Young Drivers Fatigue Development and Takeover Behaviors under Level 2.5 Automated Driving with Different Workload

by

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Abstract

Vehicle crashes are the leading cause of death and injury for teens. However, only a limited number of studies have assessed the drivers' fatigue status and takeover behaviors during semi-automated driving, especially for young drivers. This study measured fatigue development and takeover behavior based on drivers' ages, workload, and driving mode. A total of five research hypotheses were investigated in this study: First, young drivers might develop fatigue faster and more severely compared with adult drivers for both automated driving and manual driving. Second, young drivers' fatigue development was expected to be more severe under manual high workload compared with manual low workload. Third, young drivers' fatigue development was expected to be more severe under automated compared with manual driving. Fourth, young drivers' fatigue development was expected to be more severe under automated low workload compared with automated high workload. Last, young drivers' takeover performance was expected to be worse than that of adult drivers.

Two studies were conducted to research the fatigue and takeover differences among young drivers and other driver groups. Study one was performed to understand if young drivers are different from adult new drivers in fatigue development and takeovers, 9 participants were recruited for the study. Study two performed statistical hypotheses testing between young drivers and adult drivers on fatigue development and takeover behaviors, 32 participants were recruited for the study. A 2 by 2 by 3 design with 2 levels of driving modes, 2 levels of workloads, and 3 levels of participant groups was used for study one. A 2 by 2 by 2 design with 2 levels of driving modes, 2 levels of workloads, and 2 levels of participant groups was used for study two.

Electroencephalography (EEG), heart rate variability (HRV), video recording, and perceived fatigue and discomfort questionnaires were used to measure the fatigue and takeover behavior in this study. Analysis of variance (ANOVA) and Kruskal-Wallis were used to test the hypotheses in this study.

Study one found that adult new drivers are not significantly different from adult experienced drivers. They both develop fatigue more slowly and have better takeover performance compared with young drivers. Results from study two confirmed four out of five hypotheses: young drivers develop fatigue faster and more severely compared with adult drivers for both automated driving and manual driving; young drivers' fatigue development was more severe under automated driving mode compared with manual driving mode; young drivers' fatigue, especially mental fatigue was more severe under automated low workload compared with automated high workload; and young drivers' takeover performance was worse than adult drivers.

HRV data were not used to conclude this study since the breathing pattern may have an impact on HRV and cause inaccurate results. EEG data were used only for study one due to the difficulties in cleaning the equipment. Future works should focus on statistical tests on study one to confirm that adult new drivers were statistically different from young drivers in fatigue development and takeover performance. Participants should be guided on their breathing while they are driving in order to use the HRV analysis. Also, more participants could be recruited to perform factorial ANOVA to analyze the interactions between the main effects.

Chapter 1 Introduction

1.1 Background

Young drivers are frequently mentioned in driver behavior studies. They lack experience (Williams, 2003) and have a higher accident rate compared with adult drivers (McCartt et al., 2009). Vehicle crashes are the leading cause of death and injury for teenagers: in 2015, 2,333 teenagers in the United States ages 16–19 were killed and 235,845 were injured by vehicle crashes (WISQARS, 2015). Young drivers were 5 to 10 times more likely to have crashes and experience injuries compared with adult drivers (Bates et al., 2014). This evidence strongly supports the importance of understanding the crash factors among young drivers.

Existing studies of crashes involving young drivers were focused on risky driving behaviors (Jonah, 1986), statistical reports on accident rates (Williams, 2006), the influence of passengers (Simons-Morton et al., 2005), and parents' involvement (Simons-Morton & Ouimet, 2006). For example, the crash and near-crash rates among young drivers increased while performing some secondary tasks, such as cell phone use (Siebe, 2014). Young drivers' crash or near-crash rates were much higher when their passenger was young rather than adult (Simons-Morton et al., 2011). A lower level of parental control was related to risky driving, traffic violations, and higher crash rates (Hartos et al., 2000).

To understand why young drivers are more involved in risky behaviors and crashes, it is important to understand the crash factors among young drivers. Factors that cause young drivers' crashes can be generally categorized into social/situational factors (e.g., passenger, phone use, fatigue, etc.) and exposure factors (e.g., time of day, environment) (Bates et al., 2014). Among all factors, the study of fatigue has played an important role in preventing young drivers from crashing and getting injured since fatigued driving increases the risk of crash injury to car occupants for young drivers (Lam, 2003). Over half of the young drivers have reported driving while fatigued at least once a month, and 10% have reported driving while fatigued more than 1/3 of the time (Harbeck & Glendon, 2013). Moreover, when young drivers were driving fatigued, they were less likely to pull over and rest compared with adult drivers (Watling, 2014). As one of the most important situational factors for young drivers' crashes, fatigue needs to be studied to understand why and how young drivers are involved in more crashes than adult drivers. Adult drivers are less likely to be involved in crashes due to fatigue (McGwin. Jr & Brown, 1999), and thus a comparison between young and adult drivers could help us understand how age can affect fatigue while driving. Although fatigue is one of the most important crash factors, studies regarding young drivers' fatigue are limited. Fatigue can either be reported by a survey (Meng et al., 2015) or detected through a driving fatigue detection system using methods such as EEG (Jap et al., 2009), electromyography (EMG), electrocardiography (ECG) (Fu & Wang, 2014), and eye tracking(Eriksson & Papanikotopoulos, 1997). Existing studies related to fatigue and young drivers' crashes used only the reported fatigue after the driving or crash (Lam, 2003; McGwin, Jr & Brown, 1999). However, a simple fatigue report is not able to provide detailed and dynamic fatigue patterns to understand the onset of fatigue and when the fatigue started getting worse. It is important to study the pattern of the fatigue such that the onset time and severity of the fatigue can be observed dynamically. To the author's knowledge, no study has used a real-time fatigue detection system to investigate the pattern of fatigue development over time among young drivers under various driving conditions, and no studies have compared the fatigue of young drivers with that of other driver groups.

The impacts of both physical and mental fatigue among young drivers could become more pronounced with the development of new automated vehicle technology. Automated vehicles have attracted much attention these days. Many studies have been conducted to investigate drivers' behavior under different levels of automated driving. Bao et al. (2020) found that advanced driving assistance systems (i.e., crash warning systems, including forward crash warning, lane drifting warning, lane change warning, and curve speed warning) could cause young drivers to have less pedal control (i.e., brake more aggressively) and larger deceleration value. Though young drivers' performance has been studied under automated vehicle systems, to the best of the authors' knowledge, no study has provided systematic assessments of young drivers' fatigue development under automated vehicle driving.

Many factors could contribute to young drivers' fatigue development under automated driving, among which vigilance decrement plays an important role. Vigilance tasks are the tasks that require a person to maintain alertness for a long period of time to detect signals that are not frequent and predictable (Hancock, 2017; Warm et al., 2015). Vigilance decrement refers to the time-related decline in performance under vigilance tasks (Greenlee et al., 2018). Monitoring automated driving is a typical vigilance task since it requires drivers to remain alert and maintain focus to monitor the driving system for a long period of time in case any automated failure occurs. It has been confirmed that vigilance decrement has been observed during automated driving due to low task load and long duration of driving (Korber, et al., 2015; Miller et al., 2015; Mkrtchyan et al., 2012). Moreover, vigilance decrement could be more severe among young drivers due to the correlation between age and vigilance hit rate (Surwillo & Quilter, 1964). The vigilance hit rate is an inverted U shape in regard to age (Davies & Davies, 1975; D. R. Davies et al., 1984; Halperin et al., 1991; C. Lam & Beale, 1991; Seidel & Joschko, 1990), where and young drivers might be more vulnerable to vigilance decrement when monitoring automated driving and more likely to develop fatigue faster than adult drivers.

Another factor that contributes to fatigue development among young drivers under automated driving is the stress from system failure and bad performance on the takeover. Bainbridge (1983) mentioned that when operating an automated system, two tasks are required: monitoring the automated system when the system operates correctly and taking over the operation when the system is not operating correctly. During an automated driving task, drivers are required to monitor the vehicle status constantly in case any automated failure happens. A takeover is required when the automated driving system fails and the driver needs to take over control of the vehicle to prevent accidents. Young drivers' brain function (specifically executive function) and driving skills are not fully developed, which could lead to bad performance on the takeover. Executive function (EF), referring to the process of cognitive control of several behaviors, which includes inhibition and working memory (Luna, 2009), is one of the brain functions that are not fully developed among young drivers and have an impact on takeover behavior. Although the EF could start developing at an early age, some EF is not fully developed until a person's 20s (Dumontheil, 2016; Luna, 2009; Luna et al., 2004), especially their working memory and interference inhibition (Diamond, 2013; Huizinga et al., 2006). Low EF capacity could lead to poor distraction management and poor information update ability. For example, young drivers cannot update information at the moment and manage the many subtasks of driving as well as mature drivers, not considering that there are more additional secondary tasks in real-world driving (Walshe et al., 2017). When young drivers drive a level 2.5 automated driving vehicle, they might be more easily distracted due to low EF and fail to take over the automated driving system if any takeover is requested. Even though they can supervise level 2.5

automated vehicles with no distraction, they might still have takeover failure due to their limited updated information ability. Despite the fact that young drivers might safely and successfully regain driving control from a failed automated vehicle, the level of perceived stress and the corresponding fatigue development rate could be much higher for young drivers due to their immature EF. Thus, the stress from system failure and bad performance on takeover could increase the rate of fatigue development and even lead to crashes.

Drivers' driving skills will deteriorate if they have fewer non-automated driving experiences (Dragutinovic et al., 2005). If a driver does not drive manually for a long time, their driving skills will deteriorate, and their ability to handle an emergency when there is an automated failure may be reduced. So it is necessary for a driver to continue having opportunities to drive manually (Kyriakidis et al., 2019) so as to maintain their ability to handle an automated system failure. However, due to the rapid development of automated driving technology, more and more young drivers could start to experience automated driving without gaining enough manual driving experience after they obtain a driver's license, which makes it riskier when a takeover is required due to automation failure. Due to the inexperience of young drivers, they might need extra effort to take over (Sun et al., 2014), which in turn will cause stress and fatigue for them. Overall, inexperience, immature EF, and stress could all lead to young drivers' fatigue development, but it is unknown how young drivers develop fatigue under automated driving and how their fatigue patterns are different compared with those of adult drivers. Thus, researching how young drivers take over automated driving and how the takeover could affect fatigue development is very important.

In addition, young drivers are more likely to have decision errors when involved in crashes when compared with adult drivers (Mcdonald et al., 2014). For monitoring a semi-automated driving car, decisions about whether they should take over, when to take over, and how to take over are important. Any error in those decisions could cause a fatal accident. Young drivers should be able to make the right decision about a takeover while operating an automated vehicle. Since young drivers have more decision errors, their takeover performance may be worse than that of adult drivers under automated driving and they may make more potentially fatal decisions. Even though young drivers may safely handle an automated failure and successfully take over, those automated failures may cause more stress for young drivers due to their low EF, their inexperience, and the decision errors they made. In addition, Matthews et al. (1996) found that even though a stressed driver may adapt as successfully as less stressed drivers when the demand for driving is high, the stressed driver may not perform well when the demand level is low. As monitoring the automated driving vehicle is not a high-demand task, young drivers may not perform well on monitoring automated driving when they are under stress.

Workload can play an important role in fatigue development among young drivers. While young drivers are more vulnerable to vigilance decrement, raising the workload by using secondary tasks such as reading or watching a video could reduce the possibility of getting drowsy for the drivers (Miller et al., 2015). In addition, Matthews et al. (1996) found that even though a stressed driver might adapt as successfully as less stressed drivers when the demand for driving is high, a stressed driver may not perform well when the demand level is low. When the demand level is low, stressed drivers are more easily distracted by stressors and in turn have bad performance. As overseeing the automated driving vehicle alone is not a high-demand task, young drivers who suffer stress from inexperience and system failure might not perform well since they are distracted by thinking about their inexperience and the possible system failures they might have. The bad performance might further feed back into their stress and induce fatigue. When the workload is higher, young drivers might adapt better to the driving and in turn be less fatigued.

1.2 Research Problem and Aims

The research problem is how young drivers will develop fatigue during semi-automated driving compared with non-automated driving under different workloads and how they will take over during automated driving. Therefore, the specific aims of this study are to:

- Understand young drivers' fatigue development under non-automated and semi-automated driving.
- Understand young drivers' fatigue development under different workloads.
- Understand the difference in fatigue development between young drivers and adult drivers.
- Understand the difference in young drivers' behavior between non-automated and semi-automated driving.
- Understand the differences in takeover behavior between young drivers and adult drivers.

1.3 Hypotheses

To understand the above problems, young drivers' fatigue development under manual driving and level 2.5 automated driving with high and low workloads was studied. Young drivers could perceive a higher level of tension when they were driving (Taubman-Ben-Ari, 2010), which could quicken the development of fatigue (Bansevicius et al., 1997). As mentioned previously, young drivers might also face bigger challenges while handling automated failures and near-crash situations compared with experienced drivers, which could cause stress and faster fatigue development. Young drivers might be more vulnerable to vigilance decrement when monitoring automated driving and be more likely to develop fatigue faster than adult drivers, especially when the workload is low in automated driving. Moreover, young drivers will get more distracted during automated driving, and when they need to take over the automated system, they will perform worse than adult drivers. Therefore, five research hypotheses were investigated in this study:

- First, young drivers might develop fatigue faster and more severely compared with adult drivers for both automated driving and manual driving.
- Second, young drivers' fatigue development was expected to be more severe under manual high workload compared with manual low workload.
- Third, young drivers' fatigue development was expected to be more severe under automated compared with manual driving.
- Fourth, young drivers' fatigue development was expected to be more severe under automated low workload compared with automated high workload.
- Last, young drivers' takeover performance was expected to be worse than adult drivers.

Chapter 2 Literature Review

2.1 Automated Driving and Takeover

Research about automated cars has been under way since the 1920s (Kröger, 2016). Research on automated vehicles increased in the 1980s. For example, Kanade et al. (1986) proposed a project about the construction of automated vehicles, the perception system, the path planning system, the topological and obstacle map use, the system architecture of the automated vehicle, and the utilization of parallel computer architecture. Since the 1980s, more and more research and companies have been involved in the development of automated vehicles. As of 2020, twenty-nine states in the US have enacted legislation about automated driving.

The Society of Automotive Engineers has defined automated driving in 6 levels (SAE, 2018). SAE levels 0 to 2 are the features that can support drivers but cannot perform automated driving, while SAE levels 3 to 5 are the levels that have automated driving features. SAE level 0 is the lowest level, which means that the vehicle provides features that are limited, including providing warnings and assistance for the driver. Examples of SAE level 0 automated actions are automatic emergency braking, blind spot warning, lane departure warning, etc. The SAE level 1 automated vehicle can provide the steering, braking, or acceleration assistance for the driver; for example, the lane centering system or adaptive cruise control system. SAE level 2 is the last of the driver support levels; this level of automated driving can provide better steering, braking, and acceleration support to the driver. While SAE level 1 can provide either the lane centering or the adaptive cruise control functions for the driver, SAE level 2 automated driving can provide the lane centering and adaptive cruise functions at the same time. While at SAE level 0 to level 2, drivers still need to drive while the automated function is engaged, SAE level 3 to level 5 do not require the driver to drive the vehicle when the automated function is engaged. The SAE level 3 and level 4 automated vehicles can drive the vehicle under limited conditions but will not operate automatedly if the conditions are not met. The difference between level 3 and level 4 is in the takeovers. Level 3 still needs the drivers to supervise the automated driving, and when automated driving is requested, drivers still need to take over control of the vehicle. SAE level 4 will not request the driver to take over the driving at all. An example of SAE level 3 is the traffic jam chauffeur, and an example of SAE level 4 is the local driverless taxi. SAE level 5 is considered as fully automated, and the feature can operate under any condition and does not need the driver to take over the driving at all.

Figure 1. SAE Automated Levels. From SAE J3016 Levels of Driving Automation, by SAE International. Https://Www.Sae.Org/Binaries/Content/Assets/Cm/Content/Blog/Sae-J3016-Visual-Chart_5.3.21.Pdf. Copyright 2021 by SAE International.

In this paper, the automated scenario is defined as SAE level2.5 automated driving: the vehicle will have automated driving features that include more than lane centering and adaptive cruise function. However, drivers are still responsible for supervising the vehicle and are responsible for takeover if they feel the automated driving feature is making a mistake and is not safe. When the takeover is required, multiple human information processing stages are involved (B. Zhang et al., 2019). Drivers need first to perceive the visual or auditory cues of the scenario (Gold et al., 2016). Once the visual or auditory stimuli are received, the driver will have to process the information and then select the action they need to take (Zeeb et al., 2015). Once the driver has understanding of the situation and made the decision of what action to take, they will carry out the action by repositioning their hands and feet back on the pedals and steering wheel and then braking or steering the vehicle (B. Zhang et al., 2019). Response time is frequently used to measure the takeover of automated vehicles (Gold et al., 2013). Kerschbaum et al. (2015) used the hand movement response time to test the performance of a newly designed steering wheel on the takeover request. Vogelpohl et al. (2018) used the mirror check response time to measure the takeover performance of distracted drivers. Petermeijer et al. (2017) used the lane changing response time to measure the effectiveness of the vibrotactile warning signal on takeover performance. Other than the response time, the correct response rate (Petermeijer et al., 2017) and the takeover success rate are also used to measure the performance of the takeover behaviors (Sanghavi et al., 2021).

2.2 Young Drivers

There is no universal definition of the age range for young drivers. Some studies have a wider range, from 16-25-year-olds, while other studies focus on only a smaller range, from either 16 to 20 or 18 to 25 (Jonah, 1986). For example, Pelz & Schuman (1971) used 16–24 as the range for young drivers and Stewart & Sanderson (1984) used a range of 16 to 19 to study young drivers' driving risks. In recent studies, Mohamed & Bromfield (2017) used a range of 18 to 24 to study young drivers' driving behavior and attitude, while Simons-Morton et al. (2012) studied only drivers at 16 years old for the peer influence on driving behavior. These diversities in the definition of young drivers could lead to different research focuses and types of study (Jonah, 1986). Pelz & Schuman (1971) found that young drivers will have a peak of accidents while they are aged 18 and 19. Stewart & Sanderson (1984) found that the risk of accidents for young drivers aged between 16 and 19 will be twice as high as for adult drivers. Males (2009) studied all the crash reports from 1994 to 2007 and found that drivers aged between 16 and 19 have the highest fatal crash rate compared with any other age group. Thus, in this study, young drivers will be defined as drivers between 16 and 19 years old.

It is known that young drivers are overrepresented in car accidents. They tend to drive more riskily than adult drivers. Multiple factors can contribute to young drivers' risky driving. Speeding is one of the most studied factors for young drivers. Wasielewski (1984) found that driving speed is negatively related to the driver's age, and that young drivers, under 21 years old, drive 7 km/h faster than older drivers. Harrington & McBride (1970) found that young drivers received more speeding tickets than older drivers for the same amount of driving distance. Risk perception could be another reason for young drivers being over-involved in accidents. Young drivers tend to underestimate traffic risk and the negative outcomes from traffic, which can lead to an accident (Brown & Groeger, 1988). Young drivers' decision making could be heavily impacted by their peers and involved in risky driving as well (Aldridge et al., 1999). Moreover, young drivers are less concerned about impaired driving (Wilson, 1984). Although driving under the influence of substances and alcohol has been studied the most for impaired driving among young drivers, fatigue could impair the driving ability for young drivers and cause accidents as well.

2.3 Fatigue

Fatigue is considered as the state between awake and sleeping that could lead to sleep if not interrupted (Lal & Craig, 2001). If a person is fatigued, their work efficiency and their willingness to work are reduced (Brown, 1994; Grandjean, 1979). In general, fatigue can be classified as physical fatigue and mental fatigue.

Physical fatigue normally refers to muscular fatigue, which is the phenomenon of reduced muscle performance and slower and weaker muscle contraction. Muscles can produce movement, maintain posture and body position, stabilize joints, and generate heat for the body. A muscle contains thousands of muscle fibers, connective tissues, blood vessels, and nerve fibers. Figure 2 shows the anatomy of a muscle fiber.

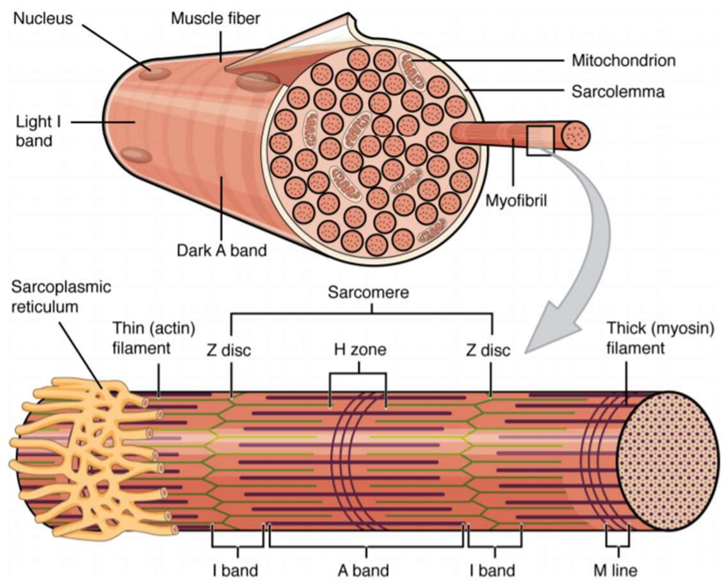


Figure 2. Muscle Fiber Anatomy (Biga et al., n.d.)

