and satisfaction scores for each signal type

Negative (– 2)	Positive (+2)	V	A	T	VA	VT	AT	VAT
Useless	Useful	0.04	0.71	1.13	1.00	1.33	1.58	1.92
Bad	Good	-0.08	0.38	0.79	0.58	0.92	1.21	1.21
Superfluous	Effective	-0.17	0.42	1.00	0.71	0.96	1.13	1.29
Worthless	Assisting	0.00	0.38	0.92	0.58	0.88	1.13	1.38
Sleep-inducing	Raising Alertness	-0.54	0.71	1.21	0.58	0.96	1.50	1.71
Overall usefulness score		**-0.15**	**0.52**	**1.01**	**0.69**	**1.01**	**1.31**	**1.50**
Unpleasant	Pleasant	0.54	0.17	0.38	0.46	0.50	0.21	0.00
Annoying	Nice	0.33	-0.13	0.08	-0.08	0.38	0.17	0.04
Irritating	Likeable	0.17	0.04	0.67	0.33	0.71	0.54	0.42
Undesirable	Desirable	0.17	0.08	0.75	0.46	0.88	0.92	0.71
Overall satisfaction score		**0.30**	**0.04**	**0.47**	**0.29**	**0.61**	**0.46**	**0.29**

There was a significant main effect of signal type on usefulness ($F(2.537, 58.340) = 14.443, p < .001, \eta_p^2 = .386$), but not on satisfaction ($F(2.498, 86.612) = 1.274, p = .291, \eta_p^2 = .053$). Also, as shown in Figure 5.7, the VAT signal (M = 1.50, SEM = .095) was perceived to be comparably the most useful signal type, followed by AT (M = 1.31, SEM = .115), VT (M = 1.01, SEM = .174), and T (M = 1.01, SEM = .168). The single visual signal was reported to be the most useless signal (M = -.15, SEM = .276).

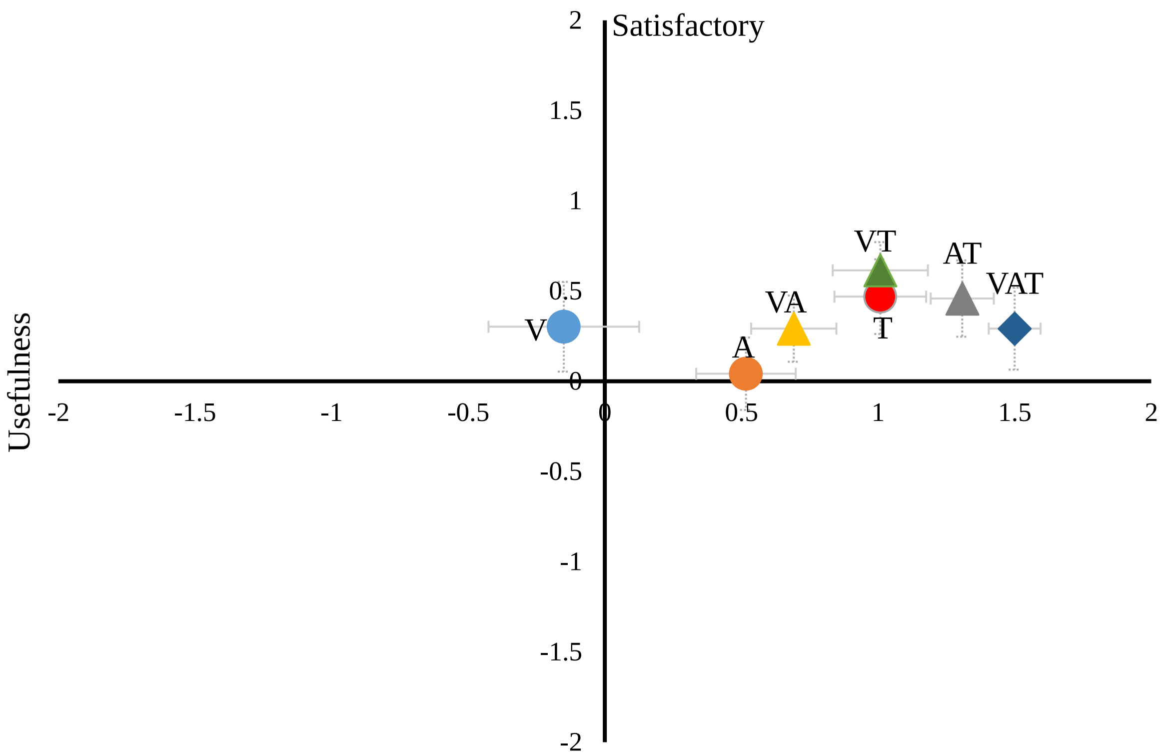


Figure 5.7. Perceived usefulness and satisfaction for each signal type

Finally, for the preference between ipsilateral and contralateral signals, 92% of participants preferred ipsilateral signals, compared to only 8% percent for contralateral signals.

5.4 Discussion

This study investigated the effects of signal direction, lead time, and signal modality on automated vehicle takeover performance. Within the signal response phase of the takeover process, single and multimodal signals that included a tactile cue were associated with shorter takeover and information processing times, while signal direction and lead time only showed differences in takeover times. Additionally, better takeover quality within the post-takeover phase was observed when drivers had a longer lead time. Finally, in terms of drivers' perception of the signals, takeover requests (TORs) that contained a tactile signal also received the highest usefulness rating, and ipsilateral signals were preferred compared to contralateral signals.

5.4.1 Signal response phase

Takeover time indicates how quickly a driver prepares to take over, while information processing time indicates the speed at which a driver initiates a lane change after receiving a TOR. Overall, both takeover time and information processing times were faster with modality signals that consisted of a tactile cue. Previous research has shown multimodal signals to be associated with faster response times and higher detection accuracy compared to unimodal signals (Diederich & Colonius, 2004; Hecht & Reiner, 2009; Hecht, Reiner, & Halevy, 2006; Ho, Reed, & Spence, 2007; Lu et al., 2013, 2012; Pitts & Sarter, 2018; Wickens, Prinet, Hutchins, Sarter, & Sebok, 2011), but in our study, we also found that even the single tactile cue had better performance compared to bi-modal signal – VA. This further confirms findings from prior work in the automated environment that suggested that tactile signaling may benefit takeover transitions in terms of speed (e.g., Huang & Pitts, 2020; Huang et al., 2019). One possible reason could be that the tactile channel was most available for receiving information, since the visual and auditory channels were already occupied by continuous input from the road and secondary tasks (Meng & Spence, 2015; Wickens, 2008). Alternatively, tactile stimuli may be processed faster compared to visual and auditory information (e.g., Pitts & Sarter, 2018). This advantage also suggests that tactile cueing may be useful for communicating a broader range of information to drivers. For example, structured tactile patterns can be used to indicate the location and speed of adjacent vehicles to support situation awareness after the TOR.

Different from our expectations, signal direction produced only a marginally significant effect on takeover time, suggesting that ipsilateral signals, where the vehicle instructs the driver on what action(s) to take, may be more beneficial for guiding drivers through a takeover situation. In contrast, Petermeijer et al. (2017) did not find a difference between signal direction. In their study, drivers were not informed that signals were directional and were instead able to make driving maneuvers based on their own interpretation of the meaning of signals. But, in our study, participants were informed of the signal direction and needed to act based on this knowledge. However, the outperformance of ipsilateral signals did not last throughout the entire signal response phase, since there were no differences in the information processing time measurement (which is the time length of the entire signal response phase). This is consistent with previous work (Cohen-Lazry et al., 2019) that also found drivers to respond faster to ipsilateral signals compared to contralateral signals. However, Cohen-Lazry et al. (2019) did not use the longer time range measurement, i.e., information processing time. Our study shows empirically that the benefits of ipsilateral signals may only be present in the initial response phase of the takeover process. One explanation for this finding could be that drivers' attention was not focused on the road, since they were engaged in a non-driving-related task. When takeover requests were presented, participants immediately experienced a response selection phenomenon, a process for which discriminating stimuli and executing an action is required, and that involves stimulus-to-response mapping (McPeek, 2014; Proctor & Vu, 2006). More specifically, during this response selection process, participants had not developed an execution plan after the takeover, but rather simply followed the signal direction to deactivate the automation and take hold of the steering wheel as quickly as possible (Cohen-Lazry et al., 2019). However, the benefits of ipsilateral, or instructional, signals in terms of takeover time could have been diluted given the time allotted (i.e., 4 and 7 seconds). With the longer headway (i.e., 7-second lead time), drivers may have not felt obligated to change lanes immediately, but rather when a possible collision was imminent (e.g., Chen et al., 2020; Petermeijer et al., 2017). In other words, when drivers received the TOR, and after assessing the time-to-collision, they might have voluntarily delayed executing their action in order to take time to determine the most appropriate maneuver to make. On the other hand, drivers in the shorter lead time condition (4 seconds) only had faster takeover times, but not information processing times (when compared to the 7-second lead time). This may be attributable to the urgency of the situation (Muttart, 2005; Scott & Gray, 2008), where drivers judged the urgency level using the distance between the subject and the lead vehicle.