As shown in Figure 2, each muscle fiber has a bundle of myofibrils in it. In a myofibril, there are two types of myofilaments, thick and thin, which are the basic contraction unit. Based on the type of myofilament the myofibril has, a myofibril could have an I band and an A band. Each I band has a midline interruption called a Z disc, and the area between two Z discs is a sarcomere. Muscle contraction occurs when the sarcomere shortens due to thick and thin myofilaments sliding past each other and overlapping. Each muscle fiber is connected by a motor neuron, which can give the muscle signals to contract. When an action potential arrives at the neuromuscular junction, ACh is released and binds to the receptors, which opens the sodium ion channels and causes the action potential in the sarcolemma, which releases calcium, sustained by adenosine triphosphate (ATP), and initiates contraction. The amount of ATP stored in muscle is very low and muscles need to break down glucose to generate more ATP to perform contractions. During the process of breaking down the glucose into ATP, lactic acid, carbon dioxide, and water will be produced as well. While a muscle is stressed, lactic acid and carbon dioxide increase and the muscle tissue becomes more acidic, which breaks the muscle metabolism and leads to lower muscle performance (Grandjean, 1979). When the muscle is fatigued, the contractions will be weaker and slower, the electromyogram (EMG) signal will decrease in frequency, the duration of sustained isometric exertions and endurance time will shorten, and there will be muscular tremor and localized pain (Basmajian & De Luca, 1985).

Mental fatigue can be defined as feelings of indolence and unwillingness to perform any kind of activity (Grandjean, 1979). It is a psychological state caused by prolonged demand for cognitive activities (Boksem & Tops, 2008). Mental fatigue can lead to impaired cognitive and behavioral performance (Boksem et al., 2005; Lorist et al., 2005). When a person is mentally fatigued, it is hard for them to focus, plan, ignore irrelevant information, and correct their mistakes (Boksem et al., 2005, 2006; van der Linden et al., 2003; van der Linden & Eling, 2006). However, mental fatigue is more complex than physical fatigue since it involves different dimensions such as mood, information processing, and behavior (Hancock & Desmond, 2001). Mental fatigue can be explained by a dual regulation system (Ishii et al., 2014). There are two systems in control of the cognitive task: the facilitation system and the inhibition system. The facilitation system can improve cognitive task performance, while the inhibition system can impair cognitive task performance. The facilitation system includes the thalamic-frontal loop, which is the loop between the limbic system, basal ganglia, thalamus, and frontal cortex. When the mental workload increases, the facilitation system will be activated and therefore performance will be improved. On the other hand, the inhibition system, which includes the insular cortex and posterior cingulate cortex, will impair performance while it is activated. Cognitive task performance is regulated by these two systems. Repeat and prolonged mental workload can break the metabolic balance and cause insufficient activation of the facilitation system, overaction of inhibition system, or both, which results in decreased cognitive task performance and fatigue. However, environmental factors can affect fatigue development as well, for example, motivation. Motivation is part of the cause of mental fatigue (Chaudhuri & Behan, 2000). When a person perceives that they did not get enough reward for the amount of effort they put in for a task, they will feel fatigue (Tops et al., 2004).

Prolonged driving can cause both physical fatigue and mental fatigue. Williamson et al. (1996) defined driving fatigue as a state of reduced mental alertness and impaired cognitive and psychomotor tasks for drivers such that the driver has an impaired ability to drive. Nilsson et al. (1997) found that fatigue is responsible for the majority of driving errors. Horne & Reyner (1995) also found that fatigue is a major reason for accidents during monotonous driving conditions. Seen et al. (2010) also found that prolonged driving can significantly induce fatigue and increase the risk of accidents. Driving fatigue has been observed after 60 minutes of driving (Skipper & Wierwille, 1986). Overall, prolonged driving could cause both mental and physical fatigue, which could impair the driver’s ability to drive and potentially cause an accident. It is important to understand fatigue development among drivers and especially among young drivers in order to understand why they are more involved in accidents and how to prevent accidents from happening.

2.4 Fatigue Measurement

There are four types of objective approaches that can detect driver fatigue (Kong et al., 2015). Physiological signals, such as EEG (Cao et al., 2014; Gharagozlou et al., 2015; Jap et al., 2009), ECG (Burton et al., 2010; Byeon et al., 2006; Egelund, 1982; Fu & Wang, 2014), electrooculography (EOG) (Eriksson & Papanikotopoulos, 1997, 1997; Y.-F. Zhang et al., 2015), and EMG (Bansevicius et al., 1997; Cifrek et al., 2009; Fu & Wang, 2014; Troiano et al., 2008), have good performance however, all the physiological methods need high-accuracy devices to acquire a clean signal for fatigue detection. The second type of fatigue detecting method is based on the driver's behavior, for example, steering wheel control (Jung et al., 2014; Krajewski et al., 2009; Li et al., 2017). Vehicle states can also reflect the fatigue of the drivers, for example, lane information (Qiong Wang et al., 2006; Sparrow et al., 2016; Wong et al., 1996), which can reflect the steering wheel control and pedal control and in turn reflect the fatigue. The last type of method to detect fatigue is the driver's physiological reaction, for example, yawning or other facial expressions (Abtahi et al., 2011; Fan et al., 2007; Saradadevi & Bajaj, 2008, 2008). On top of the objective approaches, subjective ratings on fatigue can also reflect fatigue among drivers (Di Stasi et al., 2012; Lees et al., 2018; Y.-F. Zhang et al., 2015).

EEG is considered one of the most reliable measures to detect mental fatigue and drowsiness (Artaud et al., 1995; Erwin et al., 1973; Volow & Erwin, 1973). EEG can measure the electrical activity in the human brain from the scalp. Most electrical activity collected by the EEG is generated by pyramidal neurons. The EEG will record the summation of inhibitory and excitatory postsynaptic potentials from groups of pyramidal cells near the recording electrode (Fisch & Spehlmann, 1991). The cortical neurons and cortical-to-subcortical connections are systematically interconnected. The activities reflected on the EEG represent the communications between the cortex and the subcortical structures. Once the cortex has a task, the electrical activities of the cortex will desynchronize. Lower amplitude and faster electrical activities will be presented until the task is completed and the cortex returns to a resting state (St. Louis & Frey, 2016).

The international 10-20 system is one of the most-used methods to locate the scalp electrodes and collect the EEG data for sleep studies and laboratory research. The 10-20 system uses the bony landmarks on the head to create lines, and the electrodes are placed at intervals of 10 or 20 percent of the total length of these lines. In the system, electrodes placed on the scalp are identified by a letter and number to represent the location of each electrode on the head: Fp for frontopolar; F for frontal; C for central; T for temporal; P for parietal; O for occipital; and A for prominent bone process (behind the outer ear). When the location of the electrode is on the left hemisphere, an odd number will be used after the letter, and when the electrode is on the right hemisphere, an even number will be used after the letter. A lower case "z" represents the midline of the scalp. Figure 3 shows an example of a 10-20 EEG system (St. Louis & Frey, 2016).

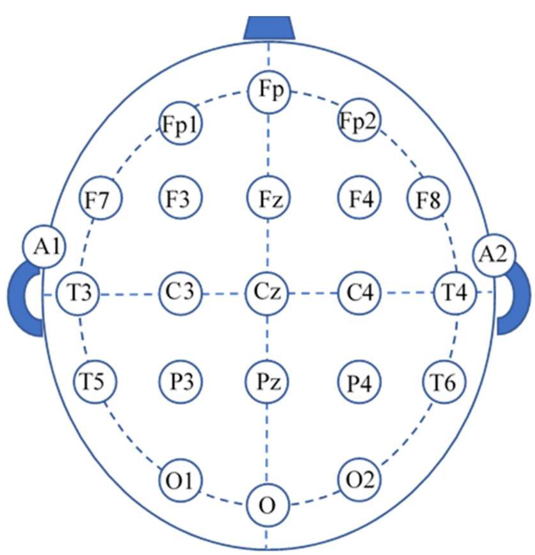


Figure 3. 10-20 EEG System

EEG data collected from the system can be filtered and transformed on different frequency bands. Four bands were important for mental fatigue detection: delta activity (0.5–4HZ), theta frequency (4–7HZ), alpha waves (8–13HZ), and beta waves (13–30 Hz). Changes in different bands can reflect different mental stages, for example, alertness, drowsiness, or sleep. When an individual is drowsy, they will have less muscle movement, fewer eye blinks, and rapid lateral eye movement, which will lead to a slow frequency rate of 0.25 to 1.0 Hz in the frontal and lateral frontal channel. When a person gets more drowsy, slower and synchronous frequencies of theta and delta activities will merge.

Normally, alpha band activities occur during the awake and relaxed stage, and the theta band will replace the alpha at the onset of sleep (Grandjean, 1988). Lal & Craig (2001) found that delta waves have been shown during the transition from being awake to drowsiness. The beta band, on the other hand, reflects the increase of alertness and arousal (Grandjean, 1988). On top of the single-band activities, an increase of (alpha+theta)/beta, and a decrease of theta/alpha were found to be positively related to the development of mental fatigue as well (Lal & Craig, 2001; Cao et al., 2014).

Another way to evaluate fatigue is through the measurement of ECG. By analyzing the heart rate (HR) and performing HRV analysis, the mental state can be reflected. HR can be used to indicate fatigue status. It is well known that the HR will decrease at the initial stage of sleep (Jones, 1990). This decrease is found while the driver is driving while sleepy as well (Jo et al., 2019). Riemersma et al. (1977) found that the HR will decrease when a person is fatigued. Jo et al. (2019) found that the HR will have a 9% decrease when the driver is driving while sleepy compared with their regular driving.

HRV measures are a sensitive indicator of fatigue (Egelund, 1982). Byeon et al. (2006) have stated that HRV analysis can be used to detect drowsiness status. A drop of measured SDNN indicates potential fatigue development since less variability between heartbeats is observed as a result of fatigue (Malik, 1996). The LF/HF decreased when the subjects were mentally fatigued (Byeon et al., 2006). HRV can measure and reflect the autonomic activity of the body that can describe the mental state of humans (Malik, 1996).

The human nervous system includes the central nervous system (brain and spinal cord) and the peripheral nervous system (connected to the central nervous system). The peripheral nervous system can be further divided into two subsystems: the somatic nervous system and the autonomic nervous system (Mai & Paxinos, 2012). The autonomic nervous system, including the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS), can regulate bodily functions and control the fight-or-flight reaction (Jänig, 1989). Figure 4 shows the human nervous system.

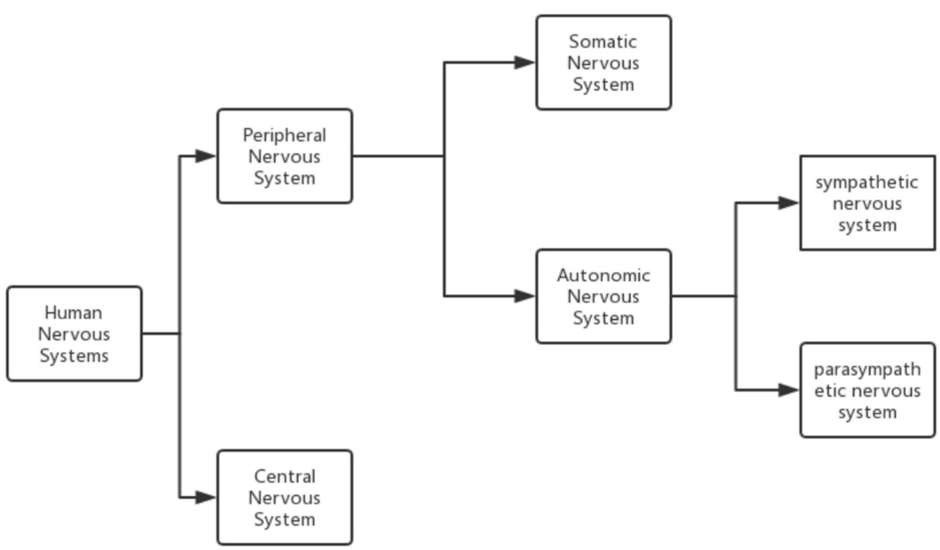


Figure 4. Human Nervous Systems

The two branches of the autonomic nervous system have opposite functions. While the SNS is responsible for the fight-flight system, the PNS is responsible for getting the human body to the rest state (Jänig, 1989). When a stressor shows up, the SNS will send signals to the body to prepare for reaction, which is called the fight-flight reaction. While an individual is in this reactive state, the body will react faster and better, but the immune system and digestive system, which are not necessary for the fight-flight reaction, will be suppressed. When the events that triggered the fight-flight reaction are over, the PNS will be active and send signals for the body to return to the baseline and rest state. Since the SNS activates when the body is in a fight-flight state, an individual will be more alert and awake when the SNS is dominant. On the other hand, when the activity in PNS is increased, the body is under the recovery stage from the fight-flight reaction and will be more fatigued. Such activities between the SNS and PNS can be reflected by the heart signals due to the heart-brain communication, as shown in Figure 5. The SNS can indirectly communicate with the heart through the spinal cord and extrinsic cardiac ganglia while the vagus nerve (parasympathetic) contains afferent fibers flowing to the brain that are connected to the medulla (Rollin McCraty et al., 2001).

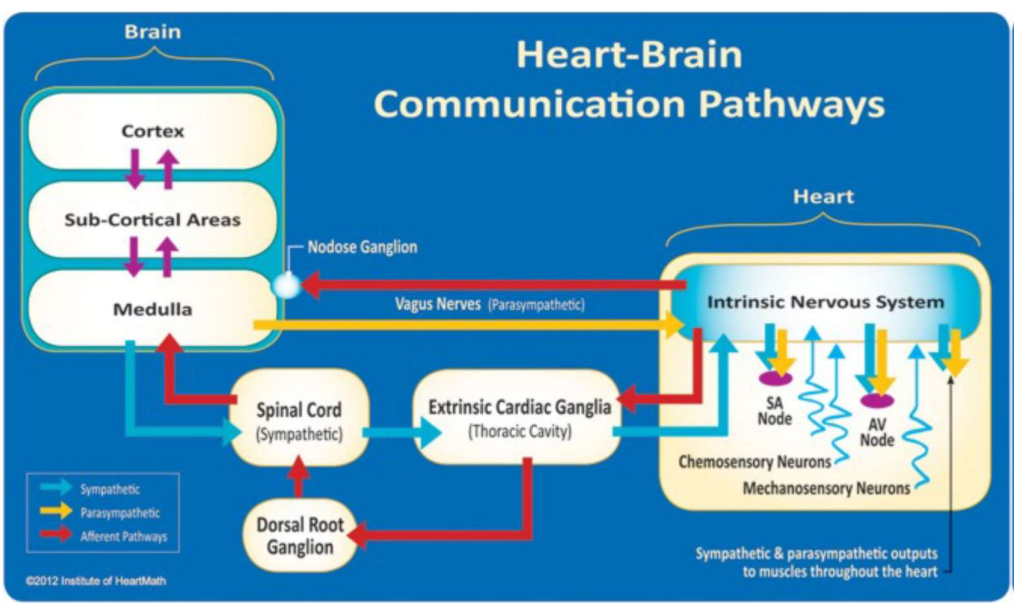


Figure 5. Heart-Brian Communication Pathways. From Science of the Heart, Exploring the Role of the Heart in Human Performance, by Rollin McCraty, Atkinson, M., & Tomasino, D, 2001, Boulder Creek, CA: Heart Math Research Center, Institute of HeartMath. Copyright 2012 by Institute of HeartMath.

HRV, the measure of the beat-to-beat changes of human heartbeats, can reflect the interplay between the SNS and PNS (Cygankiewicz & Zareba, 2013) and in turn reflect the fatigue state. Shaffer et al. (2014) found that the beat-to-beat interval will be shorter while the SNS is dominant and be longer while the PNS is dominant. Different methods can be used to analyze the HRV. Time domain analysis, frequency domain analysis, rhythm pattern analysis, and nonlinear methods are the four major methods used to analyze the HRV(Camm et al., 1996). All those methods are based on the measure of the time elapsed between two successive R-waves of the QRS signal on the electrocardiogram (RR interval/NN interval). Figure 6 shows an example of the QRS graph of the heart rate.

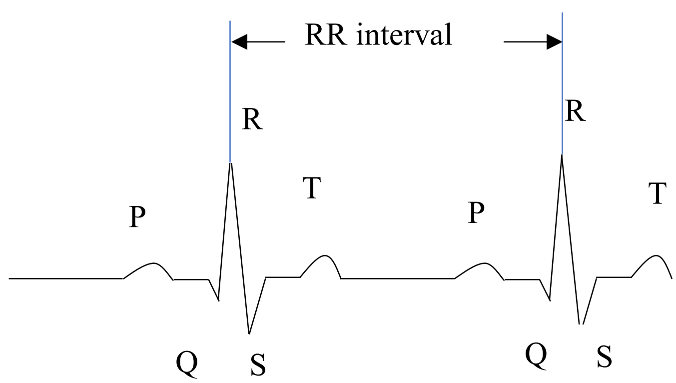


Figure 6. ECG QRS Graph and RR Interval

Standard deviation of normal to normal (SDNN) is one example of time domain measurements. It is the standard deviation of the NN intervals of the heartbeat. When an individual is healthy and at a better state, they will have a more irregular pattern between their intervals. On the other hand, when an individual is not healthy or is in a fatigued state, their heartbeats will be more similar to each other and have a less irregular pattern between the intervals. Thus, when a person is fatigued or in a poor mental state, their SNDD will decrease (Burton et al., 2010). pNN50 is another time domain analysis of the HRV measure, which is the percentage of absolute differences in successive NN values > 50 ms (Bigger et al., 1988). Similar to the SDNN, reduced pNN50 could also reflect mental fatigue (Huang et al., 2018).

HRV can be analyzed by frequency domain analysis as well, which counts the number of the RR intervals that match different frequency bands. Three bands are normally used for frequency domain analysis: high frequency (HF), which is from 0.15 to 0.4 Hz; low frequency (LF), which is from 0.04 to 0.15 Hz; and very low frequency (VLF), which is from 0 to 0.04 Hz. The ratio of LF to HF power is a commonly used HRV frequency domain analysis that can estimate the ratio between the SNS and PNS activity (Shaffer et al., 2014). When the SNS is dominant, the LF power will increase, and when the PNS is dominant, the HF will increase. Egelund (1982) found that a decreased LF/HF ratio can reflect the fatigue of a person.

Other than objective measurements, fatigue can be measured by a self-reported questionnaire for various settings and scenarios (Ferentinos et al., 2010). In general, fatigue self-report measurement can be classified on a unidimensional or multidimensional scale. Unidimensional scales normally yield a single score and are more brief and simple to use, while multidimensional scales are more detailed and can identify the underlying aspects of fatigue (Dittner et al., 2004). Examples of unidimensional scales include the brief fatigue inventory (Mendoza et al., 1999), fatigue severity scale (Krupp, 1989), FACT-F subscale (Yellen et al., 1997), and global vigour and affect (Monk, 1989). Examples of multidimensional scales are checklist individual strength (Vercoulen et al., 1994), fatigue assessment instrument (Schwartz et al., 1993), fatigue impact scale (Fisk et al., 1994), and fatigue questionnaire (Chalder et al., 1993). Although most of these fatigue scales are well validated, none of them targets driving fatigue. For example, the brief fatigue inventory was more used on cancer patients (Wang et al., 2001) and the fatigue severity scale was more used on patients with Parkinson's disease (Abe et al., 2000), sleep disorders (Lichstein et al., 1997), or brain injuries (LaChapelle & Finlayson, 1998). For current study, a multidimensional fatigue scale developed by Åhsberg et al. (1997) to target occupational work subjective fatigue could be used to measure driving fatigue. In this scale, five dimensions were found to measure fatigue, including lack of energy, physical exertion, physical discomfort, lack of motivation, and sleepiness. More detailed factors, such as sleepiness and drowsiness under the sleepiness dimension, were used to measure fatigue with an 11-grade scale from 0 to 10. Both mental and physical fatigue from driving can be evaluated by using this fatigue scale (Åhsberg et al., 1997).

Chapter 3 Research Design and Methods

Two studies were conducted to understand fatigue development and takeover behaviors among young drivers and other driver groups. The same devices and procedures were used for the two studies, with different participants and measurements.

3.1 Participants

Three groups of participants were recruited for the study: young driver, adult new driver, and adult experienced driver groups. A young driver was defined as a driver who was 16 to 19 years old (Pelz & Schuman, 1971; Stewart & Sanderson, 1984), while an adult driver was defined as a driver who was older than 21 years of age. People between the ages of 19 and 21 were not recruited for this study, and were excluded to reduce the similarity between the two test groups. An adult new driver was defined as an adult driver who had gotten their driver's license within 3 years and did not have extensive exposure to driving before they started training to get the license. A driver was also defined as new/inexperienced if they had not conducted any driving task within the past 6 months.

The constraints on participants for all three groups were the following: The participants were required be older than 16 years old; the participants had to have valid driver licenses/permits with no accidents for the last three months; the participants should not have had any injury or illness, like spinal or lower back injuries or pain; the participants should not have had implanted electrical devices, such as cardiac or bone stimulators; the participants should not have had any motion sickness from interacting with a driving simulator that could interfere with their performance in the simulated driving; the participants should not have had any caffeine withdrawal symptoms. Upon arrival in the laboratory, all the participants were required to read and sign an informed consent approved by the University of Michigan Institutional Review Boards with study ID HUM00143933.

3.2 Devices

This study used a high-fidelity modular driving simulator from Realtime Technologies, FAAC Inc, MI, as shown in Figure 7, for the participants to perform the driving task.

Figure 7. Driving Simulator Setup

To collect ECG data, a portable heart rate sensor (H10, Polar, Kempele, Finland) was used. An application generated by Elite HRV, Inc., North Carolina, was used to collect and process the ECG data. The raw data output of the ECG was the RR intervals. All ECG data were processed and calculated in the Elite HRV app.

As illustrated in Figure 8, a 14-channel dry EEG headset (Emotiv EPOC+, Emotiv Inc., CA) was used to collect the EEG data. The raw data output was the micro voltage on each channel with a sampling rate of 128 Hz.