The interaction effect between signal direction and modality on takeover time revealed that the effect of signal direction only existed in signals V and AT. Takeover times were faster with ipsilateral compared to contralateral signals for V and AT, but no differences were found between other signal types. This finding supported our speculation that different signal modalities used in previous studies may be one of the main reasons that findings between the two signal directions were conflicting (e.g., Chen et al., 2020; Cohen-Lazry et al., 2019; Petermeijer et al., 2017). While prior work only used one or two signal modalities to examine the effects of signal direction, our study compared all seven signal types. Contrary to our expectations that differences between the two signal directions would be found with unimodal signals, only the single visual and bimodal auditory-tactile signals were associated with differences in takeover times. The reasons for these differences are unclear and future research should seek to delineate explanations.

5.4.2 Post-takeover phase

Takeover quality was compared among the levels for signal direction, lead time, and signal modality after drivers successfully resumed control of the vehicle, measured by maximum resulting acceleration. Here, maximum resulting acceleration was only affected by lead time. Specifically, the 7-second time was associated with a smaller maximum resulting acceleration, thus a better takeover quality, which is in line with previous studies (Mok et al., 2015; Wan & Wu, 2018; see reviews: McDonald et al., 2019; Zhang et al., 2019). No differences were found in vehicle handling between the signal direction and signal modality factors. This indicates that the effects of signal direction and modality only existed in the signal response phase, but did not last long enough to impact post-takeover performance. In other words, after processing the TOR, drivers focused their attention on making decisions about which course of action to pursue and executing that action. Thus, the effects of signal direction and modality quickly decayed as time lapsed beyond the signal response phase. With a longer lead time, drivers have more time to process information in the driving environment and better prepare to respond to the TOR (Wan & Wu, 2018b). To improve takeover quality, Wan & Wu (2018) recommend using a minimum of 10-second lead time after they compared driving performance among six different takeover lead times, ranging from 3 to 60 seconds. Alternatively, the lead time can be designed to be context-dependent based on the urgency of the situation. Studies have found that a mismatch between the timing of a warning and the urgency of that situation may be incorrectly interpreted (Abe & Richardson, 2004; Jamson et al., 2008; R Parasuraman et al., 1997). For example, if the lead time is too long, drivers may regard an urgent signal as a false alarm and ignore/forget it, while if the lead time is too short, drivers may not have enough time to make (correct) responses and achieve a good takeover quality. In this case, the system may tailor its warning lead time to the urgency of the situation.

5.4.3 Users' preference

The usefulness and satisfaction comparisons among signal modalities revealed that the combined visual-auditory-tactile (VAT) cue was perceived to be most useful, followed by AT, VT, and T. This finding is consistent with our previous study that assessed participants' subjective perceived ease of detecting signals and found younger drivers to rate VAT, VT, and AT as the easiest to perceive (G. Huang & Pitts, 2020a). Combining this finding and results from objective measures, we infer that signals with a tactile component may be most helpful to drivers during the takeover. This may be explained by the demographics of participants in our study. It is possible that younger adults are more frequently exposed to technology that contains some form of vibration alerts. In fact, 25% of our study participants reported that their current vehicles were equipped with some type of tactile displays, such as lane departure or collision warning systems. With high utilization of visual and auditory resources in automated driving, e.g., engaging in NDRTs, drivers may find tactile signaling to be the most useful display. Additionally, 92% of participants preferred the ipsilateral over the contralateral signal. One explanation for this result could be that contralateral signals are designed based on the reverse SRC phenomenon, which is not instinctual. Thus, it may be more challenging for drivers to first identify the signal direction and then think about an action in the opposite direction of the signal. This additional step may result in less satisfaction. However, a more systematic qualitative study on signal direction preferences should be conducted.

5.4.4 Limitations and future work

Participants in this study experienced a total of 28 takeover events on an average 120-second internal. Even though our goal was to comprehensively compare all seven modality types, and we intentionally divided the experiment into four separate blocks to prevent task fatigue, this frequency of takeovers may not be completely representative of real-life automated driving. Future work may seek to reduce the number of repeated trials per participant. Similarly, variations in the takeover scenarios should be explored. We only used one type of takeover event – a construction zone. Follow-up research may include different driving environments (e.g., urban and rural areas) and conditions (e.g., varied weather). Finally, future work may also increase the sample size needed to generate more conclusive results (such as marginally significant findings). In this study, only 24 participants were recruited (during the COVID-19 pandemic).

5.5 Conclusion

This study examined the effects of signal direction, lead time, and signal modality on takeover performance in the signal response and post-takeover phases of an automated vehicle takeover process. Single and multimodal signals with tactile components showed the greatest benefits in terms of takeover and information processing times, and also were perceived as most useful. Signal direction presented only a marginally significant benefit to takeover time, particularly for ipsilateral signals that instruct drivers on which action(s) to take. Finally, the shorter lead time was associated with a faster takeover time and worse takeover quality. Since both phases one and two found significant benefits of tactile displays for takeover tasks, Chapter 6 presents an experiment that explored variations of particular types of tactile displays for improving human performance.

6. INVESTIGATING THE EFFECTIVENESS OF MEANINGFUL TACTILE SIGNAL PATTERNS TO ENHANCE TAKEOVER PERFORMANCE

A version of this chapter will be submitted to a journal for publication.

6.1 Introduction

Findings from phases one and two support the theory that tactile displays, when used as an abstract human-machine interface, benefit response times and takeover performance. This particular display type could be more important in instances where drivers engage in more non-driving-related tasks (such as texting, watching a movie, reading a book, or writing emails) that utilize visual and auditory channels (Naujoks et al., 2018). In fact, a body of literature has reported that the use of tactile cueing in complex environments could improve operators' situation awareness, result in more accurate interpretation of spatial information, and is relevant to faster processing speeds compared to visual and auditory signals (e.g., Baldwin et al., 2012; Meng & Spence, 2015; Morrell & Wasilewski, 2010; Petermeijer et al., 2015; Pitts & Sarter, 2018; Prinet et al., 2016). However, there is a lack of empirical evidence on how tactile signaling can be used to express more complex information to improve takeover performance. Therefore, this study investigated the effectiveness of a particular variation of tactile displays, i.e., meaningful tactile signal patterns, which are encoded messages that can convey meaningful and complex concepts and information using the tactile modality (Giang et al., 2010; Meng & Spence, 2015), to improve situation awareness, reduce transition times, and increase overall takeover quality.

As described in Studies 1 – 3 (Chapters 3 – 5, respectively), a takeover process is very complex since operators need to perceive and process driving and environment information, and make decisions and execute decisions in a very short time. This process can be more complicated when the driving environment has many elements that need to be processed by the driver, such as traffic and highway obstacles. Not only do drivers need to know the lane position and the speed of their own vehicle, but they also need to understand the characteristics of the external environment, such as surrounding vehicles' position and status, the road conditions, speed limits, and road signs. Given the ability of tactile cues to convey information about various parameters, e.g., direction, position (such as location), and status (such as urgency) (e.g., Meng & Spence, 2015; Tan et al., 2003; Van Erp & Van Veen, 2004), it is important to determine the extent to which meaningful tactile cues can support drivers throughout the complex takeover process.

The use of meaningful tactile signals has been explored in driving, in either an informative or instructional format. For informative signals, the tactile display was used only to represent information in the driving environment, such as the location and speed of surrounding vehicles (e.g., Telpaz et al., 2015) or potential collisions with lead vehicles (e.g., Meng, Gray, et al., 2015) in both manual and automated driving. For instructional signals, the tactile display commanded a particular action, such as instructing drivers to change to a certain lane to avoid danger or to slow down (e.g., Cohen-Lazry et al., 2019).

Studies have found both informative and instructional tactile signals to be associated with better takeover performance, such as shorter response times to TORs compared to tactile signals used only for warning purposes (Cohen-Lazry et al., 2019) or vehicles without a tactile display at all (Telpaz et al., 2015). In this study, Cohen-Lazry et al. (2019) compared the effects of meaningful (both informative and instructional) and generic (only for warning purpose) tactile signals, and found that instructional signals had shorter response times to TORs compared to informative and generic signals. However, with very limited studies on meaningful tactile signals as TORs, it is unclear whether the differences between (the two) meaningful and generic tactile signals also produce differences in other takeover performance metrics, such as information processing time or post-takeover driving performance (as used in Study 2). Thus, given their ability to convey various types of meaningful information, there is a need to examine the extent to which meaningful tactile signals could impact the entire takeover process.

Additionally, meaningful tactile displays have been presented through the seat pan and seat back (e.g., Petermeijer et al., 2017; Wan & Wu, 2018), but it is also unclear to what extent the location of the tactile information determines takeover performance. For example, Wan and Wu (2018) compared six tactile patterns that were presented on either the seat pan or seat back, or a mix of both locations, and found that signals first presented on the seat back had shorter response times. However, the tactile signals in their study did not have an associated meaning. Petermeijer et al. (2017), on the other hand, compared the effects of different tactile patterns in either back or pan, but the location was not the factor in their study.

Therefore, the goal of this study was to use tactile signals to create meaningful displays in both informative and instructional formats, that were embedded into the seat pan and seat back of a simulated vehicle, to support drivers in takeover. It was expected that both informative and instructional tactile signals would have better takeover performance in terms of response and information processing time and takeover quality compared to tactile signals without patterns. Similarly, signals presented in seat back would be associated with better takeover performance compared to seat pan (Cohen-Lazry et al., 2019; Petermeijer et al., 2017; Telpaz et al., 2015; Wan & Wu, 2018a).

6.2 Method

6.2.1 Participants

Forty participants (24 males, 16 females) were recruited to take part in this study. All participants were college students, with an average age of 23.1 years (range: 19 – 30). The self-report years of driving experience were 5.7 (range: 1 – 13). Participants were required to hold a valid U.S. driver's license, have a normal or corrected-to-normal vision, no known disorders or injuries that affect tactile sensitivity, and no known motion sickness experience. Upon the completion of the experiment, each participant was compensated at an hourly rate of $40. The study was approved by the Purdue University Institutional Review Board (IRB Protocol #: 1802020214).

6.2.2 Apparatus/Stimulus

Driving simulator

As in Studies 1 – 3, we used a medium-fidelity driving simulator, miniSim, developed by National Advanced Driving Simulator. The simulator has three 42-inch screens that display the main driving environment and one 19-inch screen that was used as the dashboard to present vehicle status information such as speed. Other accessories include a steering wheel, foot pedals, a control panel, and an adjustable seat. All data were collected at 60 Hz. The experiment setup was presented in Figure 6.1.

Figure 6.1. Experiment setup

Tactile patterns

A total of 14 C-2 tactors (developed by Engineering Acoustics, Inc.) were used in this study, with seven tactors on seat pan and seven tactors on seat back. The distribution of tactors was presented in Figure 6.2. The minimum distance between each tactor was 3.5 inches (range: 3.5 – 5.5 inches) (Ji et al., 2011; Petermeijer et al., 2015). Based on the driving scenarios, three action types that drivers needed to make were represented by tactile displays: 1) drive into the left lane (to avoid a possible collision with the lead vehicle and the vehicle located at the right blind spot, Figure 6.3 (a)); 2) drive into the right lane (to avoid a possible collision with the lead vehicle and the vehicle located at the left blind spot, Figure 6.3 (b)); 3) slow down then switch into a lane (to avoid a possible collision with the lead vehicle and vehicles in both left and right blind spots, Figure 6.3 (c)). As shown in Table 6.1, for informative signal, the vibration pattern was used to represent the surrounding vehicle status. For example, if a car was approaching behind from the left adjacent lane and the subject vehicle needed to move into the right adjacent lane, the tactile pattern simulated movement by vibrating serially tactor locations 6 → 5 → 4 on the seat back, or 11 → 12 → 13 on the seat pan. If two vehicles in both left and right adjacent lanes were approaching, all six tactors vibrated simultaneously (#s 1 – 6 for seat back or #s 8 – 13 for seat pan). For instructional signal, on the other hand, to avoid an approaching vehicle in the left blind spot, the sequential pattern 6 → 7 → 3 was played on the seat back, or 11 → 14 → 8 was presented on the seat pan. To represent both vehicles behind that were in the left and right blind spots, the signal pattern was serially 1 → 2 → 3 and 4 → 5 → 6 (two arrays of patterns vibrated at the same time) on seat back, or 10 → 9 → 8 and 13 → 12 → 11 (two arrays of patterns vibrated at the same time) on seat pan. Also, tactors #s 3, 6, 8, and 11 vibrated altogether as the baseline TOR that had no spatial meanings. In this case, drivers needed to make the appropriate maneuvering plan based on cues in the driving environment without assistance from the system. All signal patterns lasted 645 milliseconds (ms) at 250 Hz (Gray et al., 2014). That is, three a duration of 215 ms for sequential vibrations for meaningful patterns, or a single 645-ms vibration for the baseline TOR. Signal patterns were developed based on previous studies (e.g., Gray et al., 2014; Ji et al., 2011; Meng, Gray, et al., 2015; Tan et al., 2003; Telpaz et al., 2015; Wan & Wu, 2018) as well as an in-lab pilot study that evaluated the effectiveness of each signal pattern.

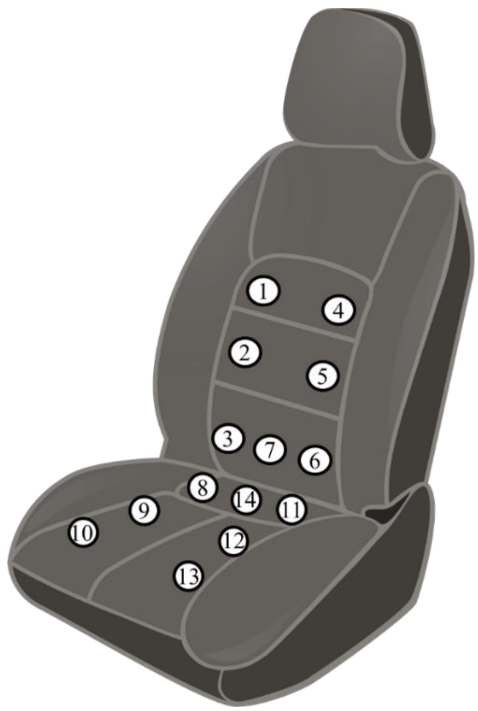


Figure 6.2. Distribution of tactors

Table 6.1. Meaningful tactile patterns in both seat back and seat pan locations

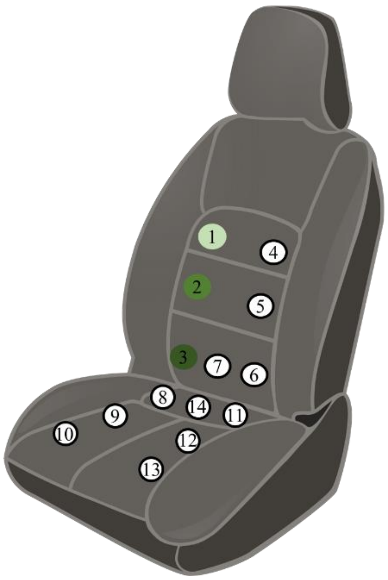
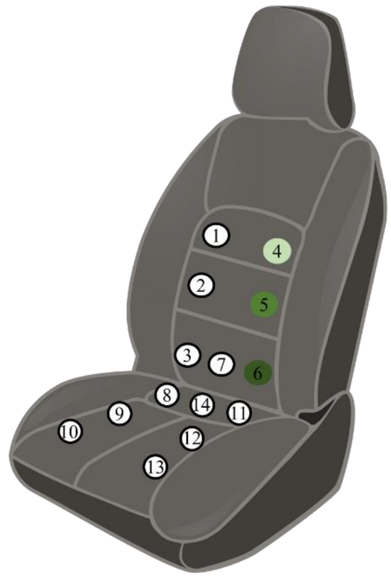
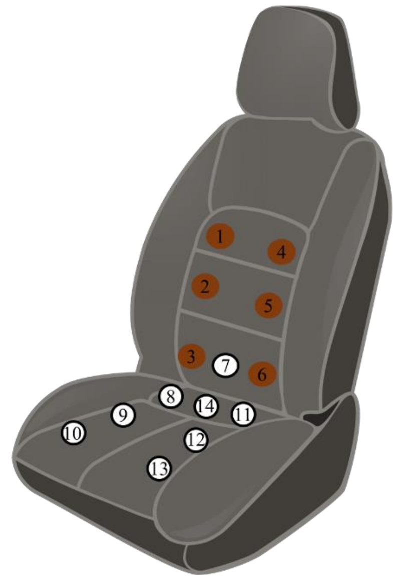
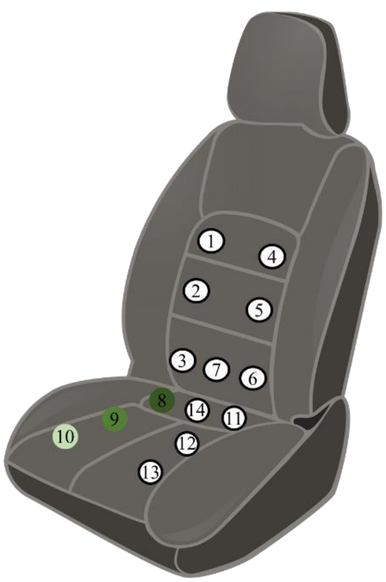
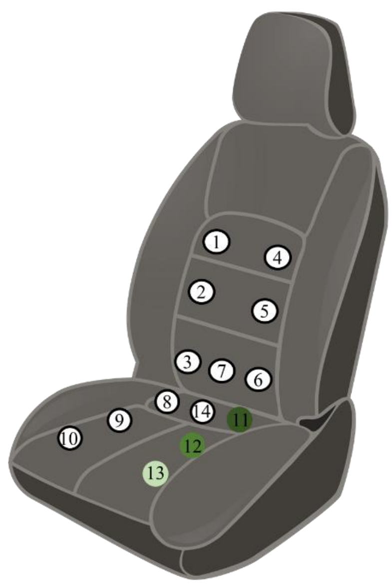
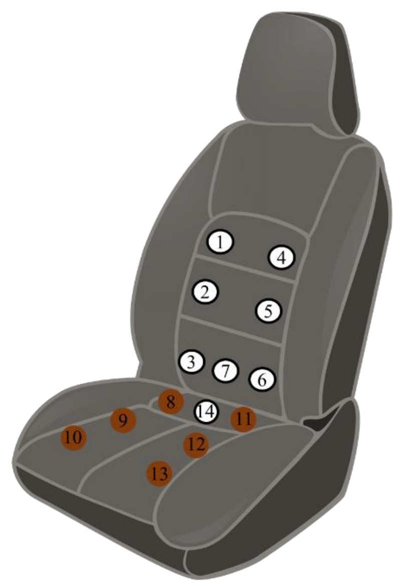
<table>
<tr><td>0 – 645 ms</td><td>0 – 215 ms</td><td>216 – 430 ms</td><td>431 – 645 ms</td></tr>
<tr><td colspan="4">Informative</td></tr>
<tr>
<td>Move to left (seat back):
3 → 2 → 1