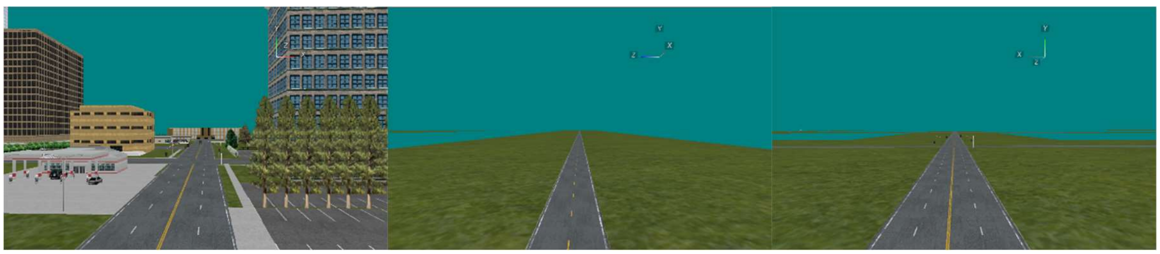
Figure 8. Illustration of EEG Setup

Two cameras (GoPro HERO4, GoPro Inc., CA) were used to collect the video recording of the driving. One camera was set on the dashboard to record the driver's eye movements and facial expressions. The second camera was set at the left behind the driver to record the overall scenario and driver behaviors.

3.3 Workloads

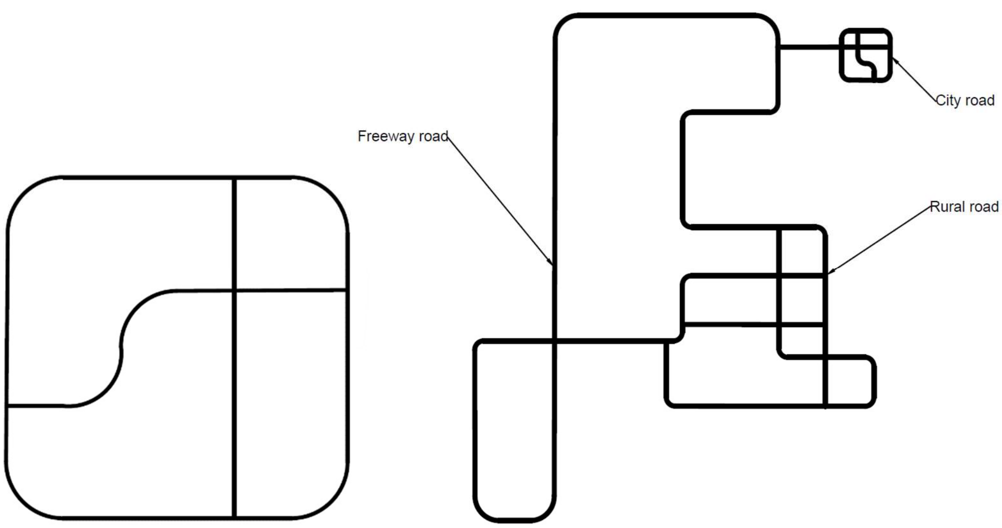
The workload was estimated in this study using a combination of weather, road condition, secondary task, and near-crash scenarios. The weather conditions can significantly influence the mental workloads during driving (Hu et al., 2011), which were generally higher in bad weather and more prominent among inexperienced drivers (Patten et al., 2006). Thus, bad weather conditions were used for the high-workload condition. In addition, reduced visibility decreased the estimation of safety margins and increased workload (Hoogendoorn et al., 2011; Waard et al., 2008). A foggy driving condition was included as a cause of the high workload in this study.

Road conditions, such as city roads and highway roads, can have different impacts on drivers' mental workloads (Sugiono et al., 2017). More complex road conditions can lead to a higher mental workload due to the drivers needing to be more careful to evaluate the traffic and speed of surrounding vehicles (Cantin et al., 2009). Three types of road conditions were used for the high and low workloads. The city road had two lanes in each direction, traffic lights, pedestrians, buildings, and shops on the side of the road. The freeway road had one lane in each direction, no traffic lights, and no pedestrians or buildings on the side. The rural road had two lanes in each direction, with traffic lights but no pedestrians or buildings on the side. Figure 9 shows an example of each type of road.



9.a. City Road 9.b. Freeway Road 9.c. Rural Road
Figure 9. Road Examples

The city road was used for the high-workload map since it was more complex, and a mix of all three types of the road was used for the low-workload map. Both maps were closed loops, as shown in Figure 10.



10. a. High Workload Map 10. b. Low Workload Map
Figure 10. Maps Used for High Workload and Low Workload

The Society of Automotive Engineers (SAE) has classified driving automation into 6 levels, from completely manual control to completely automated driving (SAE, 2018). In this study, automated driving was defined as level 2.5 automated driving. The vehicle had line centering, adaptive cruise control, and limited traffic jam chauffeur. However, automated driving may have failed due to the nature of level 2.5 driving automation and required the participants to take over control. The driving simulator used in this study has automated driving function that fits into the level 2.5 automated driving defined above. The automated failure scenarios could happen during automated driving mode under certain scenarios (i.e., sharp curve, front car sharp brake) when the simulation system could not perform fast enough for the sudden events. Since automated failure is triggered by certain scenarios, different participants may have received a different number of automated failures based on the route they chose and the driving style they had. To simulate a realistic scenario for people using a level 2.5 automated vehicle, the participants were allowed to use their personal phones as entertainment while ensuring the safe driving of the simulator.

Secondary tasks can increase the workload of young drivers (Lansdown et al., 2004), which in turn may induce fatigue. In this study, participants were asked to reply to a text message through a study phone while maintaining the velocity of driving. The text message sent to the participant was a 10 digit phone number since it can simulate both texting and dialing a phone call (He et al., 2015). The participant was asked to retype the phone number and send it back through a text message. There were 18 messages used for the high-workload scenario.

Compared with experienced adult drivers, young drivers were more likely to be involved in crash/near-crash situations (Simons-Morton et al., 2011), which may introduce higher workloads to regain control. Young drivers may also experience high perceived workloads under normal driving conditions (Gaillard, 1993). A crash/near-crash experience could lead to severe acute stress (Beck & Coffey, 2007; Winston et al., 2005), which in turn may induce fatigue. In the study, sudden crossing pedestrians were used to create a near-crash situation to potentially increase drivers' perceived workloads. A total of 10 simulated pedestrians were distributed inside the high-workload map in random locations. Pedestrians were triggered and ran into the traffic if the car was in a certain line and at a certain distance from the pedestrian. The pedestrian running speed and the distance between pedestrian and vehicle were designed so that the automated system would fail to stop since the pedestrians' movement was too sudden. Also, the crossing pedestrian was moving fast so that if the driver was not focusing on driving or not able to react fast, they would hit the pedestrian.

In summary, foggy weather, city roads, secondary tasks (replying to text messages), and near-crash scenarios (sudden running pedestrian) were used for the high workload. Clear weather; city, freeway, and rural road mix; and no secondary task or near-crash scenarios were used for the low workload.

3.4 Procedures

During the experiments, participants were asked to sit in the simulator and drive/monitor (if it was automated driving) the vehicle, driving on the predefined map for 1.5 hours. They were asked to ensure that the vehicle was driving safely and following the traffic rules. During automated driving, participants were asked to take over control of the vehicle when they believed that automated driving had failed or it was not safe to let the vehicle drive on its own. Once the driving condition recovered to normal, participants were asked to switch the driving mode back to automated driving again.

The participants who agreed to participate in the study went through initial subject screening to provide information regarding their age, driving experience, gaming experience, and caffeine use. Qualified participants received a 5-minute training on how to perform driving on the driving simulator and how to report perceived fatigue and discomfort during the test. Before starting the driving task, EPOC+ and H10 were equipped following the existing instructions. After the devices were set up, participants were given the first perceived fatigue and discomfort questionnaire before the start of the driving task. For every 30 minutes of driving, participants were asked to report fatigue. The data from EPOC+ and H10 were continuously collected for 10 minutes at the beginning of each 30-minute interval.

3.5 Measurements

This study measured both mental and physical fatigue. Perceived physical fatigue and discomfort were measured using the perceived fatigue and discomfort questionnaires. Mental fatigue was measured through the perceived fatigue and discomfort questionnaire, EEG, and ECG.

A perceived fatigue and discomfort questionnaire was used for physical and mental fatigue estimation. As shown in Appendix A, a questionnaire was developed based on an existing fatigue questionnaire (Åhsberg et al., 1997; Grant et al., 1999). Each participant was asked to fill out the perceived fatigue and discomfort questionnaire before they started the driving task and every 30 minutes during the driving task. Discomfort at each part of the body, feeling over-drained, being uninterested, and having stiff joints, tense muscles, drowsiness, sleepiness, and numbness were used to measure both physical and mental fatigue. Participants were asked to rate from 0 to 10 on those fatigue measures. Overall feelings of discomfort were also used in the questionnaire since they could reflect both physical and mental fatigue. Perceived discomfort was related to fatigue measured by EMG (Bosch et al., 2007), and the exposure to discomfort was related to fatigue and less alertness (Griefahn & Künemund, 2001). Participants were asked to mark their overall feelings of discomfort on a line with a scale of 0 to 100.

Physiological signals, including EEG and ECG, were used to measure fatigue. EEG is one of the widely used indicators for mental fatigue detection. Alpha, (alpha+theta)/beta, and theta/alpha were used to evaluate the development of mental fatigue in the participants (Cao et al., 2014; Lal & Craig, 2001). HR per minute was measured and used to detect fatigue. Both time domain and frequency domain analysis of HRV were used to measure the development of mental fatigue. Overall, ECG data, including HR, SDNN, pNN50, and LF/HF, were used as the measurement of fatigue in this study. Video recordings were also collected to analyze the driver's behavior and eye movements.

3.6 Study One: Comparing Young Drivers to Adult New Drivers

Although there is a difference between young drivers and new drivers, not many studies have considered young drivers and new drivers as two separate groups. Findings on how experience will affect driving performance among young drivers were mixed. While Williams (2003) found that both age and experience play a role in young drivers' risky driving behaviors, Yeung & Wong (2015) believe that experience does not have any effect on young drivers. To understand if it is the age difference or the experience difference that affects young drivers' fatigue development, a pilot study was first conducted to compare young drivers with both the adult experienced driver group and the adult new driver group.

A total of 15 participants were recruited for this study. There were 4 adult experienced drivers, 2 adult new drivers, and 9 young drivers. The experienced adult drivers' average age was 26.25 (*SD* =0.957), and they all drove daily with more than 6 years of experience. The adult new drivers' average age was 23.5 (*SD* = 3.53), and the average time they had had their driver's license was 2.75 months. The young drivers had an average age of 18.5 (*SD* = 0.517) years old. A 2 by 2 by 3 design was used with 2 levels of driving mode, 2 levels of workloads, and 3 levels of participant groups. Table 1 below shows the design of the experiment with the number of participants tested for each scenario filled in:

Table 1 The 3 by 2 by 2 Design of Study One

Driving mode	Workload	Adult experienced	Young new	Adult new
Automated driving	**Low workload (Baseline)**	3	3	2
	High workload	3	2	2
Manual driving	**Low workload (Baseline)**	3	2	2
	High workload	3	2	2

The perceived fatigue and discomfort questionnaire, EEG, HR, SDNN, pNN50, LF/HF, and video recording were used to measure fatigue for this study.

3.7 Study Two: Young Drivers vs. Adult Drivers

Based on the results of the first study, a second study was conducted with only two groups of participants: adult drivers and young drivers. A 2 by 2 by 2 design with 2 levels of driving mode, 2 levels of workload, and 2 levels of participant groups was used. The perceived fatigue and discomfort questionnaire, HR, SDNN, pNN50, LF/HF, and video recording were used to measure fatigue.

A total of 32 participants were recruited for this study. There were 16 adult drivers with an average age of 26.25 (*SD* = 2.864) and 16 young drivers with an average age of 18.5 (*SD* = 0.516). For each driving mode, workload, and age combination, 4 participants were randomly assigned. On average, adult drivers had had their license for 80.43 (*SD* = 38.36) months and young drivers had had their license for 24.09 (*SD* = 38.36) months.

3.8 Data Analysis

Since different people have a different baseline on their perceived fatigue and discomfort, the changes between their before-task measurements and during-task/after-task measurements were used rather than the absolute value of between-task and after-task. The before-task data were subtracted from the during-task and after-task data to balance the difference on the baseline of each participant. After the subtraction, the adjusted scale was from -10 to 10 for the perceived fatigue and -100 to 100 for overall discomfort. The -10 on adjusted perceived fatigue means that they rated 10 at the beginning and 0 after/during the task, while 10 on adjusted perceived fatigue means that they rated 0 at the beginning and 10 after/during the task. The -100 on adjusted overall discomfort means that they rated 0 at the beginning and 100 after/during the task, while 100 on adjusted overall discomfort means they rated 100 at the beginning and 0 after/during the task. The adjusted fatigue changes at 30 minutes, 60 minutes, and 90 minutes of driving were put in tableau to have a visualized result.

The RR interval was acquired from the H10. HR and HRV were calculated from the RR interval using the Elite HRV. The HRV spectral analysis needs the raw data to be at least 2 minutes long to ensure the accuracy of the analysis (Malik, 1996). Ten minutes of data were used to calculate the HRV to ensure accuracy. Overall, the HR, SDNN, pNN50, and LF/HF were calculated based on the following equations:

$$SDNN = \sqrt{\frac{\sum(RR_i - \mu)^2}{N}} \tag{1}$$

Where N is the number of the RR intervals, RR_i was ith RR interval, and μ was the mean of all RR intervals.

$$pNN50 = \frac{NN50\ count}{total\ NN\ count} \tag{2}$$

Where the NN50 was the NN intervals that differ by more than 50 ms.

$$LF/HF = \frac{power\ of\ the\ low\ frequency\ band}{power\ of\ the\ high\ frequency\ band} \tag{3}$$

Different people could have a different absolute value of HR and HRV based on different personal characteristics, such as age, gender, etc. (Malik, 1996), so it is not preferable to directly compare HRV with other subjects. Instead, HR and HRV changes at 60 minutes and 90 minutes compared with their HR and HRV data at 30 minutes of driving were calculated.

After getting the raw data from the EPOC+, the EEG data were cleaned for noise first. The fast Fourier transform (FFT) was performed to get the band power information on the alpha, beta, theta, and delta bands. Theta/alpha and (alpha-theta)/beta were calculated. Due to the individual differences, the changes at 60 and 90 minutes compared with their baseline at 30 minutes were used.

The data acquired from the video recordings were defined as follows: number of crashes: how many times the participants had a crash; number of near crashes: how many times participants had a near crash (automated driving mode: too close to the crossing pedestrians or other traffic; manual driving mode: lost control of the vehicle but did not cause any crash); number of eyes off the road: how many times participants had their eyes off the screen; eyes off road time: how long in total the participants' eyes were off the screen in seconds; average eyes off road time: eyes off road time/number of eyes off road; number of missed takeovers: how many times the participants were supposed to take over but missed the takeover; number of takeovers: how many times the participants were supposed to take over and they did take over; number of successful takeovers: how many times a takeover is needed and the participants successfully take over without causing any crashes. The video-recorded driving scenes were manually reviewed based on the definitions mentioned above and recorded in an excel file.

Takeover rate and successful takeover rate were calculated for the automated driving mode as shown in Equations 4 and 5.

$$Takeover\ rate\ = \frac{number\ of\ takeovers}{number\ of\ crashes\ +\ number\ of\ near\ crashes} \tag{4}$$

$$Successful\ takeover\ rate = \frac{number\ of\ successful\ takeovers}{number\ of\ crashes\ +\ number\ of\ near\ crashes} \tag{5}$$

Since study one does not have enough data collected on which to perform statistical analysis and hypothesis testing, mean and standard deviation were calculated for each value to compare the differences between each group.

In study two, ANOVA was used to test the difference between the groups. The assumptions were checked before the ANOVA was conducted. Four assumptions were required to perform a factorial ANOVA: interval independent data, normality, homoscedasticity, and no multicollinearity. All the independent data in this study including perceived fatigue rating, HR, SDNN, pNN50, LF/HF, number of crashes/near crashes, number of takeovers/missed takeovers, takeover rates, successful takeover rates, and eyes off the road time are all interval data, which fulfill the first assumption of ANOVA analysis. Since the age, automated scenarios, and workload do not have any correlations between each other, no multicollinearity was also fulfilled for the study. Normality and homoscedasticity were tested by statistical hypothesis testing.

There are almost 40 different methods available to check the normality of the data (Dufour et al., 1998). For example, the Kolmogorov-Smirnov test, Shapiro-Wilk test, Lilliefors test, and Anderson-Darling test are some commonly used tests. For the Anderson-Darling test, which can check whether the data are drawn from a given distribution, Anderson & Darling (1954) first defined the statistics of this test as followed:

$$AD = n\int_{-\infty}^{\infty}[F_n(x) - F^*(x)]^2\psi(F^*(X))dF^*(x) \tag{6}$$

Arshad et al. (2003) later modified the equation to simplify the calculation:

$$AD = -n - \frac{1}{n}\sum(2i-1)\{\log F^*(X_i) + \log(1 - F^*(X_{n+1-i})\} \tag{7}$$

Where $F^*(x_i)$ is the cumulative distribution function of the specified distribution, x_i are the ordered data, and n is the sample size. The p-value then is determinate based on the value of AD (D'Agostino & Stephens, 1986):

$$p = \begin{cases} e^{(1.2937-5.709AD+0.0186AD^2)}, & if\ s \geq 0.6 \\ e^{(0.9177-4.297AD \quad .38AD^2)}, & if\ 0.34 < s < 0.6 \\ 1 - e^{(-8.318+42.796AD-59.938AD^2)}, & if\ 0.2 < s < 0.34 \\ 1 - e^{(-13.436+101.14AD-223.73AD^2)}, & if\ s \leq 0.2 \end{cases} \tag{8}$$

The hypotheses of the Anderson-Darling test are:

H_0: The data follows the normal distribution

H_a: The data do not follow the normal distribution

The null hypothesis of the normality will be rejected if the p-value is less than 0.05. Razali & Wah (2011) found that the Anderson-Darling test is one of the more powerful tests for the normality test compared with the Kolmogorov-Smirnov test, Shapiro-Wilk test, and Lilliefors test. Thus, the Anderson-Darling test was used for the normality test in this study.

Levene's test was used to test the homoscedasticity of the data. Levene (1960) developed this test to check if k samples have equal variances, which is also called homogeneity of variance. The hypotheses of Levene's test are:

H_0: $\sigma_1^2=\sigma_2^2=\ldots=\sigma_k^2$

H_a: $\sigma_i^2\neq\sigma_j^2$ for at least one pair of i and j.

The test statistics of Levene's test are:

$$W = \frac{(N-k)}{k-1} \frac{\sum_{i=1}^{k} N_i(\overline{Z_{\iota.}} - \overline{Z}_{..})^2}{\sum_{i=1}^{k}\sum_{j=1}^{N_i} N_i(\overline{Z_{\iota J}} - \overline{Z_{\iota.}})^2} \tag{9}$$

Where $Z_{ij} = |Y_{ij} - \overline{Y}_{\iota.}|$, in which $\overline{Y}_{\iota.}$ can be mean, trimmed mean, or median of the ith subgroup; $\overline{Z_{\iota.}}$ are the group means of the Z_{ij}; and $\overline{Z}_{..}$ is the overall mean of the Z_{ij}. The hypothesis will be rejected if the variance is equal when $W > F_{\alpha, k-1, N-k}$.

Once all the assumptions were checked, a 2 by 2 by 2 factorial ANOVA was performed on the measures that satisfied the assumptions. A (-1,0,1) coding system was used such that each coefficient represents the difference between each level mean and the overall mean.

If the measure did not fulfill the assumptions of ANOVA, a non-parametric test was used. Three non-parametric tests are known to be alternatives to ANOVA: the Kruskal-Wallis test, Mood’s median test, and Friedman test. The Friedman test is used to analyze randomized block experiments, while both the Mood’s median and Kruskal-Wallis test the equal medians for one-way designs. Compared with the Kruskal-Wallis test, the Mood’s median test is more resilient to the outliers and errors in data; however, it is less powerful. Since the data collected had already been cleaned of errors, the Kruskal-Wallis test was used. Kruskal & Wallis (1952) developed the test statistics as follows:

$$H = \frac{12}{N(N+1)} \sum_{j=1}^{k} \left(\frac{R_j^2}{n_j}\right) - 3(N+1) \tag{10}$$

Where $N = \sum_{j=1}^{k} n_j$, in which n_j is the number of samples for each group, k is the number of groups, and R_j is the rank sum of each sample.

The hypotheses of the Kruskal-Wallis test are:

H_0: $S_1 = S_2 = \ldots\ldots = S_k$

H_a: $S_i \neq S_j$ for at least one pair of i and j.

The null hypothesis will be rejected when $H > \chi^2_{\alpha, k-1}$.

On top of the Kruskal-Wallis test, data that does not follow the normal distribution were also transformed to perform the ANOVA analysis. Two data transformation methods, Box-cox transformation(Cook & Weisberg, 1999) and Johnson transformation(Yeo & Johnson, 2000) have were commonly used to transform the nonnormal distributed data to the normal distribution. Compare with the Box-cox transformation, Johnson transformation does not have restriction on the data. Since the data used in this study includes the negative numbers, Johnson transformation was used. Johnson transformation can be defined as:

$$\psi(\lambda, y) = \begin{cases} \dfrac{(y+1)^{\lambda} - 1}{\lambda} & , if \lambda \neq 0, y \geq 0 \\ \log(y+1) & , if \lambda = 0, y \geq 0 \\ \dfrac{-[(-y+1)^{2-\lambda} - 1]}{2-\lambda} & , if \lambda \neq 2, y < 0 \\ -\log(-y+1) & , if \lambda = 2, y < 0 \end{cases} \tag{11}$$

Where y is the list of number you need to transform and λ can be defined based on the type of transformation you need.