</td>
<td>Move to right (seat back):
6 → 5 → 4

</td>
<td colspan="2">Brake (seat back):
1, 2, 3, 4, 5, and 6 (altogether)

</td>
</tr>
<tr>
<td>Move to left (seat pan):
8 → 9 → 10

</td>
<td>Move to right (seat pan):
11 → 12 → 13

</td>
<td colspan="2">Brake (seat pan):
8, 9, 10, 11, 12, and 13 (altogether)

</td>
</tr>
</table>

Table 6.1 continued

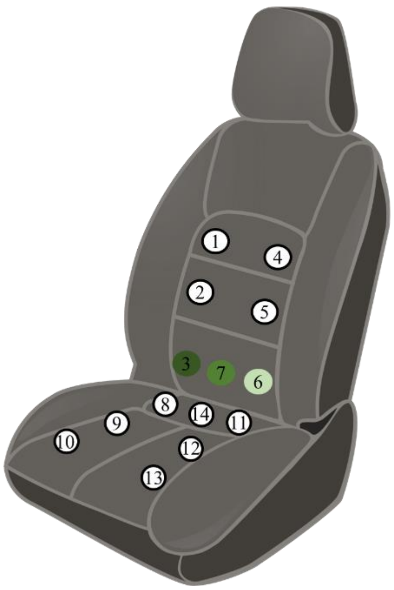
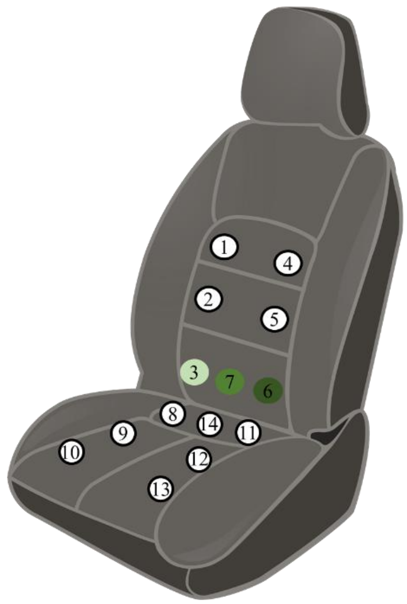
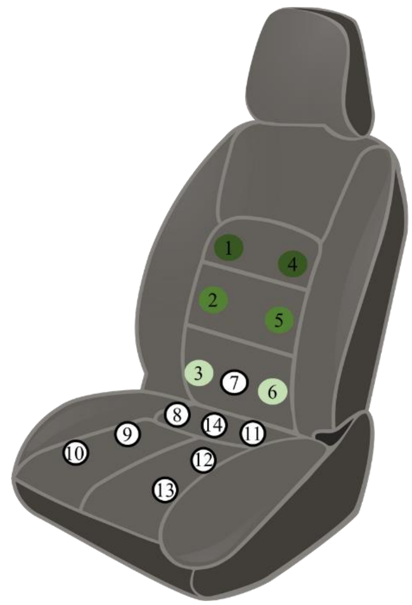
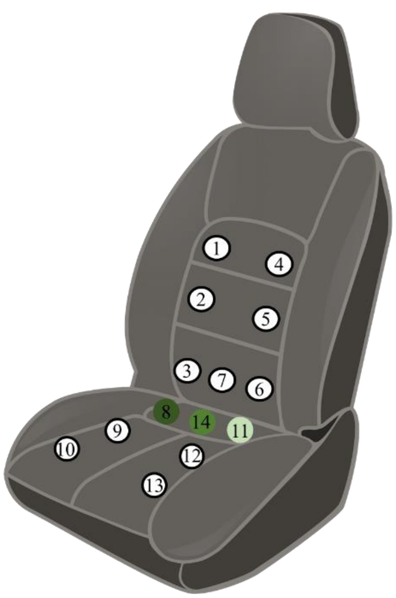
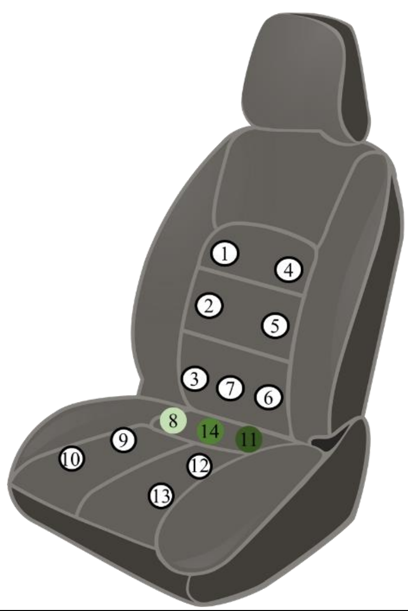
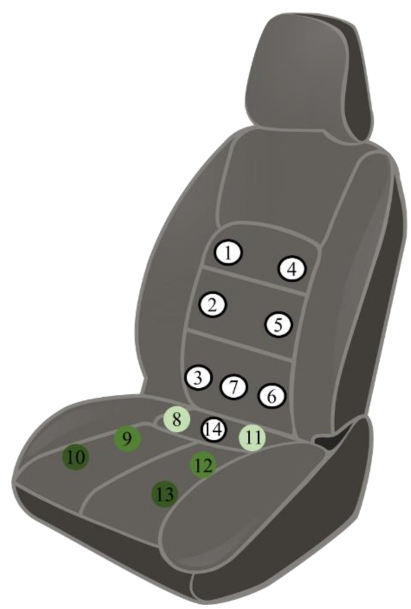
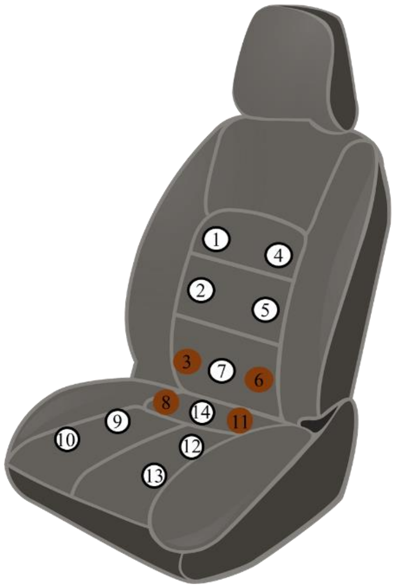
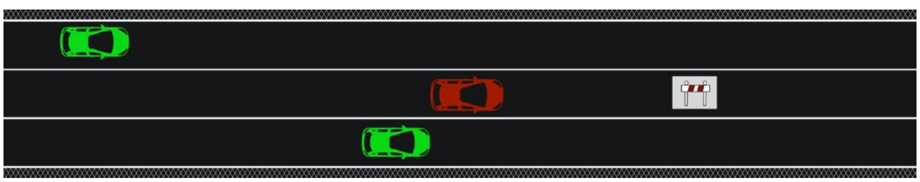
<table>
<tr><td colspan="3">Instructional</td></tr>
<tr>
<td>Move to left (seat back):
3 → 7 → 6
</td>
<td>Move to right (seat back):
6 → 7 → 3
</td>
<td>Brake (seat back):
1 → 2 → 3 and 4 → 5 → 6
</td>
</tr>
<tr>
<td>Move to left (seat pan):
8 → 14 → 11
</td>
<td>Move to right (seat pan):
11 → 14 → 8
</td>
<td>Brake (seat pan):
10 → 9 → 8 and 13 → 12 → 11
</td>
</tr>
</table>

Table 6.1 continued

Baseline:

3, 6, 8, and 11





(a)

(b)

(c)

Figure 6.3. Three required takeover action types based on the location of surrounding vehicles and the obstacle ahead: drive into to the left lane (a); drive into to the right lane (b); and slow down (c)

6.2.3 Driving scenario

Similar to Study 2, participants rode in an SAE Level 3 automated vehicle in the center of a three-lane highway at the speed of 60 mph. A leading vehicle was constantly 7 seconds ahead of the subject vehicle (Eriksson & Stanton, 2017; Petermeijer et al., 2017). Two vehicles maintained a steady distance of 176 feet behind the subject vehicle in both left and right adjacent lanes. A construction zone could appear at any point during the drive. When this happened, the vehicle would send a TOR in one of the seven tactile formats, indicating a need to take over. At the same time, the lead vehicle immediately stopped in front of the construction zone, leaving a 7-second lead time for drivers to complete the takeover and make action plans (i.e., either switch the lane immediately or brake then change the lane). To execute the takeover, participants first needed to tap on the brake to cancel the automation, then move their hands to the steering wheel and foot to the brake/gas pedal. After the takeover, two response types were available: change lanes (drive into either left lane or right lane) or brake (slow down to allow the two vehicles behind pass the subject vehicle first) then change lanes, based on the locations of the two vehicles behind (Figure 6.3 a,b,c, above). The two response types were similar to real-world driving when an obstacle is present ahead, and drivers can only move to adjacent lanes or brake to avoid a collision. For the lane-change response, participants were required to directly switch to the most available lane after processing the tactile information and the information in the driving environment, and maintain good driving performance (e.g., maintain the speed at 60 mph and stay in the center of the lane) as they would in real-life driving during manual driving. After passing the construction zone, drivers needed to immediately move back to the middle lane and reactivate the automation by pressing a button on the steering wheel. For the brake response, participants needed to decrease the speed of the vehicle (to avoid hitting the lead vehicle) and wait until the trailing vehicles in both adjacent lanes passed their vehicle, then move into either the left or right lane. Similar to the lane-change response, after changing the lane, drivers were asked to maintain good driving until passing the construction zone and move back to their original lane, then reactivate the automation.

6.2.4 Procedure

Participants first signed the consent form, indicating the agreement of participating in the study. Next, a pre-questionnaire was provided to collect participants' demographic information.

Then, participants performed a 15-min training session. For the first part of training, tactile patterns were presented to participants to learn their meanings. Half of the participants were only exposed to the informative signal, and the other half experienced the instructional signal (a between-subject design). After successfully interpreting all tactile patterns, they participated in the second part of the training, where they practiced takeover procedures and manually drove the vehicle with all tactile patterns and locations. For the actual experiment, 18 takeover trials were completed, with an interval of 2 to 3 minutes between each takeover event (Li et al., 2019; Petermeijer et al., 2017). Correspondingly, 18 TORs, i.e., 16 meaning tactile signals and two baseline signals, were presented. Eight out of the 16 meaningful tactile signals were presented in the seat back, and the other eight were presented in the seat pan. Additionally, half of the takeover trials required immediate lane changes (i.e., lane-change response), and the other half needed a brake response first (i.e., brake response). To prevent fatigue due to the number of takeover tasks, the 18 takeover trials were divided into four blocks, with the 16 meaningful tactile patterns in four blocks and the two baseline patterns in one block. A five-minute break was provided between each of the two blocks, during which participants also completed a short questionnaire about their subjective ratings on signal patterns and locations. All signal locations and response types were randomized, and the block sequence and signal information type were counterbalanced. To divert participants' attention away from the road (prevent participants from preparing for takeover in advance), a TED talk video was played during each block, which utilized visual and auditory modalities, but would not interfere with the tactile channel. The experiment lasted approximately 80 minutes. After the experiment, participants completed a 10-minute debriefing session where they filled out a post-experiment questionnaire about the experiment.

6.2.5 Dependent Measures

Takeover performance was measured using time- and driving-related metrics. Time-related metrics included response time and information processing time. Response time (in seconds) was measured between the onset of TOR and the initial contact of the brake pedal (Society of Automotive Engineers, 2015). Information processing time (in seconds) was calculated as the time between the presentation of the tactile signal and the initiation of a lane change, as used in Study 2. Response time indicated how quickly a driver reacted to tactile signals, while information processing time measured signal information processing and decision-making efficiencies.

Maximum resulting acceleration (in m/s^2) was the driving-related metric, calculated by the square root of the sum of squared maximum longitudinal and lateral accelerations, as used in Study 2. Here, a smaller value indicates better vehicle control and higher takeover quality.

Similarly to Study 2, to assess drivers' subjective ratings on tactile patterns and locations, which may provide additional design insights on tactile displays, as well as examining possible impacts of subjective preferences on takeover performance, a technology acceptance questionnaire was used (Petermeijer et al., 2017; Van Der Laan et al., 1997). It consists of nine items with a 5-point Likert scale ranging from -2 to 2. The usefulness score was the average score of items 1, 3, 5, 7, and 9, and the satisfaction score was computed by averaging items 2, 4, 6, and 8. See Table 6.2 for a summary.

6.2.6 Data Analysis

This study employed a 2 (information type: informative and instructional) × 2 (response type: lane change and brake) × 3 (location: seat back, seat pan, and baseline) full factorial design. A linear mixed-effects model was used to compare the effects of information type (between-subject factor), and response type and signal location (within-subject factors) on the dependent measures. Post-hoc comparisons with Bonferroni corrections were conducted to compare means between factor levels. Greenhouse–Geisser estimates were used to correct the degrees of freedom for sphericity tests that were violated. The significance level was set at $p < 0.05$. Partial eta squared (η_p^2) was presented as the effect size.

6.3 Results

6.3.1 Response time

There was a significant main effect of location ($F(2,76) = 13.418, p < .001, \eta_p^2 = .261$) and response type ($F(1,38) = 41.047, p < .001, \eta_p^2 = .519$) on response times (see Figure 6.4). Specifically, the baseline (mean (M) = 1.326 s, standard error of mean (SEM) = .052) had shortest response times compared to seat back (M = 1.448 s, SEM = .041) and seat pan (M = 1.507 s, SEM = .044). Also, drivers in lane change responses (M = 1.542 s, SEM = .051) had longer response times compared to brake responses (M = 1.312 s, SEM = .038). No main effect of information type ($F(1,38) = .277, p = .602, \eta_p^2 = .007$) on response time was found.

Two significant interaction effects: location × information type ($F(2,76) = 3.237, p = .045, \eta_p^2 = .078$), and location × response type ($F(2,76) = 10.364, p < .001, \eta_p^2 = .214$) were found. For location × information type, no difference between locations was found with informative signal. However, with instructional signal, seat back (M = 1.505 s, SEM = .058) and seat pan (M = 1.545 s, SEM = .063) had longer response times compared to the baseline (M = 1.297 s, SEM = .074). For location × response type, the baseline (M = 1.362 s, SEM = .069) had the shortest response time compared to seat back (M = 1.581 s, SEM = .053) and seat pan (M = 1.684 s, SEM = .064) in lane-change response, but no difference was found in brake response, see Figure 6.4.

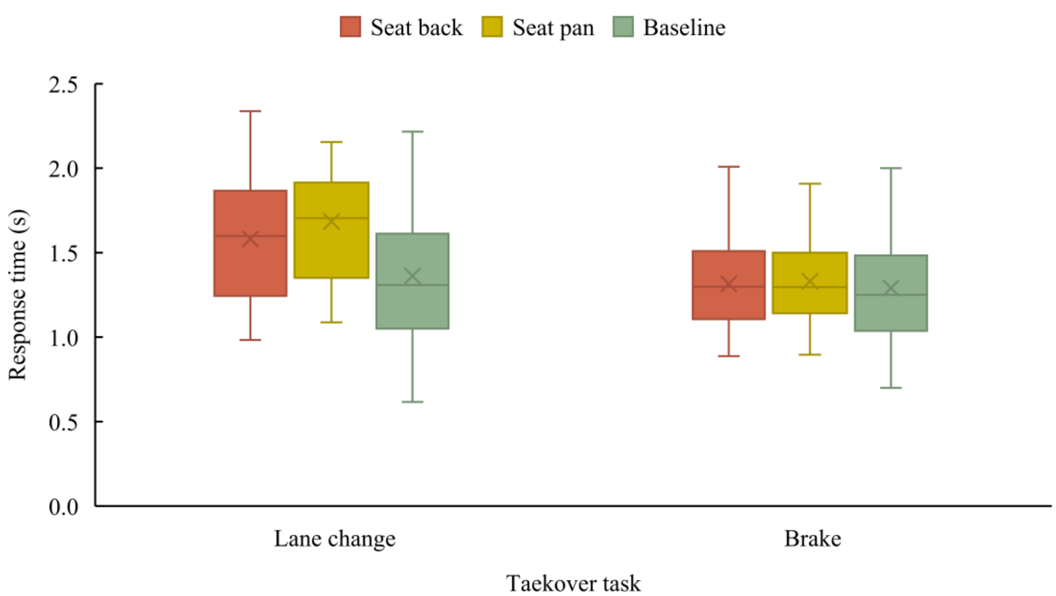


Figure 6.4. Response time as a function of location and response type

6.3.2 Information processing time

A significant main effect of response type ($F(1,38) = 813.832, p < .001, \eta_p^2 = .955$) was found on information processing time (see Figure 6.5). Here, participants with lane-change response (M = 4.708 s, SEM = .079) had shorter information processing time compared to brake response (M = 6.721 s, SEM = .076). No main effect of location ($F(1.64, 62.2) = .788, p = .436, \eta_p^2 = .020$) nor information type ($F(1,38) = .305, p = .584, \eta_p^2 = .008$) was found.

The analysis also revealed a significant location × response type ($F(1.70, 64.66) = 4.526, p = .019, \eta_p^2 = .106$) interaction effect. Specifically, seat pan (M = 4.821 s, SEM = .094) had marginally longer information processing time than the baseline (M = 4.563 s, SEM = .105) in lane-change response. No other differences were found.