Chapter 4 Results

4.1 Study One: Comparing Young Drivers to Adult New Drivers?

4.1.1 Perceived Fatigue and Discomfort Questionnaire Results

The discomfort rating for each part of the body was compared between the young driver group and the adult driver groups, and no significant difference was found in the ratings. Figure 11 and Figure 12 show the averaged adjusted overall feeling about the simulated drive. The adjusted overall feeling is on a scale of 100 to -100, where 100 means participants feel more comfortable compared with the time before they started driving, while 0 means they feel the same as the time before they started driving and -100 means they feel extreme discomfort. Similar to the adjusted overall feeling, the adjusted over-drained was on a -10 to 10 scale, where -10 means participants felt better and 10 means they felt extremely over-drained.

Figure 11 shows the adjusted ratings on overall feeling and feeling over-drained under automated driving mode. There is a clear trend that the young drivers had earlier fatigue onset (at 60 minutes) and a higher level of fatigue compared with the adult groups. For the high workload after 30 minutes, ratings for over-drained and overall feeling for adult experienced drivers were only 0.33 and -11.17 points lower than the young drivers. After 60 minutes, young drivers started showing more fatigue than adult experienced drivers. Ratings for over-drained and overall feeling for adult experienced drivers were 4.77 and -53.17 points lower than young drivers. After 90 minutes of driving, the difference for over-drained and overall feeling between adult experienced and young drivers went to 4.33 and -68 points.

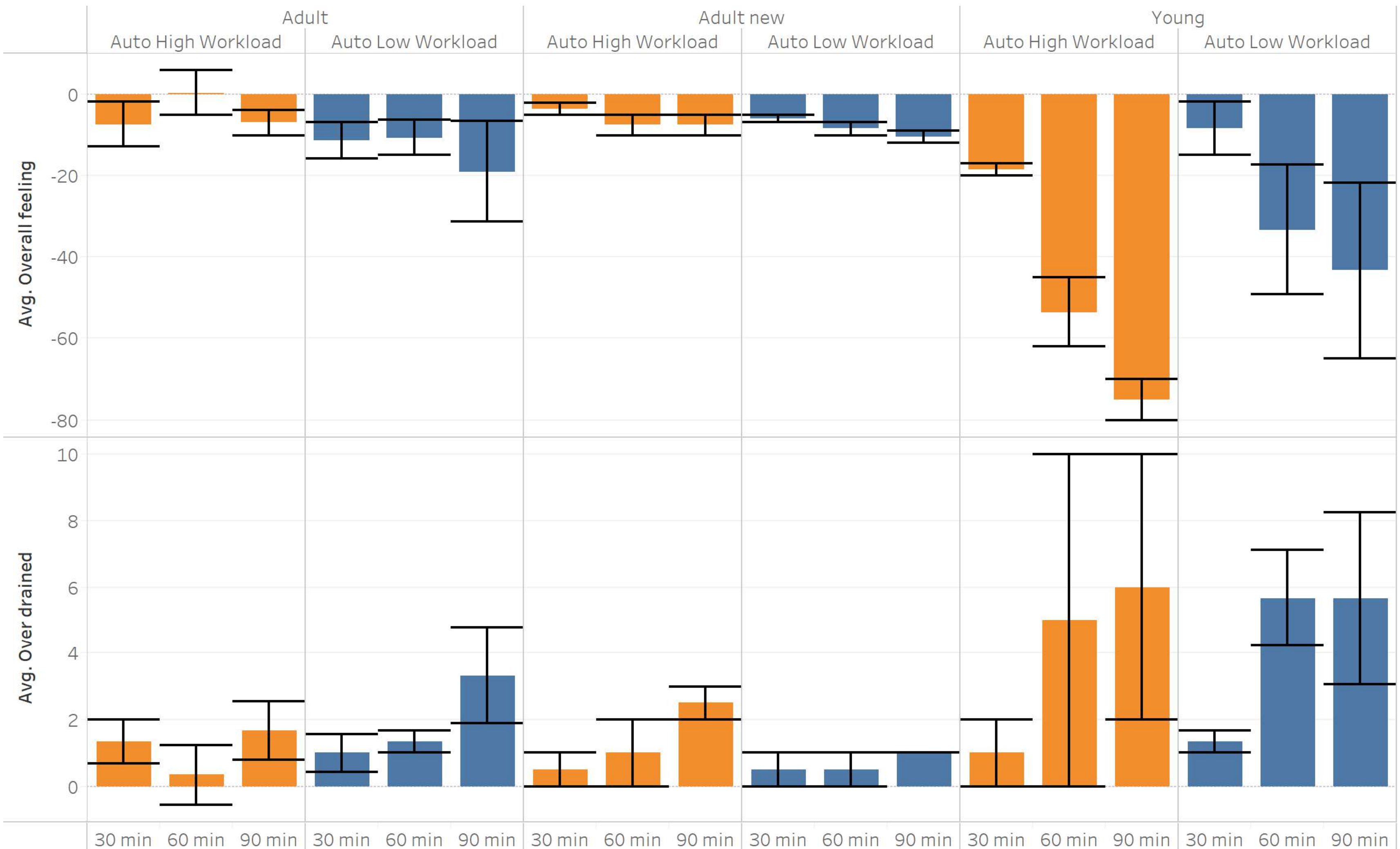


Figure 11. Comparison of Overall Feeling and Feeling Over-Drained with Error Bar for Automated Driving

No significant difference was observed between adult new drivers and adult experienced drivers. For the high workload after 30 minutes, ratings for over-drained and overall feeling for adult new drivers were only 0.5 and -15 points lower than the young drivers. After 60 minutes, young drivers started showing more fatigue than adult new drivers. Over-drained and overall feeling ratings for adult new drivers were 4 and -46 points lower than young drivers. After 90 minutes of driving, the difference for over-drained and overall feeling between adult new and young drivers went to 3.5 and -67.5 points.

A similar trend was found for the automated low-workload scenario. Over-drained and overall feeling ratings for adult experienced drivers were only 0.33 and 3 points lower than young drivers after 30 minutes of driving. After 60 minutes, young drivers started showing more fatigue than adult drivers. Over-drained and overall feeling ratings for adult experienced drivers were 4.34 and -22.66 points lower than young drivers. At 90 minutes of driving, the difference for over-drained and overall feeling ratings between adult experienced drivers and young drivers went to 2.34 and -24.33 points. Over-drained and overall feeling ratings for adult new drivers were only 0.83 and -2.33 points lower than young drivers after 30 minutes of driving. After 60 minutes, young drivers started showing more fatigue than adult new drivers. Over-drained and overall feeling ratings for adult new drivers were 5.17 and -24.80 points lower than young drivers. At 90 minutes of driving, the difference for over-drained and overall feeling ratings between adult experienced drivers and young drivers went to 4.67 and -32.80 points.

Comparing the low workload and high workload among young drivers shows that the young drivers felt more drained and less comfortable when the workload was high.

Figure 12 shows the adjusted ratings on overall feeling and feeling over-drained under manual driving mode.

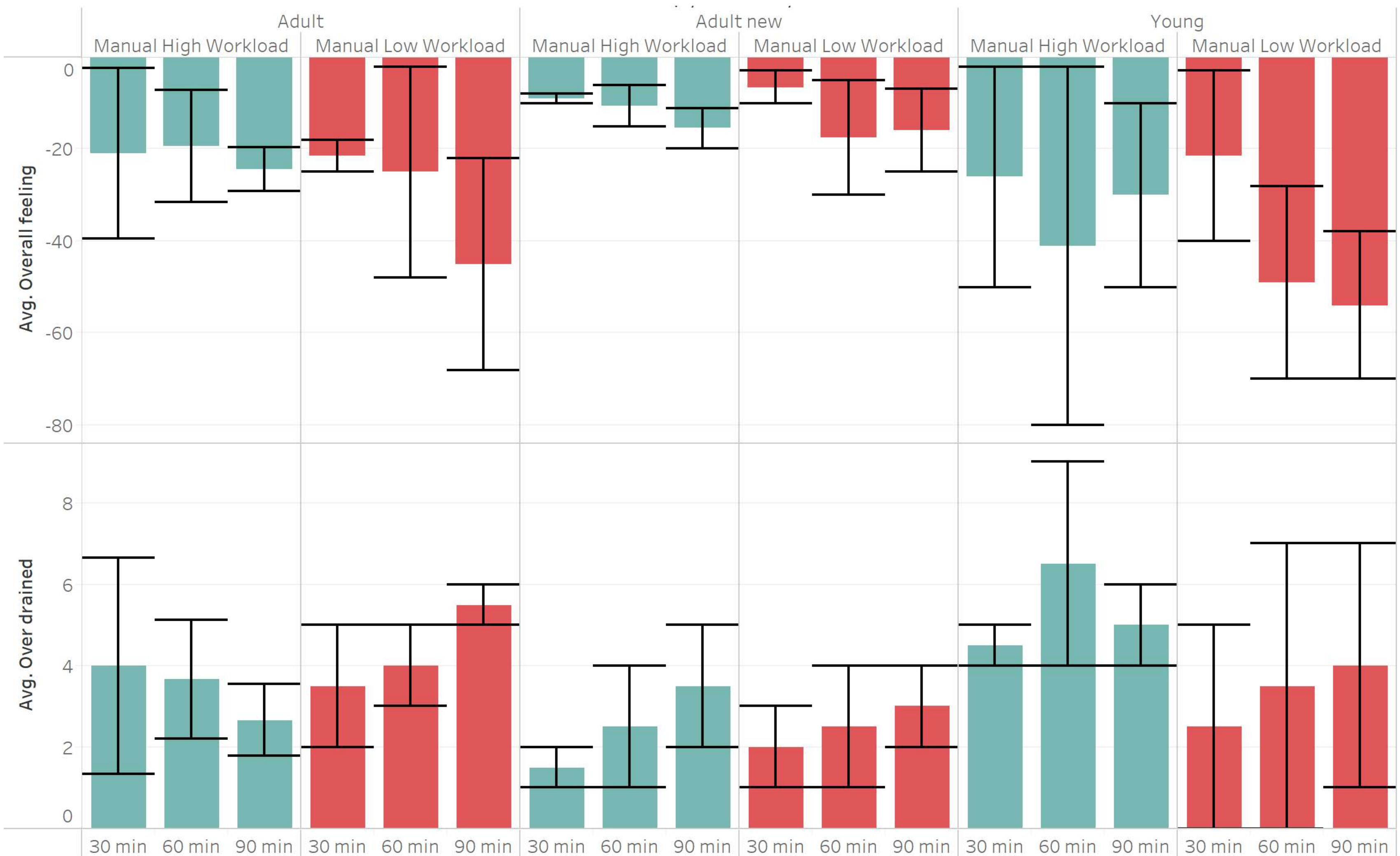


Figure 12. Comparison of Overall Feeling and Feeling Over-Drained with Error Bar for Manual Driving

Similar results were found for the manual driving mode as for the automated driving mode. Young drivers developed fatigue faster and more severely than both adult experienced drivers and adult new drivers. At 30 minutes of the manual high workload, overall feeling rating for young drivers was 17 points lower than adult new drivers and 5 points lower than adult experienced drivers. The difference got even bigger at 60 minutes of driving, where young drivers were 21.7 points lower than adult experienced drivers and 30.5 points lower than adult new drivers. At 90 minutes of driving, overall feeling rating for young drivers was 5.77 points higher than adult experienced drivers and 14.5 points higher than adult new drivers. For the over-drained ratings, at 30 minutes of driving, young drivers were 0.5 points lower than adult experienced drivers but 3 points higher than adult new drivers. At 60 minutes of driving, young drivers were 2.83 points higher than adult experienced drivers and 4 points higher than adult new drivers. After 90 minutes of driving, young drivers were 2.33 points higher than adult experienced drivers and 1.5 points higher than adult new drivers.

Similar results were also found in the manual low workload. At 30 minutes of driving, young drivers rated their overall feeling 15 points lower than adult new drivers but the same as adult experienced drivers. At 60 minutes of driving, the difference for overall feeling between young drivers and adult new and adult experienced drivers went up to 31.5 points and 14 points. After 90 minutes of driving, young drivers rated their overall feeling 38 points higher than adult new drivers and 9 points higher than experienced drivers. The young drivers rated the over-drain less than adult experienced drivers but still higher than adult new drivers. At 30 minutes of driving, young drivers were 1 point lower than adult experienced drivers but 0.5 points higher than adult new drivers. At 60 minutes of driving, young drivers were 0.5 points lower than adult experienced drivers but 1 point higher than adult new drivers. After 90 minutes of driving, young drivers were 1.5 points lower than adult experienced drivers and 1 point higher than adult new drivers.

Figure 13 shows the results of the adjusted subjective mental fatigue rating under automated driving mode. The results of the drowsiness, sleepiness, and uninterested ratings were consistent with the overall feeling, in which the young drivers had an earlier onset of fatigue and the overall fatigue level by the end of the task was also higher compared to the adult groups. Young drivers' fatigue onset was clear from 30 minutes of high-workload driving. Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 3.5, 5, and 4.17 points lower and ratings for adult new drivers were 4, 4, and 5 points lower than young drivers after 30 minutes of driving. After 60 minutes of driving, drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 3.67, 4.17, and 3 points lower than young drivers, while ratings for adult new drivers were 3, 3, and 5 points lower than young drivers. After 90 minutes of driving, the differences for drowsiness, sleepiness, and uninterested ratings between adult experienced drivers and young drivers went to 2.67, 4.33, and 4.33 points, and the differences between adult new drivers and young drivers were 2.5, 3, and 4 points.

A similar trend was found for the low-workload scenario. Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were only 0.33, 0.67, and -1.67 points lower than young drivers after 30 minutes of driving. Adult new drivers were 4, 1.17, and 0.5 points lower compared with young drivers. After 60 minutes, young drivers started showing more fatigue than adult drivers on all three measures. Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 4, 1.77, and 2.67 points lower than young drivers, while ratings for adult new drivers were 6.67, 4, and 5.5 points lower than young drivers.

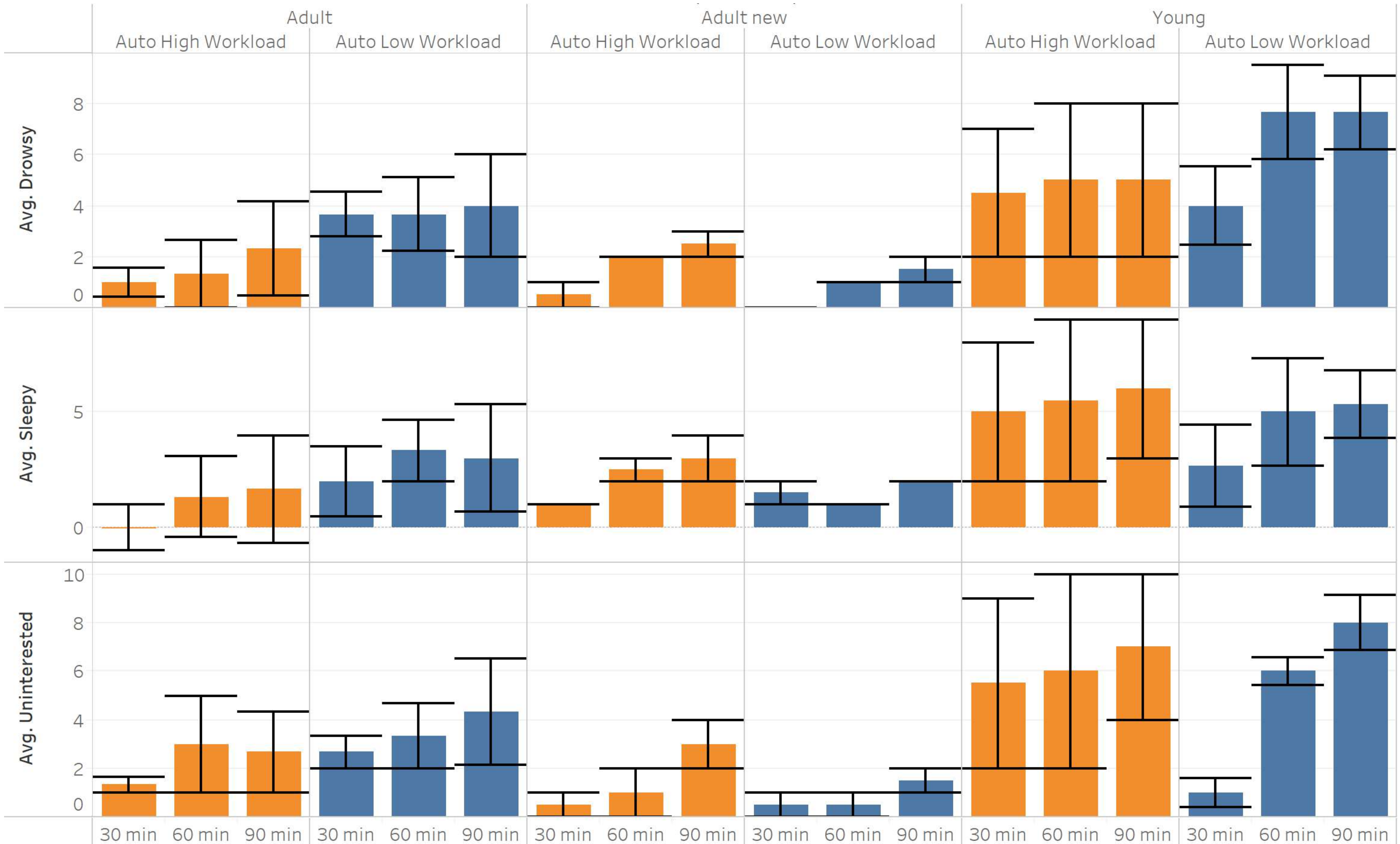


Figure 13. Subjective Mental Fatigue with Error Bar for Automated Driving

After 90 minutes of driving, the differences for drowsiness, sleepiness, and uninterested ratings between adult experienced drivers and young drivers went to 3.67, 2.33, and 3.67 points, and the differences between adult new drivers and young drivers went to 6.17, 3.33, and 6.5 points. For both high workload and low workload, adult new drivers' ratings were significantly lower than for the young driver group. Among the young drivers, they felt drowsier when they were at the low workload compared with the high workload.

Figure 14 shows the results of the adjusted subjective mental fatigue ratings under manual driving mode. The results of the drowsiness, sleepiness, and uninterested ratings were consistent with the overall feeling, in which the young drivers had an earlier onset of fatigue and the overall fatigue level by the end of the task was also higher compared with the adult groups. Adult new drivers showed a significant difference from young drivers for both high workload and low workload. Young drivers' fatigue onset was clear from 30 minutes of high-workload driving. Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 2.17, 3.17, and 2 points lower and ratings for adult new drivers were 3, 4, and 3 points lower than young drivers after 30 minutes of driving. After 60 minutes of driving, drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 3.67, 4.17, and 3 points lower than young drivers, while ratings for adult new drivers were 3, 3, and 5 points lower than young drivers. After 90 minutes of driving, the differences for drowsiness, sleepiness, and uninterested ratings between adult experienced drivers and young drivers went to 1, 1.5, and 1.77 points, and the differences between adult new drivers and young drivers were -1, -0.5, and 1.5 points.

For the manual low workload, adult experienced drivers had a higher rating, but adult new drivers still had a lower rating compared with young drivers.

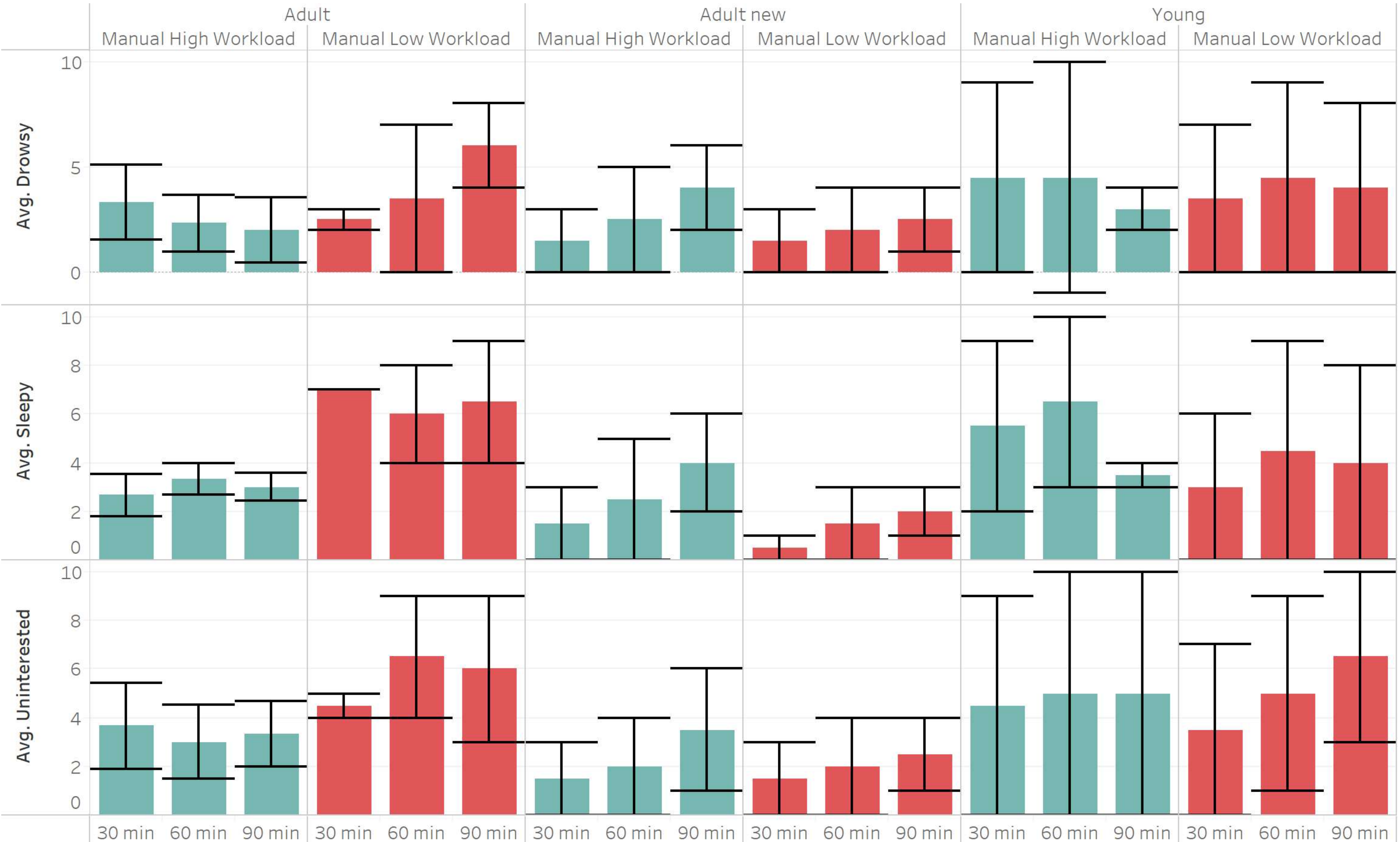


Figure 14. Subjective Mental Fatigue with Error Bar for Manual Driving

Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 1, -4, and -1 points lower than the young drivers after 30 minutes of driving. Drowsiness, sleepiness, and uninterested ratings for adult new drivers were 2, 2.5, and 2 points lower compared with young drivers. After 60 minutes, young drivers started showing more fatigue than adult drivers on all three measures. Drowsiness, sleepiness, and uninterested ratings for adult experienced drivers were 1, -1.5, and -1.5 points lower than young drivers, while ratings for adult new drivers were 2.5, 3, and 3 points lower than young drivers. After 90 minutes of driving, the difference for drowsiness, sleepiness, and uninterested ratings between adult experienced drivers and young drivers went to -2, -2.5, and 0.5 points, and the difference between adult new drivers and young drivers went to 1.5, 2, and 4 points from young drivers. For both high workload and low workload, adult new drivers' ratings were significantly lower than those of the young drivers group. Among the young drivers, they felt drowsier when they were at the low workload compared with the high workload.