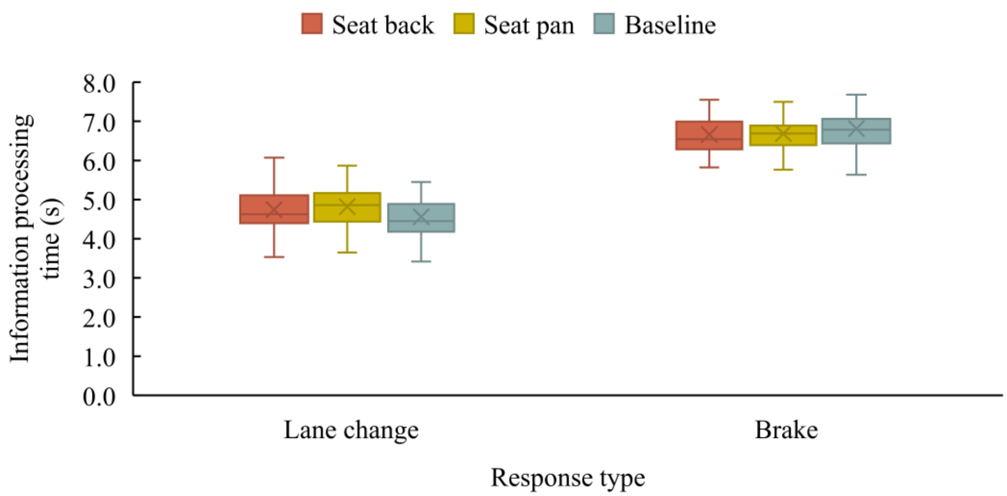


Figure 6.5. Information processing time as a function of location and response type

6.3.3 Maximum resulting acceleration

There was a significant main effect of location ($F(2, 76) = 7.178, p = .001, \eta_p^2 = .159$) and response type ($F(1, 38) = 8.851, p = .005, \eta_p^2 = .189$) on maximum resulting acceleration (Figure 6.6). Post-hoc analyses revealed that drivers in the baseline (M = 10.82 m/s^2, SEM = .079) had smaller maximum resulting acceleration compared to participants who received signals on seat back (M = 12.00 m/s^2, SEM = .425) and seat pan (M = 11.64 m/s^2, SEM = .254). Also, lane-change response (M = 12.02 m/s^2, SEM = .344) had larger maximum resulting acceleration compared to brake response (M = 10.96 m/s^2, SEM = .343). The trajectories of the two response types (see Figure 6.7) indicated that after receiving a TOR, even though the initial lane-change time with brake response may longer, but the overall trajectory was smoother than the lane-change response. No main effect of information type was found ($F(1, 38) = .108, p = .744, \eta_p^2 = .003$).

There was also a significant location × information type ($F(2, 76) = 3.352, p = .043, \eta_p^2 = .081$) interaction effect. Specifically, with instructional signals, seat back (M = 12.36

m/s^2, SEM = .602) and seat pan (M = 11.44 m/s^2, SEM = .360) had larger maximum resulting acceleration compared to the baseline (M = 10.38 m/s^2, SEM = .482). But with informative signals, no difference was found.

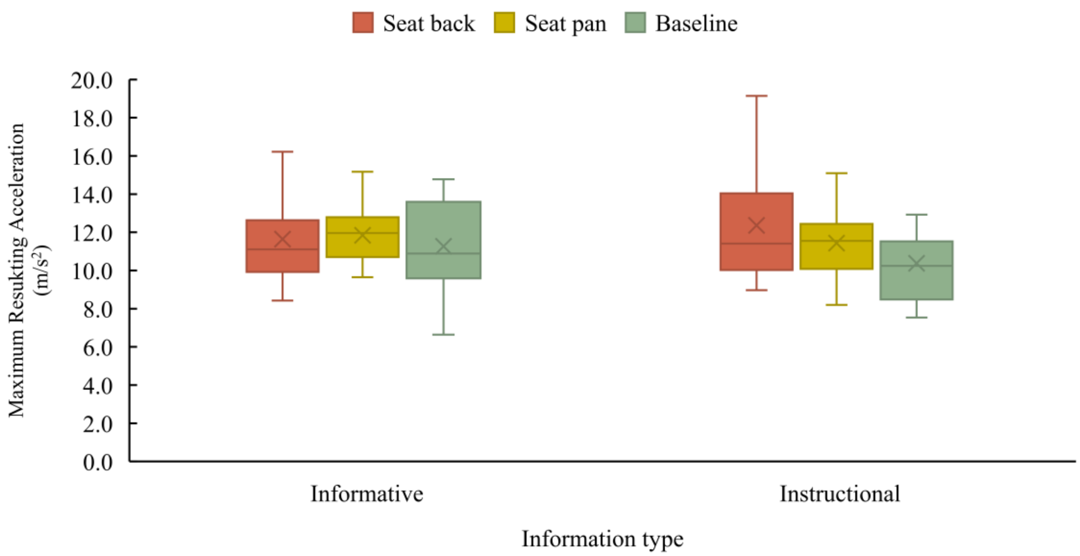


Figure 6.6. Maximum resulting acceleration as a function of location and information type

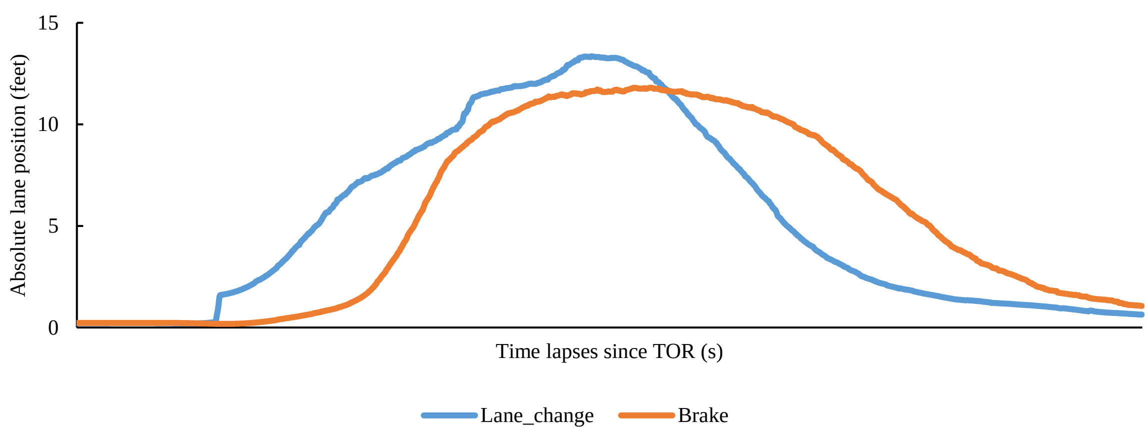


Figure 6.7. Takeover trajectories for each response type 20 seconds within takeover request

6.3.4 Subjective measures

As shown in Table 6.2, there was a significant main effect of location ($F(2,76) = 5.797, p = .005, \eta_p^2 = .132$) on usefulness score. Post-hoc analyses showed that seat back received the highest usefulness rating (M = 1.21, SEM = .090) compared to seat pan (M = 0.81, SEM = .113) and the baseline (M = 0.74, SEM = .138). No main effect of information type ($F(1,38) = .023, p = .880, \eta_p^2 = .001$) nor interaction effect were found. Similarly, there was a significant main effect of location ($F(1.61, 61.32) = 8.794, p = .001, \eta_p^2 = .188$) on satisfaction score. Here, seat back gained higher satisfaction score (M = 0.73, SEM = .100) compared to seat pan (M = 0.13, SEM = .152). No main effect of information type ($F(1,38) = .053, p = .819, \eta_p^2 = .001$) nor interaction effect were found.

Table 6.2. Average usefulness and satisfaction scores for each location

Negative (– 2)	Positive (+2)	Seat back	Seat pan	Baseline
Useless	Useful	1.35	0.88	0.73
Bad	Good	1.13	0.35	0.60
Superfluous	Effective	1.10	0.65	0.63
Worthless	Assisting	1.25	0.98	0.65
Sleep-inducing	Raising Alertness	1.23	1.18	1.10
Overall usefulness score		**1.21**	**0.81**	**0.74**
Unpleasant	Pleasant	0.80	0.18	0.53
Annoying	Nice	0.63	0.18	0.63
Irritating	Likeable	0.60	0.05	0.40
Undesirable	Desirable	0.90	0.10	0.53
Overall satisfaction score		**0.73**	**0.13**	**0.52**

6.4 Discussion

This study investigated the effects of meaningful tactile patterns in informative and instructional formats embedded in the seat back and seat pan of a semi-autonomous vehicle. Overall, meaningful tactile signals (presented either in the seat back or pan) had longer response times and worse takeover quality compared to the baseline signal. However, no takeover performance difference was found between informative and instructional signals. Subjective ratings revealed that signals presented in the seat back were perceived as most useful and satisfying.