Figure 15 shows the results of the perceived adjusted physical fatigue under automated driving. The results were consistent with overall feeling and mental fatigue. Young drivers had an earlier onset of fatigue compared with the adult groups. The adult new group has significant differences compared with the young driver group. Among different driving conditions, young drivers are more likely to have stiff joints and numbness under high workload and tense muscles for both low workload and high workload.

For the high-workload driving, young drivers had a higher fatigue rating from the first 30 minutes of driving compared with both adult experienced drivers and adult new drivers.

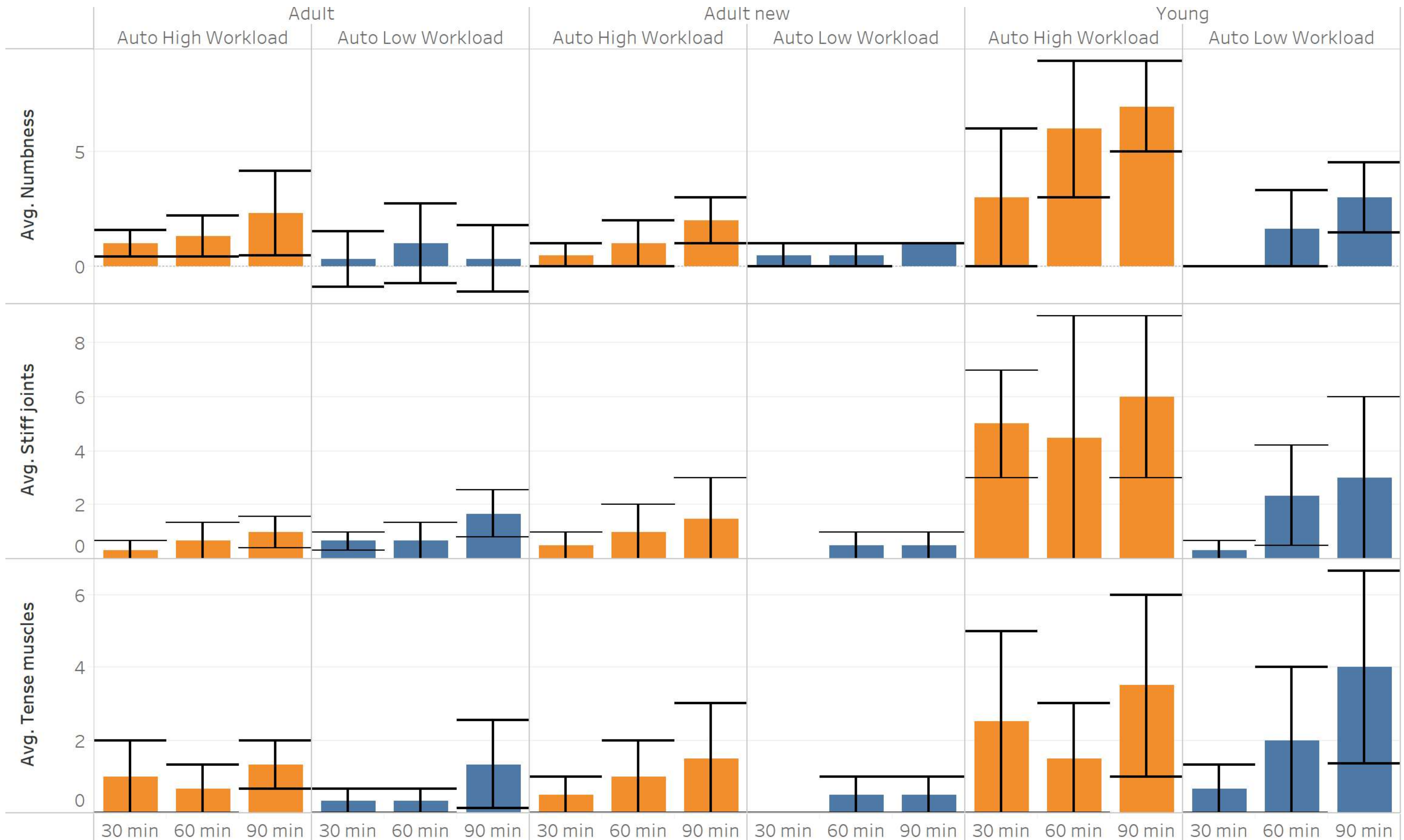


Figure 15. Physical Fatigue with Error Bar for Automated Driving

At 30 minutes of driving, numbness, stiff joints, and tense muscles ratings for adult experienced drivers were 2, 4.77, and 1.5 points lower than young drivers, and ratings for adult new drivers were 2.5, 4.5, and 2 points lower than young drivers.After 60 minutes of driving, the differences for numbness, stiff joints, and tense muscles ratings between adult experienced drivers and young drivers were 4.67, 3.83, and 0.83 points, while the difference for ratings between adult new drivers and young drivers were 5, 3.5, and 0.5 points. After 90 minutes of driving, the differences for numbness, stiff joints, and tense muscles ratings between adult experienced drivers and young drivers were 4.67, 5, and 2.17 points, and the difference for ratings between adult new drivers and young drivers were 5, 4.5, and 2 points.

For the first 30 minutes of driving at low workload, numbness, stiff joints, and tense muscles ratings for adult drivers were not too much different from the young drivers. At 60 minutes of driving, the differences for numbness, stiff joints, and tense muscles ratings between adult experienced drivers and young drivers went up to 0.67, 1.66, and 1.67 points, and the differences between adult new drivers and young drivers were at 1.17, 1.83, and 1.5 points. At 90 minutes of driving, the differences numbness, stiff joints, and tense muscles ratings between adult experienced drivers and young drivers went to 2.67, 1.33, and 2.77 points, and the differences between adult new drivers and young drivers were 2, 2.5, and 3.5 points. Among young drivers, they had more physical fatigue under the high workload compared with the low workload, while the adult physical fatigue was similar between different workloads.

Figure 16 shows the results of the perceived adjusted physical fatigue under manual driving mode. No significant difference has been observed between young driver and the adult driver groups on stiff joints and numbness.

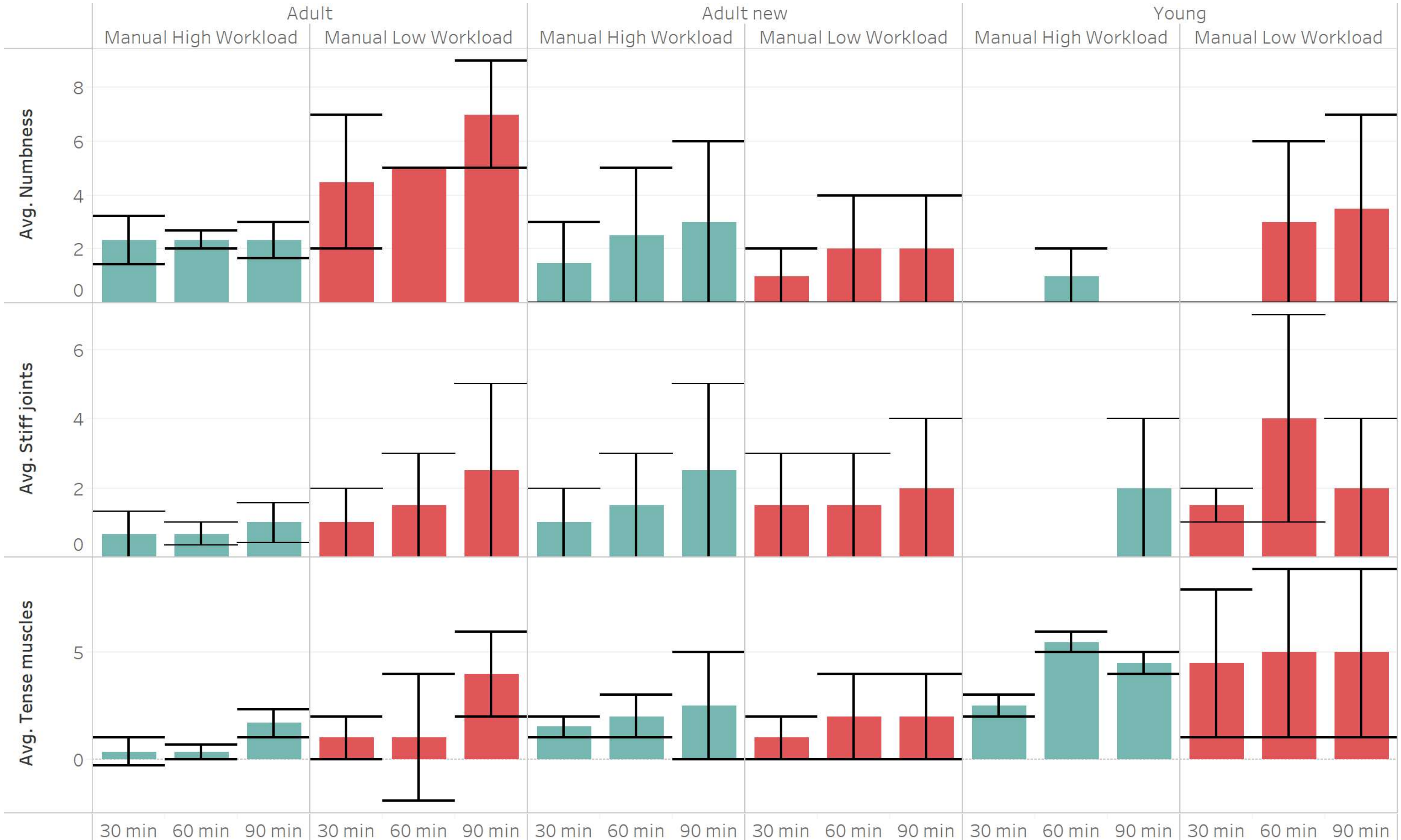


Figure 16. Physical Fatigue with Error Bar for Manual Driving

However, young drivers still show higher ratings on tense muscles compared with the adult driver groups. For the high workload, at 30 minutes, adult experienced drivers and adult new drivers rated 2.17 and 1 points lower than young drivers on tense muscles. At 60 minutes, adult experienced drivers and adult new drivers rated 5.17 and 3.5 points lower than young drivers. After 90 minutes of driving, the difference between adult driver groups and the young driver group went to 2.83 and 2 points.

4.1.2 ECG Results

The ECG data show a different trend among young drivers compared with the adult group. Figure 17 shows that under automated driving the young drivers' group had a higher HR decrease at 60 minutes of driving, and the decrease got even worse at 90 minutes of driving. At 60 minutes of driving, young drivers decreased 3 points at high workload while adult experienced drivers decreased 2.33 points and adult new drivers decreased 4 points. Such decrease went up to 4 points for young drivers but only 3.33 points for adult experienced drivers and 0.5 points for adult new drivers at 90 minutes of driving. For the low workload, at 60 minutes, young drivers decreased 3 points while adult experienced drivers decreased 0 points and adult new drivers decreased 3.5 points. At 90 minutes of driving, young drivers decreased 6.5 points while adult experienced drivers decreased only 4.33 points and adult new drivers decreased 4 only points. For manual driving modes, young drivers had a higher HR decrease than adult driver groups, especially for the high workload. At 60 minutes of driving, young drivers decreased 4 points, while adult experienced drivers decreased 2 points and adult new drivers increased 0.5 points. At 90 minutes of driving, young drivers decreased 5 points, while adult experienced drivers decreased 1.67 points and adult new drivers decreased 0.5 points. Figure 18 shows the HR decreasing data under manual driving modes.

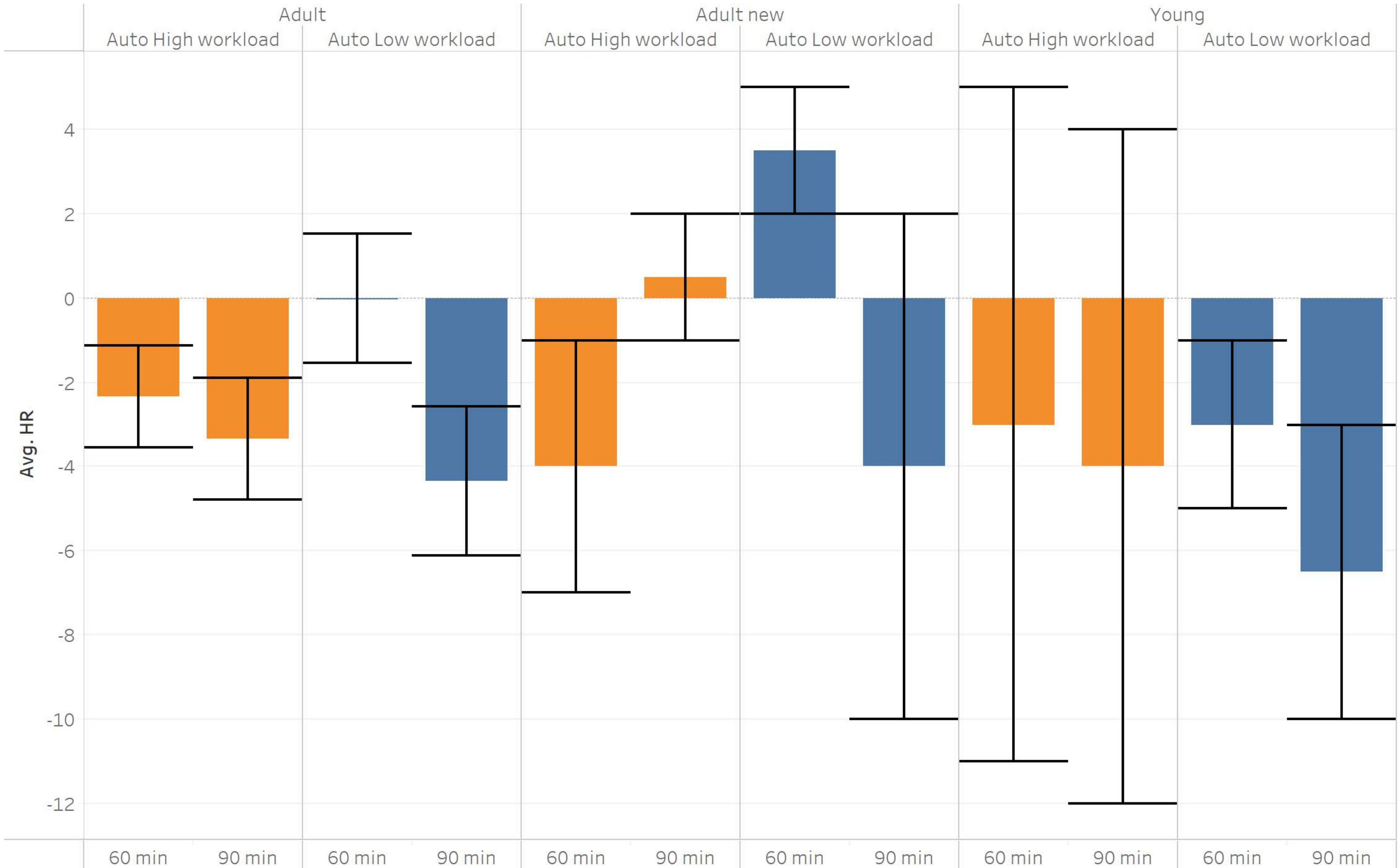


Figure 17. HR Decreasing under Automated Driving

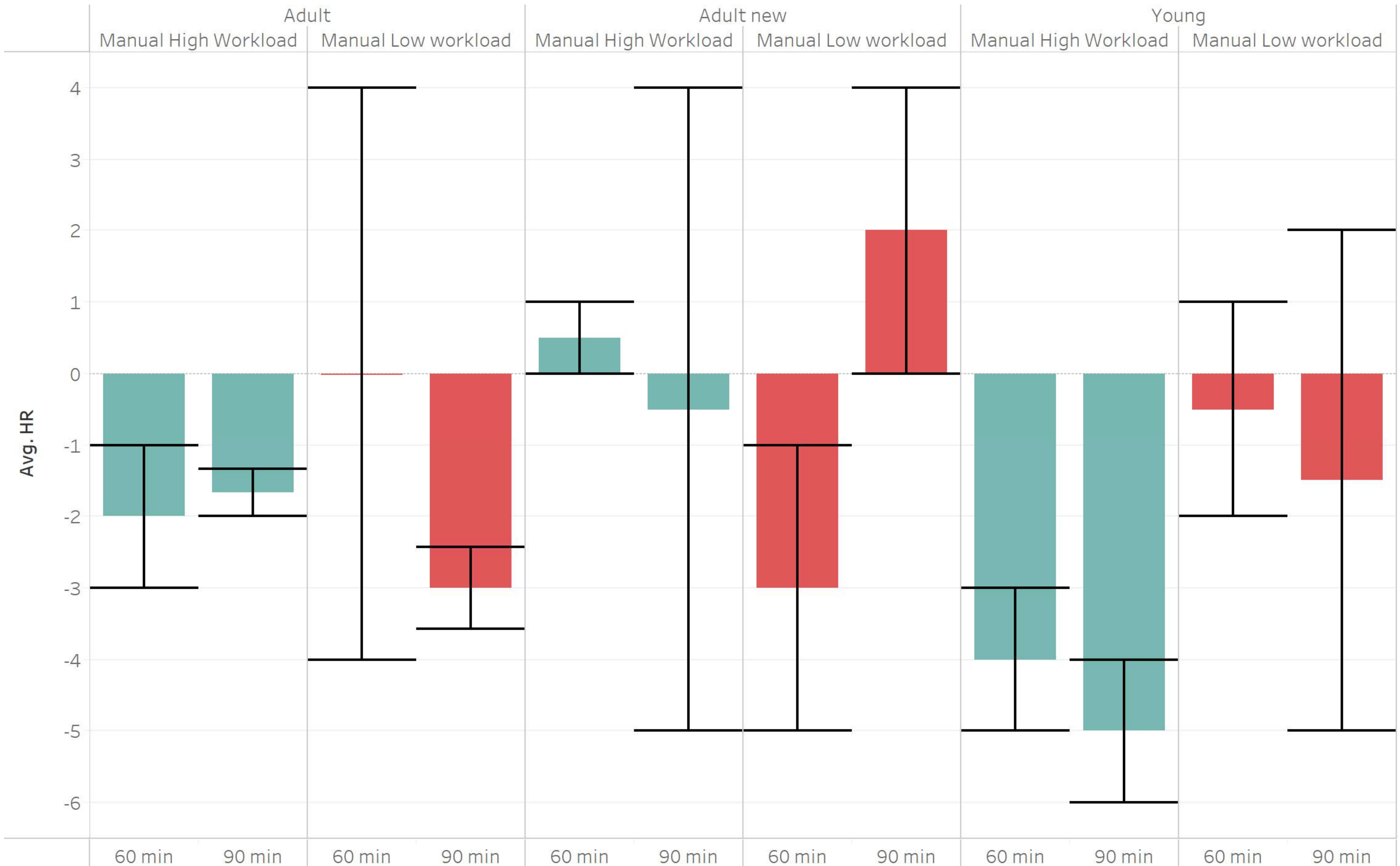


Figure 18. HR Decreasing under Manual Driving

Figure 19 shows the time domain analysis of HRV. The HRV time domain shows that the young drivers had an increase in SDNN and pNN50 compared with adults. The level of SDNN and pNN50 was also higher by the end of the task for young drivers compared with other groups. For the high workload, at 60 minutes of driving, average SDNN changes for young drivers was 34.26, while the average for adult experienced drivers was 4.51 and the average for adult new drivers was 9.04. At 90 minutes of driving, average SDNN for young drivers was 53.04, while the average for adult experienced drivers was 6.30 and the average for adult new drivers was 8.80. The increase from 60 minutes of driving to 90 minutes of driving was 18.17 for young drivers and only 1.79 for adult experienced drivers and -0.24 for adult new drivers. The low workload had similar trends to the high workload. After 60 minutes of driving, average SDNN for young drivers was 0.09, while the average for adult experienced drivers was 6.89 and the average for adult new drivers was 16.35. At 90 minutes of driving, average SDNN for young drivers was 19.69, while the average for adult experienced drivers was 9.02 and average for adult new drivers was 5.2. The increase from 60 minutes of driving to 90 minutes of driving was 19.6 for young drivers and only 2.13 for adult experienced drivers and -11.15 for adult new drivers.

A similar trend was found for pNN50. For the high workload, average pNN50 for young drivers was 0.12 at 60 minutes of driving, while the average for adult experienced drivers was 0.03 and the average for adult new drivers was 0. At 90 minutes of driving, average pNN50 for young drivers was 0.18, while the average for adult experienced drivers was 0.04 and the average for adult new drivers was 0.02. The increase from 60 minutes of driving to 90 minutes of driving was 0.06 for young drivers and only 0.01 for adult experienced drivers and 0.03 for adult new drivers. No clear trend was found for the low workload.

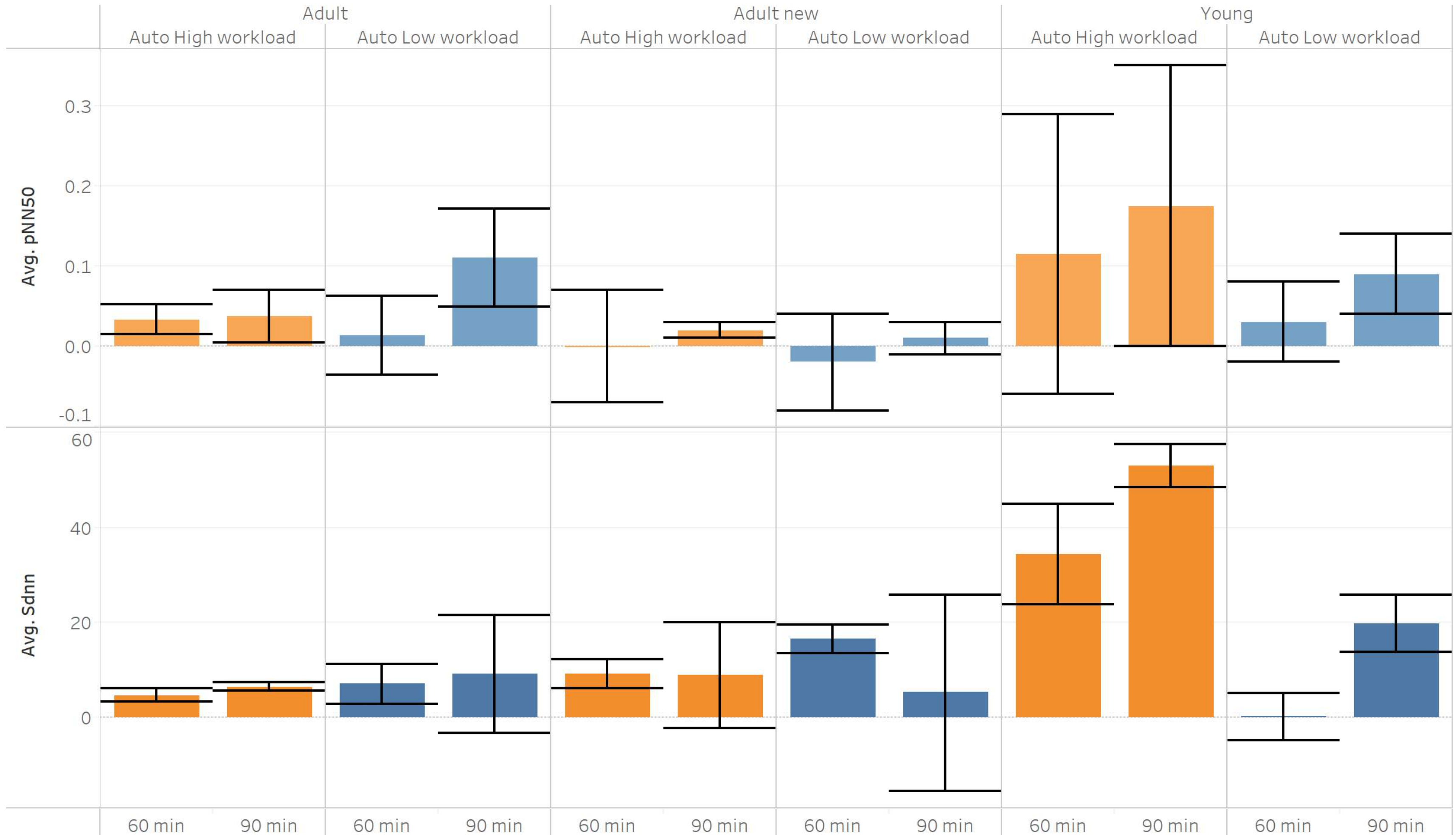


Figure 19. HRV Time Domain Analysis for Automated Driving

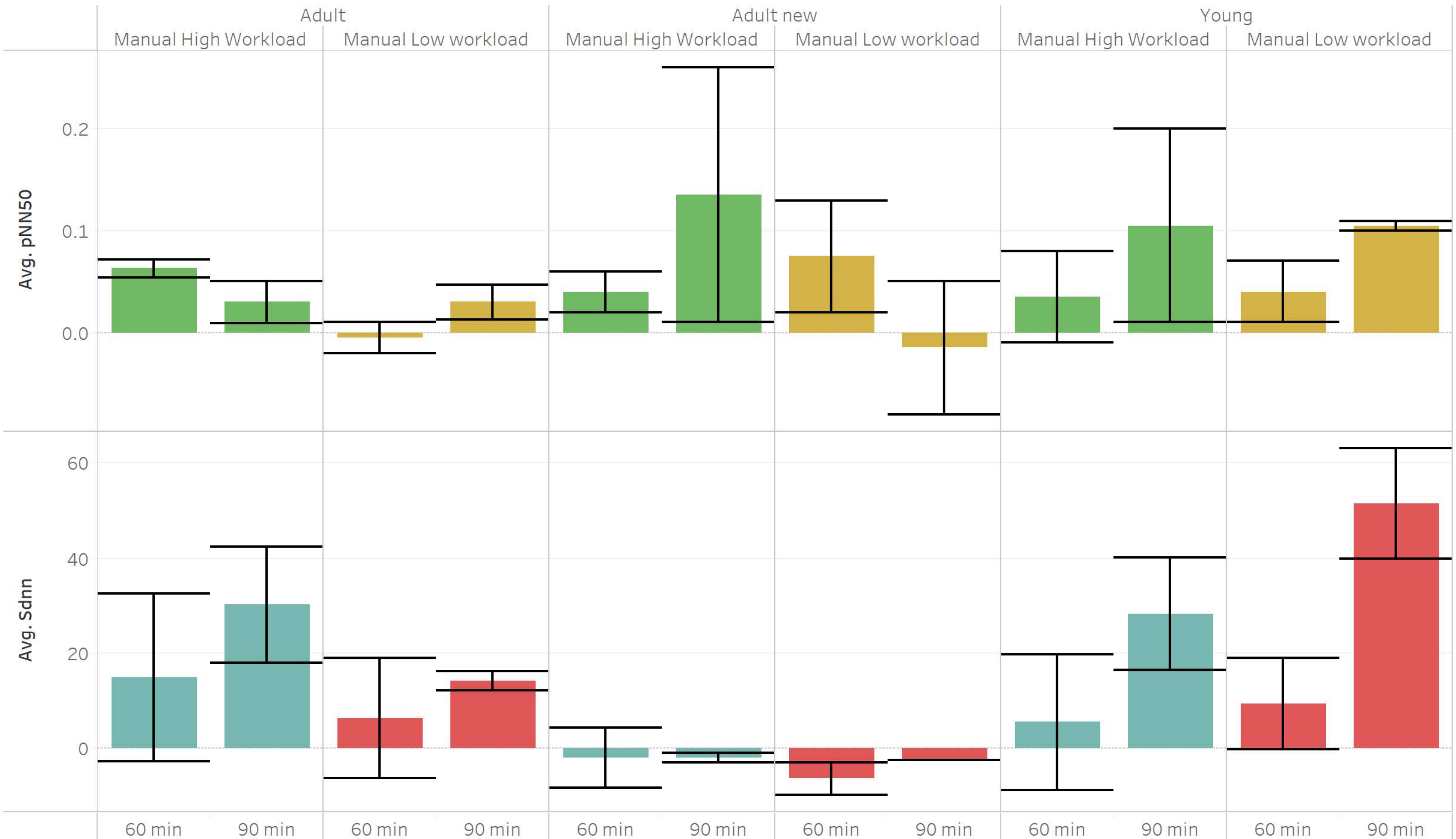


Figure 20. HRV Time Domain Analysis for Manual Driving

Among the manual driving results, young drivers had a higher increase in SDNN as well. For the high workload, at 60 minutes of driving, average SDNN for young drivers was 5.50, while the average for adult experienced drivers was 15 and the average for adult new drivers was -2.03. At 90 minutes of driving, average SDNN for young drivers was 28.30, while the average for adult experienced drivers was 30.2 and the average for adult new drivers was -1.96. The increase from 60 minutes of driving to 90 minutes of driving was 22.8 for young drivers and only 15.2 for adult experienced drivers and -0.06 for adult new drivers. The low workload had similar trends to the high workload. After 60 minutes of driving, average SDNN for young drivers was 9.33, while the average for adult experienced drivers was 6.3 and the average for adult new drivers was -6.4. At 90 minutes of driving, average SDNN for young drivers was 51.4, while the average for adult experienced drivers was 14.15 and the average for adult new drivers was -2.51. The increase from 60 minutes of driving to 90 minutes of driving was 42.07 for young drivers and only 7.85 for adult experienced drivers and 3.89 for adult new drivers.

PNN50 was found to increase more among young drivers under the manual low workload. Average pNN50 for young drivers was 0.04 at 60 minutes of driving, while the average for adult experienced drivers was -0.01 and the average for adult new drivers was 0.08. At 90 minutes of driving, average pNN50 for young drivers was 0.11, while the average for adult experienced drivers was 0.03 and the average for adult new drivers was -0.02. The increase from 60 minutes of driving to 90 minutes of driving was 0.05 for young drivers and only 0.04 for adult experienced drivers and -0.09 for adult new drivers. No clear trend was found for the low workload. No significant difference was found for the manual high workload.

Figure 21 and Figure 22 show the results of the frequency domain analysis for automated driving mode and manual driving mode. No clear difference was found between the

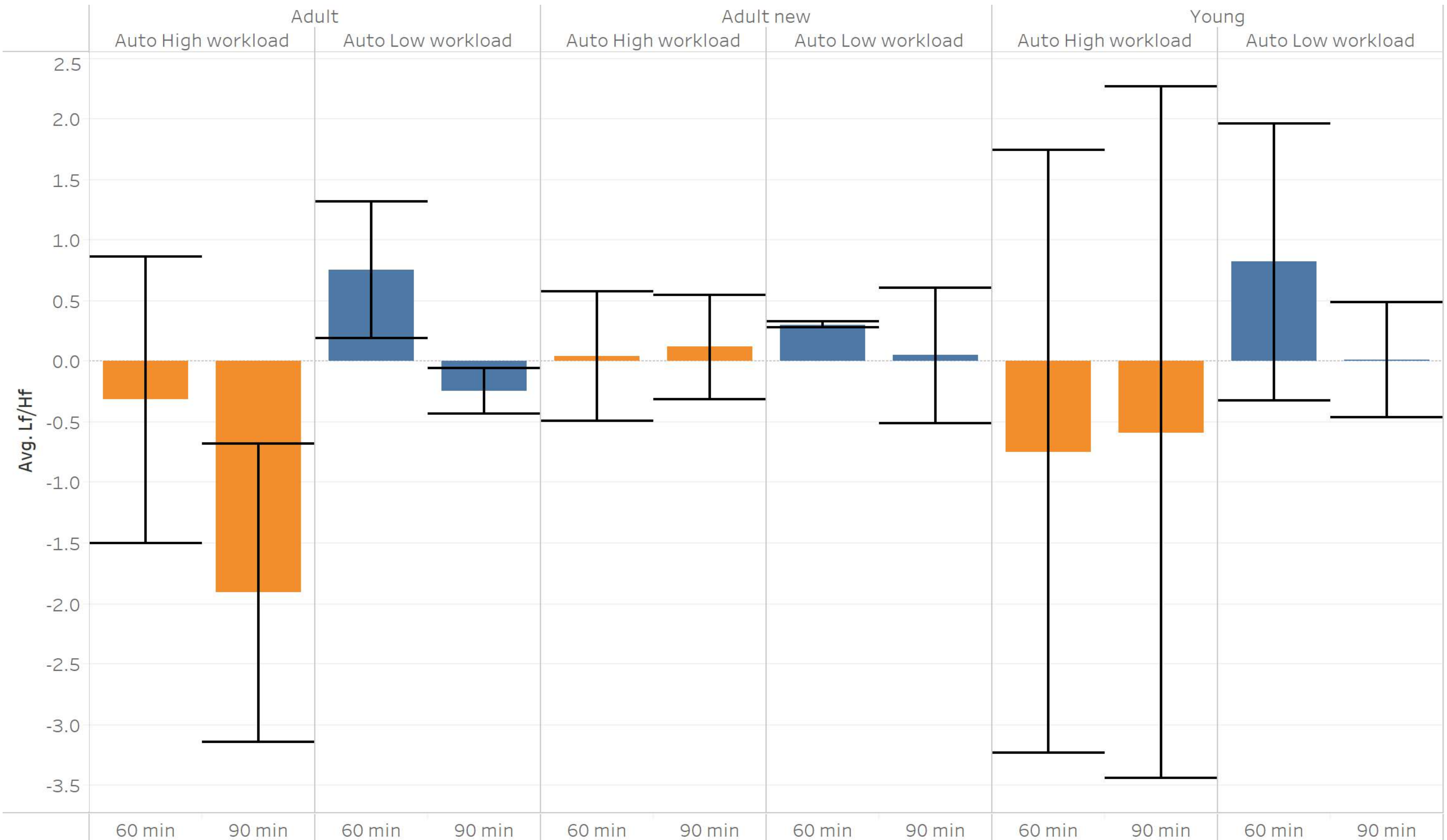


Figure 21. HRV Frequency Domain Analysis for Automated Driving Mode

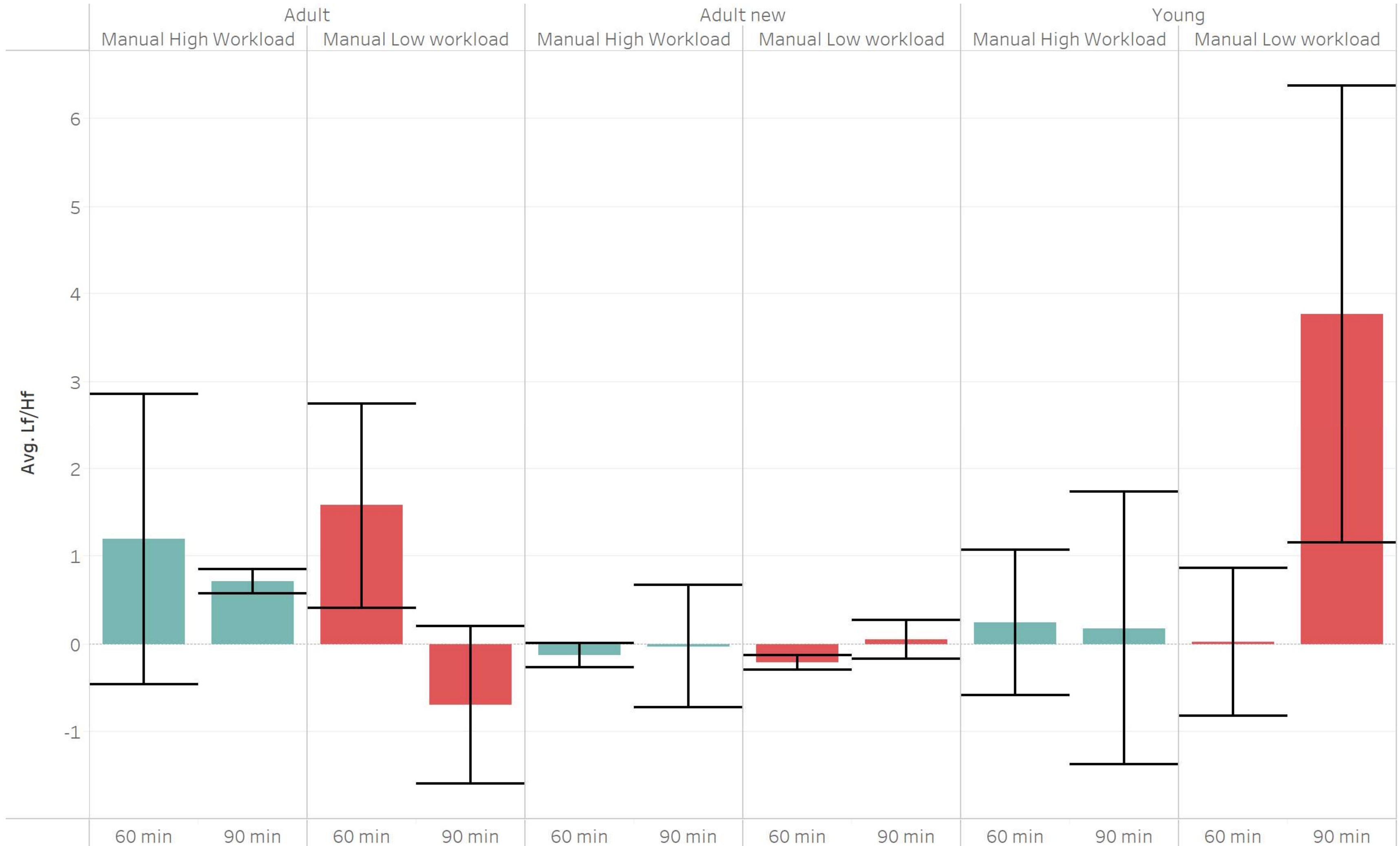


Figure 22. HRV Frequency Domain Analysis for Manual Driving Mode

young driver group and the adult driver group under automated driving mode In the manual low workload scenario, young drivers had a higher LF/HF reading at 90 minutes. LF/HF for young drivers was 3.77 at 90 minutes of driving, while the LF/HF for adult experienced drivers was -0.69 and adult new drivers was 0.06.

4.1.3 EEG Results

Figure 23, Figure 24, and Figure 25 show the EEG measurements of alpha, (theta + alpha)/beta, and theta/alpha changes among the participants. No error bar was calculated since some groups had only 1 set of data left after the data cleaning. No clear pattern was found for the data.