6.4.1 Signal response phase

Similar to the findings in Study 3, takeover performance measures were categorized into time- and driving-related metrics, representing the takeover signal response and post-takeover phases, respectively. For the signal response phase, response and information processing times were measured. Contrary to our expectations, the baseline signal (without a pattern) had shorter response times compared to meaningful signals presented in the seat back and seat pan. This finding is consistent with a previous study (Petermeijer et al., 2017), which also found the static signal (similar to our baseline signal) had faster response times compared to signals with patterns. This could be explained by the amount of information that needed to be processed. Signals without patterns only served as a TOR or warning signal, while signals in the seat back and pan not only served as an alert, but also conveyed information about surrounding vehicles and about how to maneuver. For meaningful signals, drivers needed additional time to perceive and comprehend the meaning of the signals, which led to a longer response time. Especially for patterned signals, which consists of three tactors, people may not be able to interpret the meaning after the activation of the very first tactor of the pattern, and thus they waited until (all vibrations of) the signal was complete before responding. But with the baseline signal, for which all four tactors vibrated concurrently, drivers could have interpreted the meaning of the signal within 215 ms, resulting in a faster response. Alternatively, the baseline condition in our study may have a higher intensity, given that it utilized four tactors vibrating at the same time. In contrast, only one tactor was vibrating at any moment for all signal patterns for lane-change responses (which accounted for 50% of response types). According to the literature, higher intensities of tactile stimuli have been found to be associated with higher perceived urgency and faster response times (e.g., Diederich & Colonius, 2008; Lee & Spence, 2008). This explanation may be further illustrated by the finding that drivers had longer response times when making lane-change responses compared to brake responses. Here, either six or two tactors were activated instantaneously for the brake response in informative or instructional signal patterns, respectively. An increase in the number of tactors could have led to higher signal intensity and thus faster response times. Future follow-up work should investigate the effects of signal intensity on responses. If the finding still holds true, an intra-modal matching task may be needed to equate the intensities of tactile signals. Regardless, the finding that meaningful signals had longer response times compared to baseline signals is an important consideration for the design of interfaces that convey instructional/informative information to drivers.

Additionally, no main effects of location on information processing time was found, which did not meet our expectation. This suggests that the difference between the meaningful tactile patterns (in the seat back and pan) and the baseline signal only existed in response time, but not in information processing time. This result is consistent with the findings in Study 2 that the main effects of multimodal TORs was found in the initial takeover signal response phase (as measured by takeover time), but no difference was observed when it came to the entire signal response phase (measured by information processing time). One possible reason for this could be that the effects of signals, which lasted for only 645 ms, may be decayed in the memory since they were not continuously presented during the takeover, such as real-time tactile feedback to present the surrounding vehicle position or show the available lanes to move into through the entire signal response phase. This finding implied that the performance impairments of the meaningful tactile patterns in response time might have been mitigated as the driver processed more information in the driving environment and prepared to takeover.

6.4.2 Post-takeover performance

Post-takeover performance was measured by maximum resulting acceleration. Surprisingly, meaningful signals (presented via the seat back and pan) had larger maximum resulting acceleration compared to signals in the baseline condition, indicating a poorer post-takeover quality with meaningful signal patterns. Furthermore, the discovery of an interaction between location and information type showed that the seat back and pan only had a larger maximum resulting acceleration compared to the baseline for instructional signals. A similar effect was also found in time-metrics, i.e., that patterned signals only had longer response times compared to the baseline only when the signal was instructional. One possible explanation for this finding may be that with informative signals, which provide information about the location and status of elements in the environment, drivers could have had a higher level of situation awareness (Endsley, 1995), leading to better takeover performance. In addition to drivers' visual search in the driving environment after perceiving TOR, the informative signal used the tactile modality to convey information about the driving environment, which, according to the Multiple Resource Theory (Wickens, 2008), should facilitate concurrent processing, leading to a shorter time to regain awareness and better vehicle control. On the other hand, with instructional signals, drivers were commanded to follow the instruction to make maneuvers without learning about the driving environment. Deprived of the ability to focus on regaining situation and environmental awareness by being engaged in the non-driving-related task, drivers may have performed the post-takeover task with more uncertainty and greater task load (e.g., not only maneuvering the vehicle, but also trying to regain situation awareness during the post-takeover phase), which impaired their takeover quality. Future research can confirm this hypothesis using eye-tracking to compare drivers eye gaze points on the side mirrors to check the surrounding vehicles between the informative and instructional signal conditions.

6.4.3 Informative vs. instructional signals

Our study took an initial attempt to compare the tactile patterns that represent two information types in automated vehicle takeover. Overall, no main effects of information type were found on response time, information time, nor maximum resulting acceleration. This indicates that the effects of the two tactile patterns on takeover performance were similar, regardless of the differences in their actual meanings. In other words, people may have spent similar amounts of time and efforts to process and comprehend both informative or instructional signals, and execute the maneuvering plan. In theory, once a person has been trained to interpret the meaning of patterns, it may not matter whether the signal is informative or instructional. For example, a left-turn green arrow and a red traffic light being presented simultaneously is similar to the two information types in our study. In general, the red traffic light (i.e., the instructional signal) requested drivers to stop, while the green arrow (i.e., the informative signal) informs people that they are allowed to turn left. Even though drivers may need a longer time to process and comprehend the meanings of the green arrow and red light, with more traffic knowledge and experience, they can interpret these meanings automatically (without a deeper information processing). This implies that meaningful tactile displays could be used to convey multiple types of information to facilitate communications between users and the system, and improve situation awareness once people know the meaning of signals well enough.

6.4.4 Perceived usefulness and satisfaction

Subjective ratings on signal information type and location revealed that drivers had higher perceived usefulness and satisfaction on signals embedded in the seat back. However, no preference difference was found between the two information types. Wan and Wu (2018) also compared the six vibration patterns that started from one location then moved to the other locations, e.g., seat back → seat pan → seat back → seat pan or back left → back right → back left → back right, and also found no subjective score differences. In their study, patterns initially presented in the seat back had faster response times compared to those in the seat pan, even though all signal patterns were generic (non-informative and non-instructional) and only served as TOR. According to the authors, tactile sensitivity in the back region is higher than the hip, which may also explain why in our study, participants reported higher usefulness for signals in the seat back. Additionally, vibrations presented in the seat pan may be more invasive, based on a few participants' reports during the experiment debriefing session. Also, no subjective rating difference between the two information types further confirms the objective measure findings in that the effects of the two meaningful patterns on the takeover task may be very similar. A more systematic user study may be necessary to compare preferences between locations that may have tactile interfaces (e.g., seat back, seat pan, seat belt, steering wheel, or pedals), as well as patterns of signals that have various meanings.

6.4.5 Limitations

One limitation of the study is that the driving scenario was relatively simple, even though drivers had three maneuvering action options (i.e., drive into the left lane, right lane, or brake first then switch lanes). Once participants were familiarized with the takeover scenarios, they might have been less motivated to collect as much information from the driving environment as they would in the real-life scenario when the takeover is required. For example, in a real-life scenario, drivers may need to quickly obtain characteristics of the external environment, such as the speed limits, road conditions, the surrounding vehicle locations and speeds, or the cause of the takeover event. However, in our study, drivers only needed to understand the meanings of the tactile cues and avoid collisions, and the cause of the takeover event was always the construction site. Future studies may increase the elements in the driving environment, as well as the variabilities of takeover events.

6.5 Conclusion

In summary, this study examined how meaningful tactile patterns in informative and instructional formats embedded in seat back and seat pan affected takeover performance. Overall, when the signal is instructional, signals with patterns (either on seat back or seat pan) had worse takeover performance in terms of response time and maximum resulting acceleration compared to signals without patterns which only had a warning purpose. Additionally, tactile information presented in the seat back was perceived as most useful and satisfying.

7. CONCLUSION

7.1 Summary

Multimodal displays that present information in the visual (V), auditory (A), and/or tactile (T) sensory channels have been found to be associated with better task performance (e.g., Diederich & Colonius, 2004; Hecht et al., 2006; Ho et al., 2007; Lu et al., 2013, 2012; Pitts & Sarter, 2018; Wickens et al., 2011) in many complex environments. Given the pervasion of automated systems, such as automated vehicles, speech systems, or smart homes technology, multimodal displays could serve as reliable human-machine interfaces (HMIs) to facilitate communication between human operators and automated systems. Especially since nearly all current systems have some form of limitation, and often need humans to intervene. To date, there is still limited empirical evidence on human performance with respect to transitioning from automated to manual control in human-automation systems – a context where multimodal displays could be used as decision support.

Additionally, a wide range of users have been suggested to benefit from automated systems, such as the ever-growing older adult population, i.e., those aged 65 years and above, who may have declines in perceptual, cognitive, and/or psychomotor abilities. Yet, it is unclear how individual differences, such as the non-chronological age factors that make up one's daily life activities, impact performance when transitioning from automated to manual control in joint human-automation systems.

Therefore, the goal of this dissertation was to fill the above gaps in the research literature and to examine the effects of 1) multimodal displays, and 2) factors related to individual differences (most notably, non-chronological age factors) on transitioning from automated to manual control in human-automation systems. Automated driving was used as the testbed.

Four human-subject experiments were conducted to answer this research question, and are presented in Chapters 3 – 6. Study 1 (Chapter 3) examined whether the non-chronological age factor, engagement in physical exercise, was associated with performance differences in the automated vehicle takeover signal response phase between younger and older drivers. The findings revealed that bi- and trimodal signals, especially with a tactile component, was associated with faster brake response times for both age groups, but more pronounced for older adults. Also, engaging in physical exercise was found to be correlated with smaller maximum brake force.