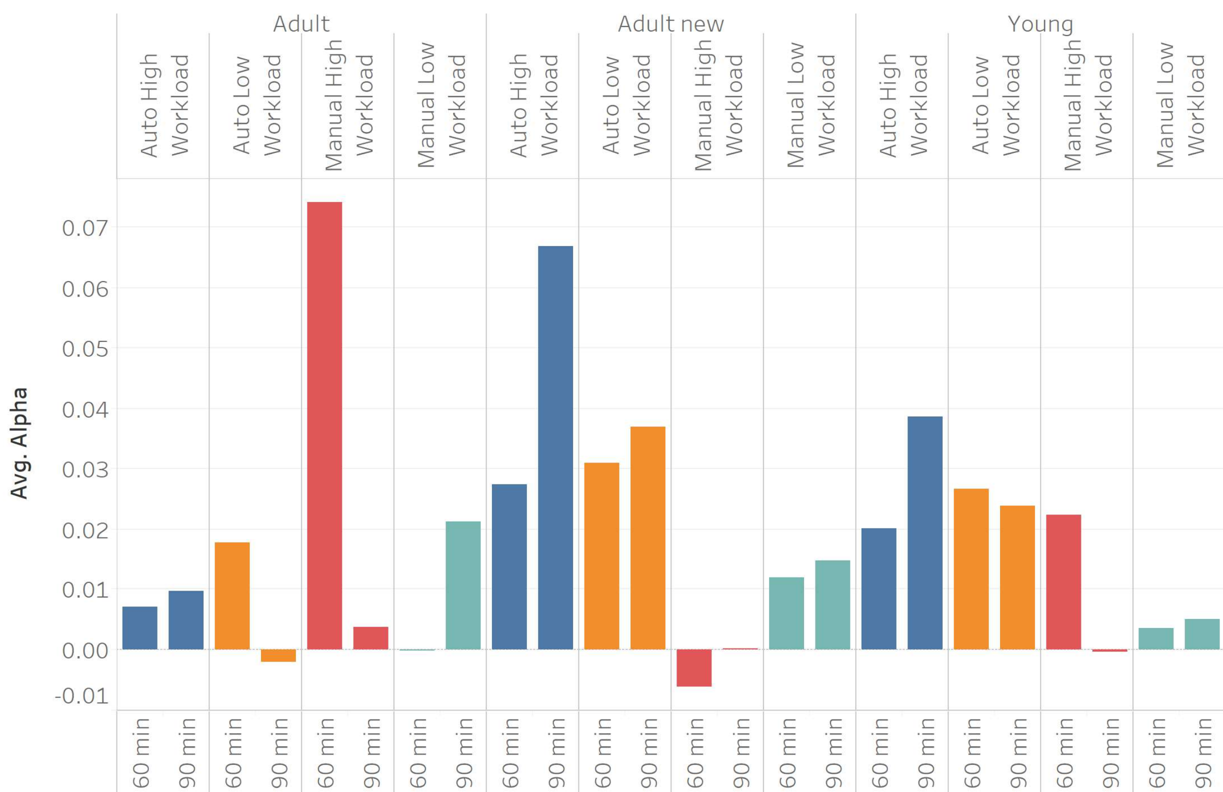


Figure 23. EEG Alpha

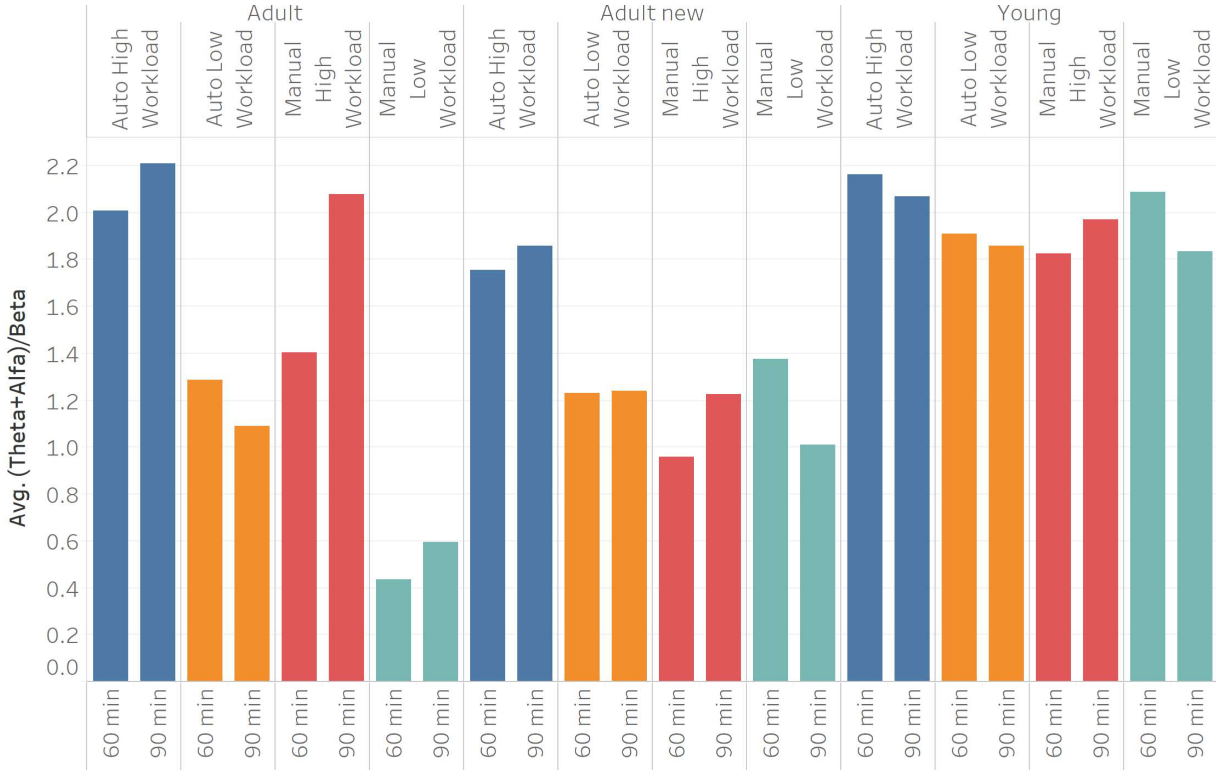


Figure 24. EEG (Theta + Alpha)/Beta

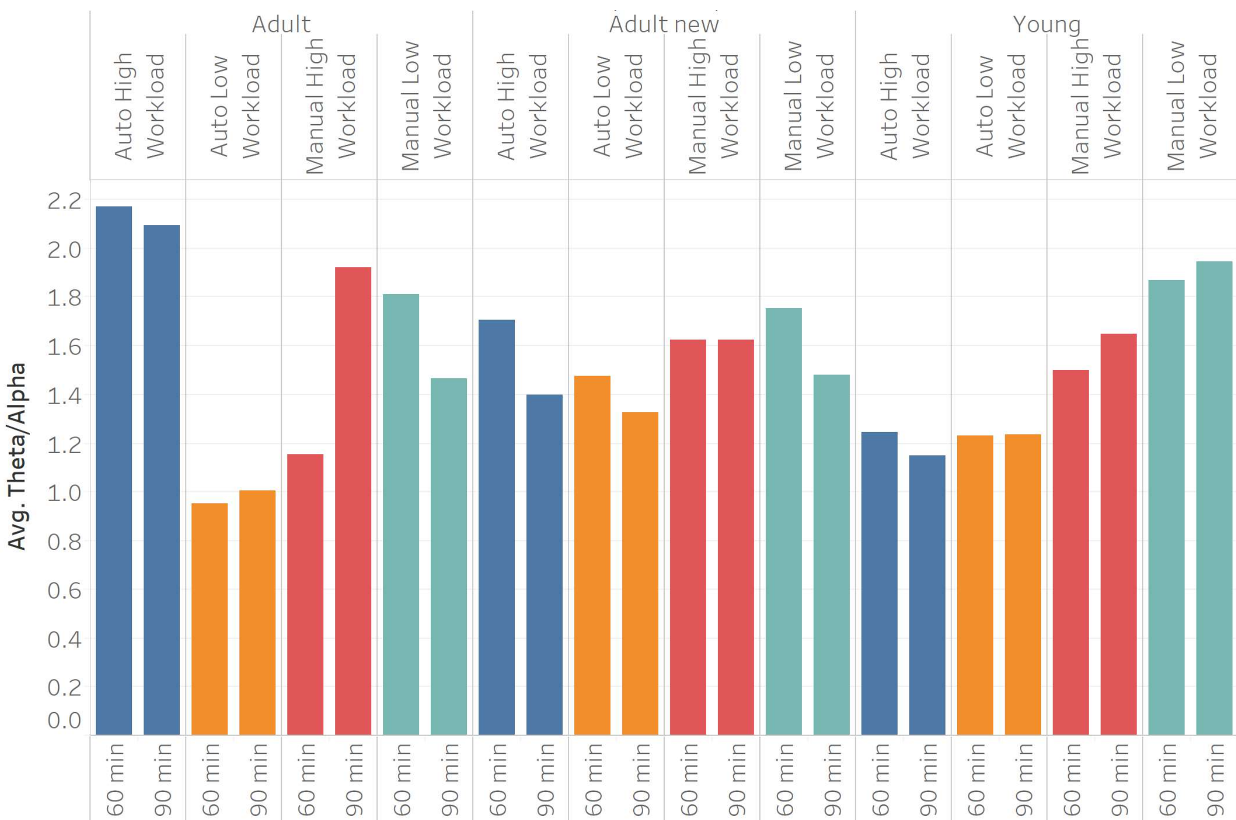


Figure 25. EEG Theta/Alpha

4.1.4 Driving Behavior Performance Results

Figure 26 shows the total crash numbers among different groups and scenarios. The young driver group shows a higher number of crashes for both automated low workload and automated high workload. Young drivers had an average of 0.3, 0.3, and 0 crashes at 30, 60, and 90 minutes of driving under automated low workload, while both adult experienced drivers and adult new drivers had 0 crashes at any time under automated driving. Under the automated high workload, young drivers had an average of 2.5, 1.5, and 1.5 crashes at 30, 60, and 90 minutes of driving, while adult experienced drivers had 2, 2, and 0 crashes and adult new drivers had 0 crashes over the whole of the automated high workload driving. Under the manual low workload, young drivers had 1, 0, and 1 crashes at 30, 60, and 90 minutes of driving, while no adult drivers had any crashes at all under manual low workload. For the manual driving high workload, young drivers had fewer crashes ($M = 2$, 1, and 0 at 30, 60, and 90 minutes) compared with adult new drivers (M = 3, 1, and 0 at 30, 60, and 90 minutes) but more crashes compared with adult experienced drivers, who did not have any crashes under manual high workload driving. Moreover, young drivers' crash numbers were even higher under the automated high workload. The adult new group did not have any crashes for automated driving modes.

Figure 27 shows the average number of near crashes under manual driving mode. Since the near crashes under automated driving were more related to the route the participants chose than the real driving performance of the driver, that mode is not shown in the figure.

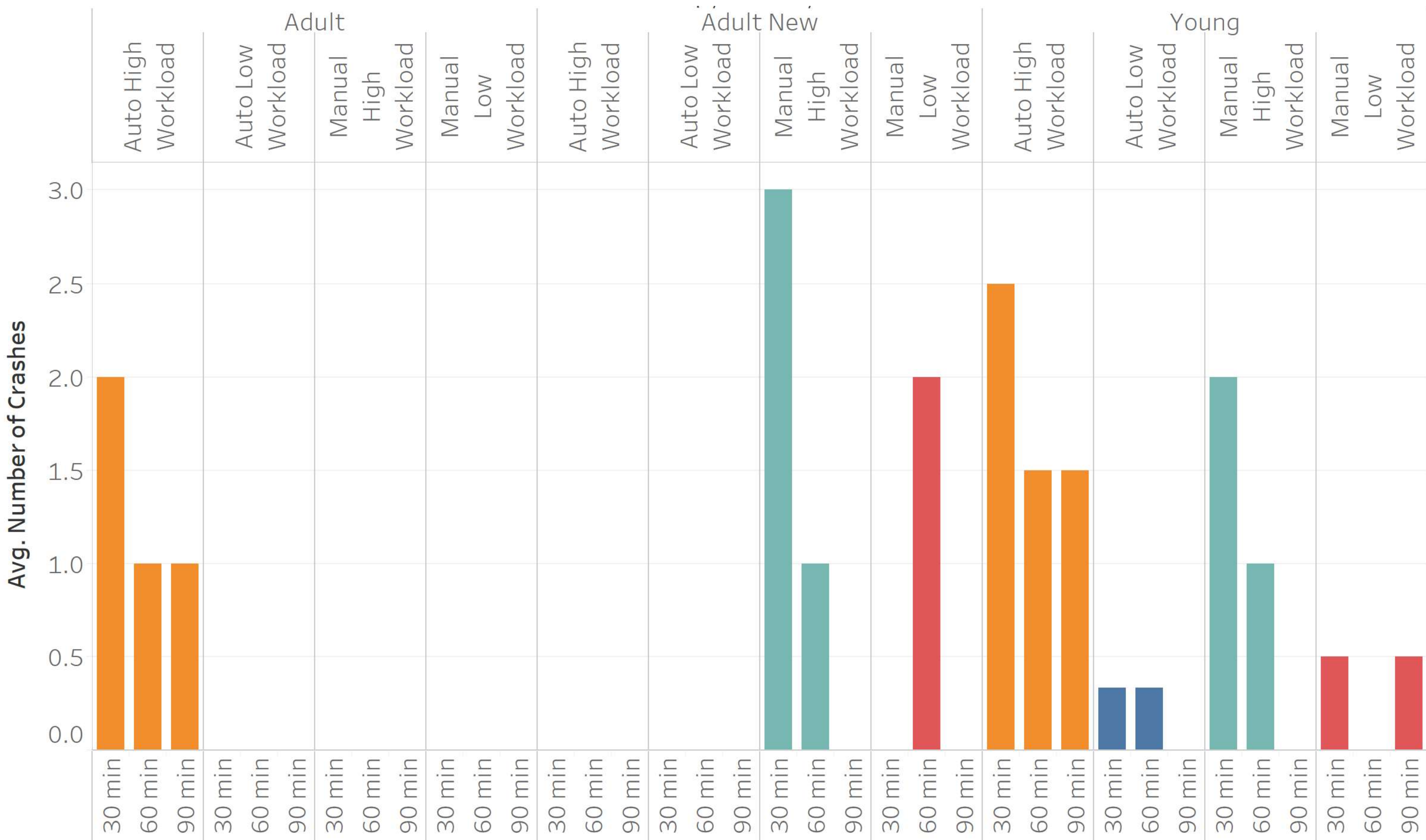


Figure 26. Average Total Crashes

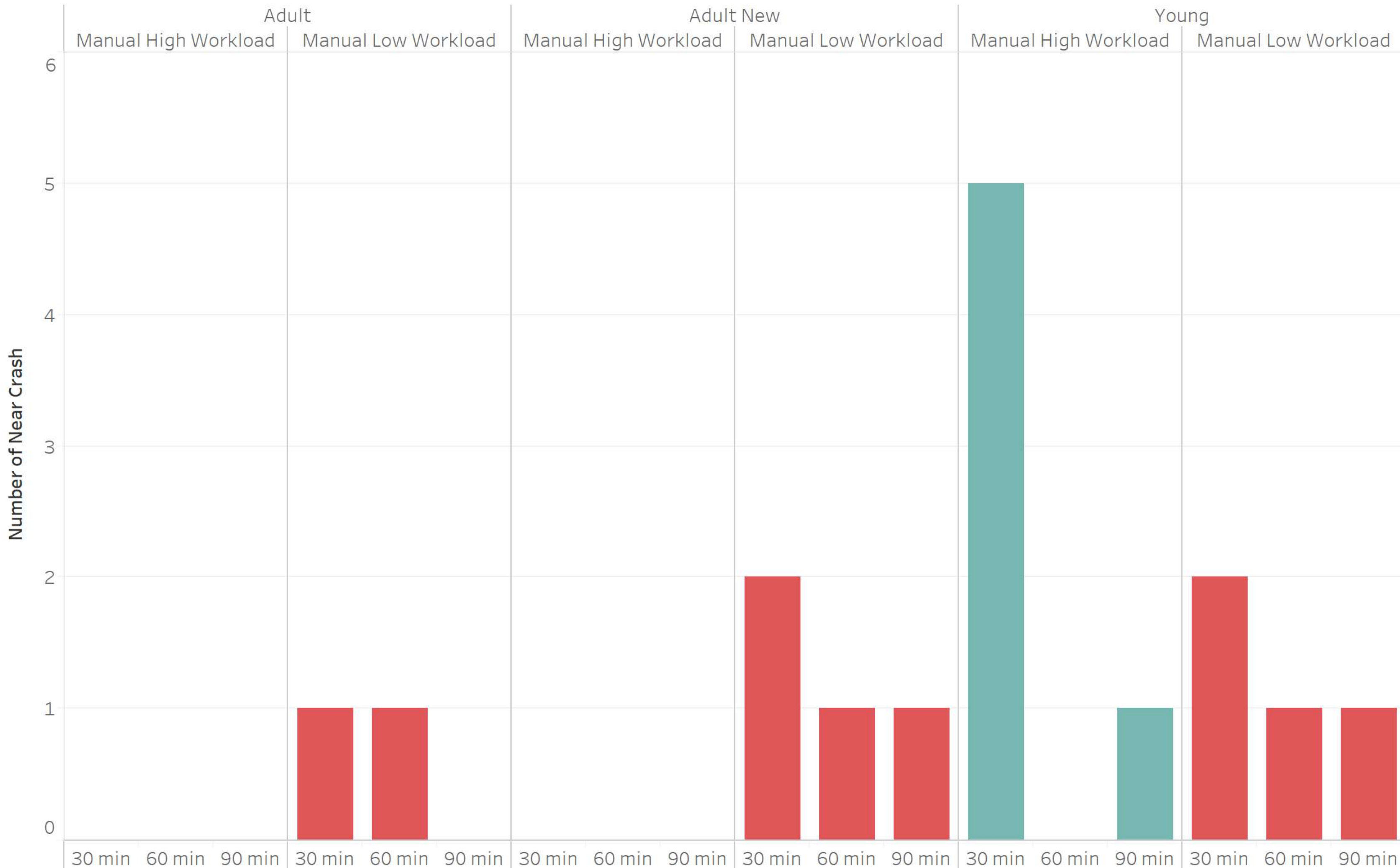


Figure 27. Average Total Near Crashes

No significant difference was observed between young drivers and adult drivers under the low workload, but young drivers were involved in more near crashes (M = 5, 0, and1 at 30, 60, and 90 minutes of driving) under manual high workload than other driver groups. No significant difference was found between the adult new group and the adult experienced group for both high workload and low workload.

Figure 28 shows the average number of eyes off road. The young driver group shows a higher number of eyes off road compared with the other two groups when the workload is high. Under automated driving mode, young drivers' average eyes off road times were 21 and 27 higher than adult experienced drivers and adult new drivers at 30 minutes. At 60 minutes of driving, young drivers were 49 and 48 higher than adult experienced drivers and adult new drivers. At 90 minutes of driving, young drivers were still 19 and 23 higher than adult experienced drivers and adult new drivers. For the manual driving modes, young drivers' average eyes off road times were 20.5 and 10.5 times higher than adult experienced drivers' and adult new drivers' at 30 minutes. At 60 minutes of driving, young drivers were 16.5 and 8.5 times higher than adult experienced drivers and adult new drivers. At 90 minutes of driving, young drivers were 18.5 and 25.5 times higher than adult experienced drivers and adult new drivers. The adult new group had the lowest number of eyes off road times, especially when the workload was low.

Different from the number of eyes off road, the average eyes off road time is higher among experienced adult groups compared with the young group for both automated driving modes, especially under the low workload, as shown in Figure 29. At 30, 60, and 90 minutes of driving, adult experienced drivers

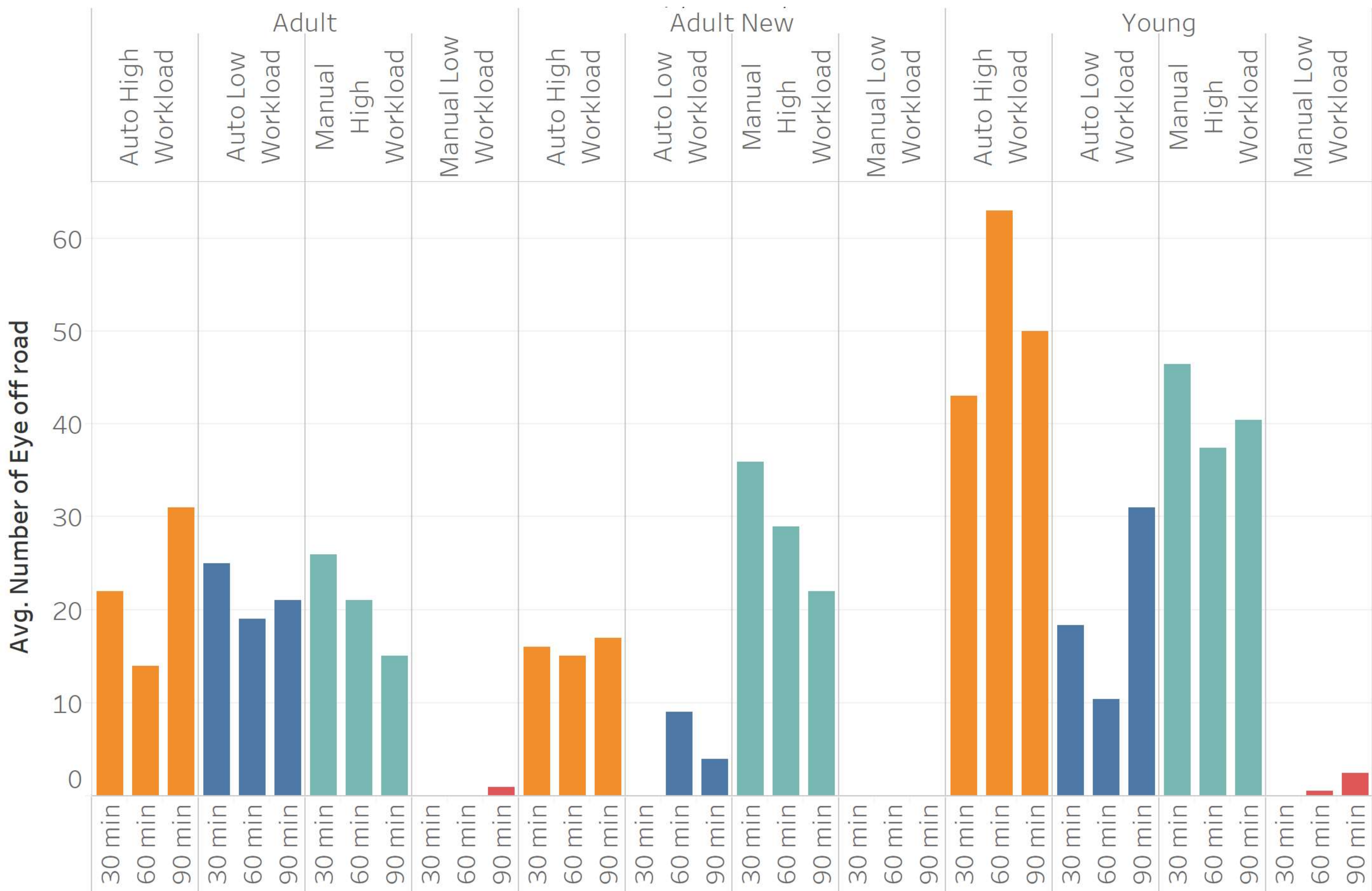


Figure 28. Average Number of Eyes Off Road

under auto high workload had 5.59, 4.64, and 4.29 seconds of average eyes off road time, while the adult new drivers had 3.25, 2.13, and 2.41 seconds and young drivers had 2.04, 2.72. 3.39 seconds. Under auto low workload, adult experienced drivers had 9.16, 3.89, 6.38 seconds of average eyes off road time at 30, 60, and 90 minutes of driving. Adult new drivers had 0, 3.67, and 12.25 seconds and young drivers had 2.13, 2.41, 3.49 seconds of eyes off road time at 30, 60, and 90 minutes of driving.

4.1.5 Takeover Performance Results

The number of failures to take over is shown in Figure 30. The young driver group shows much lower success in takeover, especially when the workload is high. Young drivers fail to take over 3, 2.5, and 2.5 times under automated high workload, while the adult experienced drivers had only 2, 1, and 1 times at 30, 60, and 90 minutes of driving. Adult new drivers had no failures to take over at all under the high workload scenario.

For each takeover, what the participant was doing right before they were taking over was also analyzed, as shown in Figure 31. In Figure 31, the green filling means the participant successfully took over, the red filling means the participant failed to take over and caused a crash, and the yellow filling means the participant failed to take over but no crash happened. The young driver group had a much higher rate of failure to take over. Also, when the takeover happened, the young drivers were more often on the phone rather than monitoring compared with the adult groups. Table 2 shows the percentage of each behavior while they were taking over. The young drivers were over 2 times more often on the phone when they needed to take over, one of them even falling asleep when they needed to take over.