Study 2 (Chapter 4) went one step further and investigated the effects of age, physical exercise, and signal modality on post-takeover phase. Preliminary results indicated that older adults had a higher maximum resulting jerk compared to younger adults. However, the differences in decision-making time and maximum resulting jerk were narrower for the exercise group (compared to the non-exercise group) between the two age groups, further highlighting the benefits of physical exercise on task performance in complex environments.

Due to COVID-19 restrictions, Study 2 was only considered a pilot study. The focus of Study 2 shifted to address non-age-related gaps in the multimodal literature and explored the effects of various characteristics of human-machine interfaces on takeover performance. Specifically, Study 3 (Chapter 5) examined the effects of takeover signal direction (ipsilateral vs. contralateral), lead time (4 vs. 7 seconds), and modality (uni-, bi-, and trimodal combinations of visual, auditory, and tactile signals) on automated vehicle takeover performance. Overall, similarly, single and multimodal signals with a tactile component were associated with the faster takeover and information processing times, and were perceived as most useful. Ipsilateral signals showed a marginally significant benefit to takeover times compared to contralateral signals. Finally, a shorter lead time was associated with faster takeover times, but also poorer takeover quality.

Findings in Studies 1 – 3 revealed particular benefits of tactile displays in takeover performance. Finally, Study 4 (Chapter 6) used this knowledge to examine how meaningful tactile patterns, as opposed to abstract tactile signals in Studies 1 – 3, affected takeover performance. Overall, in only the instructional signal group, meaningful tactile patterns (either in the seat back or seat pan) had worse takeover performance in terms of response time and maximum resulting acceleration compared to signals without patterns. Additionally, tactile information presented in the seat back was perceived as most useful and satisfying.

In summary, this work represents critical first steps towards examining the effects of employing multimodal and meaningful tactile displays, as well as considering non-chronological age factors in the design of systems in complex human-automation systems to improve human task performance.

7.2 Intellectual Merit and Broader Impact

This dissertation work contributes to the knowledge base in three research areas: aging (and gerontechnology), multimodal interfaces, and automation.

For aging, as the fastest-growing age group, it is important to determine non-chronological age factors that may cause individual differences in how older adults interact with technology. This work investigated the effects of engagement in physical exercise, on older adults' cognition and physical abilities to interact with complex technologies. Results could help aging, human factors, and inclusive design researchers develop more substantial frameworks that describe how non-chronological factors affect performance on complex tasks. Specifically, the effects of non-chronological factors reported in the current literature were only investigated in simple tasks or tasks in simple environments. The findings related to physical exercise in this dissertation contribute to the literature by showing that the benefits of non-chronological age factors also exist in complex environments. Our findings further highlight the need to consider non-chronological age factors in research on older adults and in the development of theories on successful aging (e.g., living in healthy and engaging lifestyles; Franklin & Tate, 2009). Additionally, findings from this dissertation research may help designers to better develop the next-generation of automated systems that may help older adults to maintain active and productive lifestyles. For example, the positive correlation between physical exercise and automation takeover performance found in this dissertation work could inform the design of adaptive technologies that are sensitive to various cognitive and physical abilities.

With respect to multimodal displays, this work evaluated its application in assisting with machine-to-human transitions in complex environments, especially the use of meaningful tactile information. Results contribute to the multimodal information literature, which can be used in future HMI studies to investigate the effects of meaningful multimodal (compared to only tactile) cues in complex systems for a wide range of user groups. Traditionally, in the literature, the benefits of multimodal signaling have been mostly found for abstract signals (e.g., only for warning purposes) and/or with only younger populations. The findings from this dissertation add to this literature and show that displays containing a tactile component can convey more complex information in human-automation systems. It also highlighted that the benefits of multimodal information presentation carry over to older populations in the context of human-automated systems. Results may have broader implications for the design of next-generation human-machine interfaces to facilitate communication within joint human-automation systems. In particular, in complex environments, one sensory modality may be overloaded with information. Thus, the application of multimodal displays could help to better distribute information across multiple sensory channels. For example, during a takeover event, if the visual channel is occupied, a concurrent meaningful tactile interface can inform the driver of a potential threat and/or the most appropriate maneuvering plan without interference by information conveyed in the visual channel. Additionally, the findings regarding ipsi- and contralateral signals may also inform the design of multimodal displays. Given potential differences in takeover times, designers should employ only one of the two display types to avoid drivers confusing the meaning of alerts.

Finally, for automation, this work can aid research communities in informing models specific to automation takeovers as well as function/task allocation between machines and humans. The empirical data related to handoffs in this dissertation provided unique details for both phases of the automated vehicle takeover process. These findings can help researchers refine takeover models and develop automated takeover specific frameworks. Additionally, this research adds more support for the expected roles of humans when interacting with intermediate levels of automation. Thus, results may also assist researchers, practitioners, and designers to better understand 1) methods for transferring control from a machine to a human and 2) approaches for communicating machine intention to humans. This work used takeover requests presented via multiple sensory channels, and objective and subjective findings showed that a multimodal approach could be reliable in terms of guiding the attention of a wide range of operators in complex automated systems. Thus, multimodal displays should be considered as one possible method to facilitate communications between operators and automated systems, as well as to convey critical system information when it is necessary.

7.3 Future work

This dissertation work contributes a better understanding of aging, multimodal display, and automated systems. However, many unanswered questions still exist in the three areas.

First, for aging, this dissertation first identifies one physical factor – engagement in aerobic physical exercise. Follow-up research should explore ways to collect more precise data on exercise frequency and type, and/or conduct longitudinal studies over a specific timeframe to compare performance before and after the intervention of physical exercise (Marottoli et al., 2007). For instance, a longitudinal study with interventions of physical exercise could help to determine whether exercise leads to improvements in task performance (compared to only correlations). Similarly, some participants performed different types of aerobic exercises, and previous work (Diamond, 2015; Peruyero et al., 2017) suggests that enhancements to cognition are a function of exercise type, intensity, and duration. Thus, future work may attempt to control these variables. Additionally, future research may also quantify the influence of other types of exercises, such as anaerobic, as well as cognitive and social non-chronological age factors on task performance in complex systems.

Additionally, the meaningful tactile patterns in this dissertation only represent two types of information in automated systems. Future work may design patterns that can convey more complex information and messages that are similar to how human communicates in verbal language, to enable humans to make decisions while their visual and auditory channels are occupied. It may be most appropriate to commence conducting in-lab experiments by designing, fabricating, and testing innovative tactile displays, and later evaluating applications of tactile information presentation in more applied automated systems, such as autonomous vehicles, surgical operating rooms, and flight decks.

Finally, for automated systems, common designed-induced Human Factors issues, such as operations that lead to various mental states (e.g., fatigue, mind wandering, or emotion) at the time when a takeover is needed, may cause unwanted consequences. The next step of research could be to investigate the impacts of various mental states on the control of autonomous dynamic systems, and use human performance modeling to predict mental states, human behavior, and performance, based on real-time data (e.g., physiological measurements and performance metrics).

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PUBLICATIONS

Journal articles (based on the dissertation work):

1. **Huang, G.**, Luster, M., Karagol, I., Park, J. W., & Pitts, B. J. (2020). Self-Perception of Driving Abilities in Older Age: A Systematic Review. *Transportation Research Part F: Traffic Psychology and Behaviour*, 74, 307–321.
2. **Huang, G.**, & Pitts, B. J. (Accepted). The Effects of Age and Physical Exercise on Multimodal Signal Perception: Implications for Semi-autonomous Vehicle Takeover Requests. *Applied Ergonomics*.
3. **Huang, G.**, & Pitts, B. J. (Under Review). Takeover Requests for Automated Driving: The Effects of Signal Direction, Lead Time, and Modality on Takeover Performance.
4. **Huang, G.**, & Pitts, B. J. (In Preparation). Effects of informative and instructional tactile signaling on Automated Vehicle Takeover Performance

Conference proceedings (based on the dissertation work)

1. **Huang, G.**, & Pitts, B. J. (Under review). Driver-Vehicle Interaction: The Effects of Physical Exercise and Takeover Request Modality on Automated Vehicle Takeover Performance between Younger and Older Drivers.
2. **Huang, G.**, & Pitts, B. J. (2021). Automated Vehicle Takeover: A Pilot Study on the Effects of Age, Physical exercise, and Takeover Request Modality on Post-takeover Performance. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (accepted).
3. **Huang, G.**, & Pitts, B. (2020). Age-Related Differences in Takeover Request Modality Preferences and Attention Allocation During Semi-autonomous Driving. In *International Conference on Human-Computer Interaction* (pp. 135-146). Springer, Cham.
4. **Huang, G.**, & Pitts, B. J. (2020). The Effects of Engagement in Physical Exercise on Semi-autonomous Takeover Request Perception between Younger and Older Adults. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 64, No. 1, pp. 27-27). Sage CA: Los Angeles, CA: SAGE Publications.
5. **Huang, G.**, Steel, C., Zhang, X., & Pitts, B. (2019). Multimodal cue combinations: a possible approach to designing in-vehicle takeover requests for semi-autonomous driving.

In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 63, No. 1, pp. 1739-1743). Sage CA: Los Angeles, CA: SAGE Publications.