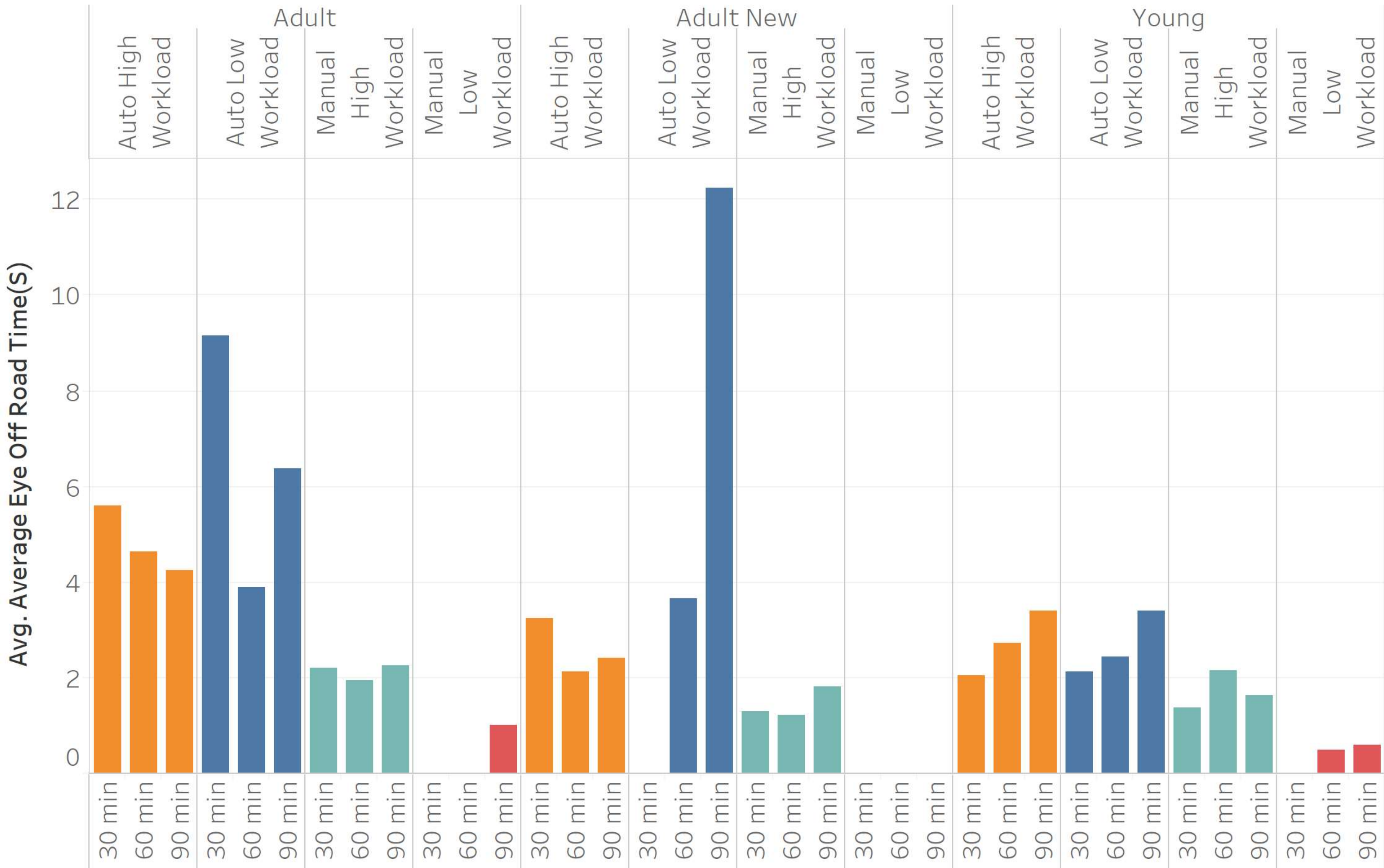


Figure 29. Average Eyes Off Road in Seconds

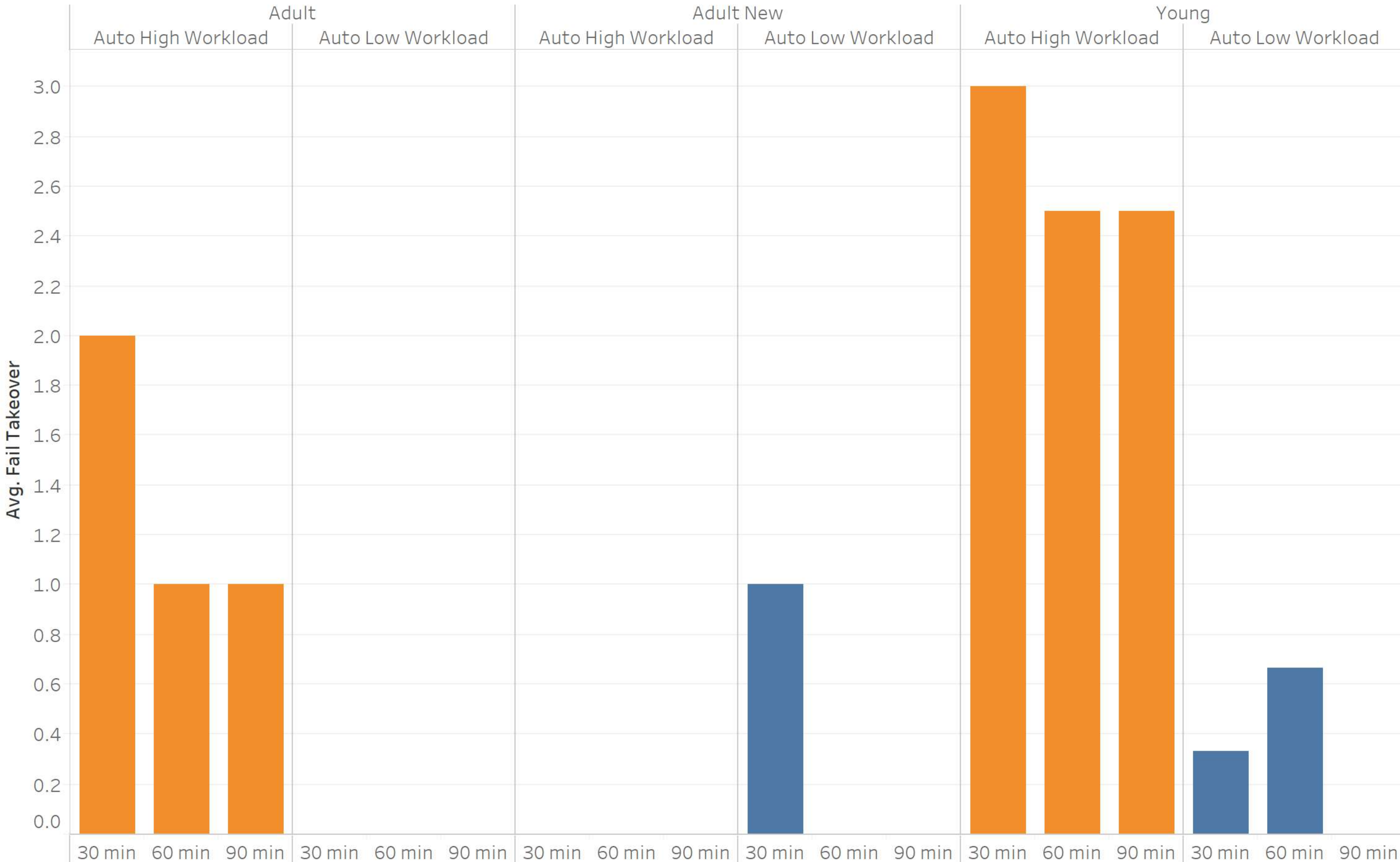


Figure 30. Failure to Take Over

Time	Group	scenario	Takeover 1	Takeover 2	Takeover 3	Takeover 4	Takeover 5	Takeover 6	Takeover 7	Takeover 8	Takeover 9	Takeover 10	Takeover 11	Takeover 12
30 min	Adult Experienced	Auto High	monitoring	monitoring	monitoring	monitoring	monitoring							
60 min	Adult Experienced	Auto High	monitoring	monitoring	monitoring	monitoring	on phone							
90 min	Adult Experienced	Auto High	on phone	monitoring	monitoring									
30 min	Adult Experienced	Auto Low	monitoring											
60 min	Adult Experienced	Auto Low	monitoring	monitoring	monitoring									
90 min	Adult Experienced	Auto Low												
30 min	Adult New	Auto Low	monitoring	monitoring										
60 min	Adult New	Auto Low												
90 min	Adult New	Auto Low	monitoring											
30 min	Adult New	Auto High	monitoring	monitoring	monitoring	monitoring								
60 min	Adult New	Auto High	monitoring	monitoring	monitoring	monitoring	monitoring							
90 min	Adult New	Auto High	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring
30 min	Young	Auto Low	monitoring	monitoring										
60 min	Young	Auto Low	monitoring											
90 min	Young	Auto Low												
30 min	Young	Auto Low	monitoring	monitoring	monitoring									
60 min	Young	Auto Low												
90 min	Young	Auto Low											Successfuly take over	
30 min	Young	Auto High	monitoring	on phone	on phone	monitoring	monitoring							
60 min	Young	Auto High	monitoring	monitoring	on phone	monitoring	sleeping							
90 min	Young	Auto High	monitoring	monitoring	monitoring	monitoring							fail to take over, crash	
30 min	Young	Auto High	monitoring	on phone	monitoring	monitoring	on phone	monitoring	monitoring					
60 min	Young	Auto High	on phone	monitoring	on phone	on phone	on phone	on phone						
90 min	Young	Auto High	monitoring	monitoring	on phone	monitoring	monitoring	monitoring	monitoring	monitoring			fail to take over, but no crash	
30 min	Young	Auto Low	monitoring	monitoring										
60 min	Young	Auto Low	monitoring	monitoring										
90 min	Young	Auto Low	on phone											

Figure 31. Examples of Takeover Behaviors

Table 2 Behaviors before Taking Over

	Monitoring	On Phone	Sleeping
Adult Experienced	88%	12%	0%
Adult New	100%	0%	0%
Young	72%	26%	2%

4.2 Study Two: Young Drivers vs. Adult Drivers

4.2.1 Factorial ANOVA on HR and LF/HF

The Anderson-Darling test was performed to test all the measures' normality for the ANOVA test. Among all the data, only the HR ($AD = 0.216$, $p = 0.838$) and LF/HF ($AD = 0.603$, $p = 0.113$) have the normal distribution. Equal variance was tested by the Levene test; both HR ($W = 1.65$, $p = 0.141$) and LF/HF ($W = 0.49$, $p = 0.841$) have equal variance between groups. For the data does not follow the normal distribution, Johnson transformation was performed. SDNN, pNN50, overall feeling, and average eyes off road time in seconds were transformed into the normal distribution. The rest of the data was failed to perform the transformation with $p>0.1$. After the Levene's test, eyes off road time in seconds ($W = 3.54$, $p = 0.009$) were excluded for the ANOVA since it failed the test for equal variance. Kruskal-Wallis test was used for other measurements does not fulfill the assumptions of the ANOVA analysis.

A 2^3 factorial ANOVA was conducted to compare the main effects of age, driving mode, and workload as well as their inaction effects on the HR and LF/HF. Table 3 shows the ANOVA table on HR at 60 minutes of driving. Only the age was statistically significant at $p < 0.05$. The main effect of age group yielded an F value of $F(1, 24) = 8.81$, $p = .007$, indicating that the heart rate changes were significantly lower for the young group ($M = -3.63$, $SD = 4.18$) than for adult drivers ($M = 1$, $SD = 4.80$). No other main effects or interactions were found significant. With the effect size of 4.63 at $\alpha = 0.05$, the power of this analysis was found to be 0.707.

Table 3. ANOVA on HR Changes at 60 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	312.875	44.696	2.30	0.060
Linear	3	271.375	90.458	4.66	0.011*
Group	1	171.125	171.125	8.81	0.007*
Driving mode	1	45.125	45.125	2.32	0.140
Workload	1	55.125	55.125	2.84	0.105
2-Way Interactions	3	40.375	13.458	0.69	0.565
Group*Driving mode	1	3.125	3.125	0.16	0.692
Group*Workload	1	36.125	36.125	1.86	0.185
Driving mode*Workload	1	1.125	1.125	0.06	0.812
3-Way Interactions	1	1.125	1.125	0.06	0.812
Group*Driving mode*Workload	1	1.125	1.125	0.06	0.812
Error	24	466.000	19.417		
Total	31	778.875			

At 90 minutes of driving, the age group remains statistically significant at $p < 0.05$. The main effect of age group yielded an F value of $F(1, 24) = 7.98$, $p = .009$, indicating that the heart rate changes were still significantly lower for the young group ($M = -4.88$, $SD = 5.25$) than for adult drivers ($M = 0.38$, $SD = 5.08$). With the effect size of 5.26 at $\alpha = 0.05$, the power of this analysis was found to be 0.701. No other main effects or interactions were found significant. Table 4 shows the ANOVA table for HR at 90 minutes of driving.

Table 4. ANOVA on HR Changes at 90 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	359.00	51.286	1.86	0.122
Linear	3	273.50	91.167	3.30	0.038*
Group	1	220.50	220.500	7.98	0.009*
Driving mode	1	12.50	12.500	0.45	0.508
Workload	1	40.50	40.500	1.47	0.238
2-Way Interactions	3	61.00	20.333	0.74	0.541
Group*Driving mode	1	8.00	8.000	0.29	0.595
Group*Workload	1	40.50	40.500	1.47	0.238
Driving mode*Workload	1	12.50	12.500	0.45	0.508
3-Way Interactions	1	24.50	24.500	0.89	0.356
Group*Driving mode*Workload	1	24.50	24.500	0.89	0.356
Error	24	663.00	27.625		
Total	31	1022.00			

Table 5 shows the ANOVA on LF/HF at 60 minutes of driving. The main effect of age group yielded an *F* value of $F(1, 24) = 5.98$, $p = .022$, indicating that the LF/HF changes were significantly lower for the young group ($M = 0.261$, $SD = 1.301$) than for adult drivers ($M = 1.469$, $SD = 1.345$). With the effect size of 1.208 at $\alpha = 0.05$, the power of this analysis was found to be 0.625. No other main effects or interactions were found significant.

Table 5. ANOVA on LF/HF Changes at 60 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	17.3264	2.4752	1.27	0.307
Linear	3	12.1135	4.0378	2.07	0.131
Group	1	11.6765	11.6765	5.98	0.022*
Driving mode	1	0.1938	0.1938	0.10	0.756
Workload	1	0.2433	0.2433	0.12	0.727
2-Way Interactions	3	5.2020	1.7340	0.89	0.461
Group*Driving mode	1	1.1138	1.1138	0.57	0.457
Group*Workload	1	1.6517	1.6517	0.85	0.367
Driving mode*Workload	1	2.4365	2.4365	1.25	0.275
3-Way Interactions	1	0.0109	0.0109	0.01	0.941
Group*Driving mode*Workload	1	0.0109	0.0109	0.01	0.941
Error	24	46.8704	1.9529		
Total	31	64.1968			

No significant change was found on LF/HF at 90 minutes of driving between any main effects or their interactions. Table 6 shows the ANOVA table of LF/HF changes at 90 minutes.

Table 6. ANOVA on LF/HF Changes at 90 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	23.705	3.3864	1.03	0.434
Linear	3	1.472	0.4908	0.15	0.929
Group	1	0.650	0.6498	0.20	0.660
Driving mode	1	0.813	0.8128	0.25	0.623
Workload	1	0.010	0.0098	0.00	0.957
2-Way Interactions	3	15.626	5.2086	1.59	0.218
Group*Driving mode	1	0.769	0.7688	0.23	0.633
Group*Workload	1	12.326	12.3256	3.76	0.064
Driving mode*Workload	1	2.531	2.5313	0.77	0.388
3-Way Interactions	1	6.607	6.6066	2.02	0.168
Group*Driving mode*Workload	1	6.607	6.6066	2.02	0.168
Error	24	78.640	3.2766		
Total	31	102.344			

Table 7 shows the ANOVA test result on the transformed SDNN data for 60 minutes of driving. Significant difference was found on effects of driving mode and workload. Driving mode yielded an F value of $F(1, 24) = 6.37$, $p = .019$, indicating that the SDNN changes were significantly lower for the manual driving mode ($M = 0.005$, $SD = 0.802$) than for automated mode ($M = -0.614$, $SD = 0.877$). With the effect size of 0.619 at $\alpha = 0.05$, the power of this analysis was found to be 0.476. Workload yielded an F value of $F(1, 24) = 6.91$, $p = .015$, indicating that the SDNN changes were significantly lower for the low workload ($M = -0.627$, $SD = 0.732$) than for high workload ($M = 0.018$, $SD = 0.928$). With the effect size of 0.619 at $\alpha = 0.05$, the power of this analysis was found to be 0.507. The three way interaction between group, driving mode, and workload was also found to be significant with an F value of $F(1, 24) = 9.64$, $p = .005$. Table 8 shows the ANOVA test result on the transformed SDNN data for 90 minutes of driving. No significant difference was found between different group, driving mode, and workload at 90 minutes of driving.

Table 7 ANOVA on Transformed SDNN at 60 Minutes of Driving

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Model	7	12.7040	1.81486	3.77	0.007
Linear	3	7.2112	2.40374	4.99	0.008*
Group	1	0.8133	0.81326	1.69	0.206
Driving mode	1	3.0689	3.06890	6.37	0.019*
Workload	1	3.3291	3.32907	6.91	0.015*
2-Way Interactions	3	0.8473	0.28242	0.59	0.630
Group*Driving mode	1	0.0003	0.00030	0.00	0.980
Group*Workload	1	0.4999	0.49989	1.04	0.319
Driving mode*Workload	1	0.3471	0.34707	0.72	0.404
3-Way Interactions	1	4.6455	4.64554	9.64	0.005*
Group*Driving mode*Workload	1	4.6455	4.64554	9.64	0.005*
Error	24	11.5659	0.48191		
Total	31	24.2699			

Table 9 shows the ANOVA on transformed pNN50 data at 60 minutes of driving. The main effect of workload yielded an F value of $F(1, 24) = 6.76$, $p = .016$, indicating that the pNN50 were significantly lower at high workload (*M* = -0.569, *SD* = 1.068) than low workload (*M* = 0.211, *SD* = 0.613). No other main effects or interactions were found significant. With the effect size of 0.78 at α = 0.05, the power of this analysis was found to be 0.611.

Table 8 ANOVA on Transformed SDNN at 90 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	8.6187	1.2312	1.53	0.206
Linear	3	6.3157	2.1052	2.61	0.075
Group	1	2.8612	2.8612	3.55	0.072
Driving mode	1	0.2701	0.2701	0.34	0.568
Workload	1	3.1844	3.1844	3.95	0.058
2-Way Interactions	3	1.5896	0.5299	0.66	0.586
Group*Driving mode	1	0.2083	0.2083	0.26	0.616
Group*Workload	1	0.7979	0.7979	0.99	0.330
Driving mode*Workload	1	0.5834	0.5834	0.72	0.403
3-Way Interactions	1	0.7135	0.7135	0.89	0.356
Group*Driving mode*Workload	1	0.7135	0.7135	0.89	0.356
Error	24	19.3415	0.8059		
Total	31	27.9603			

Table 9 ANOVA on Transformed pNN50 at 60 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	10.3225	1.47464	2.05	0.090
Linear	3	7.0733	2.35775	3.27	0.039*
Group	1	1.9873	1.98728	2.76	0.110
Driving mode	1	0.2189	0.21888	0.30	0.587
Workload	1	4.8671	4.86709	6.76	0.016*
2-Way Interactions	3	3.2257	1.07525	1.49	0.242
Group*Driving mode	1	0.0080	0.00802	0.01	0.917
Group*Workload	1	2.6912	2.69120	3.74	0.065
Driving mode*Workload	1	0.5265	0.52651	0.73	0.401
3-Way Interactions	1	0.0235	0.02347	0.03	0.858
Group*Driving mode*Workload	1	0.0235	0.02347	0.03	0.858
Error	24	17.2915	0.72048		
Total	31	27.6139			

Table 10 shows the ANOVA on transformed pNN50 data at 90 minutes of driving. The main effect of age group yielded an *F* value of $F(1, 24) = 10.02$, $p = .004$, indicating that the pNN50 were significantly lower for adult drivers (*M* = -0.383, *SD* = 1.010) than young drivers (*M* = 0.601, *SD* = 0.767) at 90 minutes of drive. No other main effects or interactions were found significant. With the effect size of 0.984 at α = 0.05, the power of this analysis was found to be 0.75.

Table 10 ANOVA on Transformed pNN50 at 90 Minutes of Driving

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Model	7	13.3143	1.90205	2.46	0.047
Linear	3	8.6367	2.87891	3.72	0.025*
Group	1	7.7461	7.74611	10.02	0.004*
Driving mode	1	0.0320	0.03196	0.04	0.841
Workload	1	0.8587	0.85866	1.11	0.302
2-Way Interactions	3	4.5597	1.51991	1.97	0.146
Group*Driving mode	1	1.8919	1.89195	2.45	0.131
Group*Workload	1	2.5738	2.57380	3.33	0.081
Driving mode*Workload	1	0.0940	0.09398	0.12	0.730
3-Way Interactions	1	0.1179	0.11788	0.15	0.700
Group*Driving mode*Workload	1	0.1179	0.11788	0.15	0.700
Error	24	18.5555	0.77314		
Total	31	31.8698			

Table 11, 12 and 13 shows the ANOVA test result on the transformed overall feeling data at 30, 60 and 90 minutes of driving. No significant difference was found between different group, driving mode, and workload at 30 minutes of drive. But after 60 minutes of drive, age group yielded an F value of $F(1, 24) = 4.65$, $p = .041$, indicating that the overall were significantly lower for young drivers ($M = -0.344$, $SD = 1.055$) than adult drivers ($M = 0.441$, $SD = 0.930$) at 60 minutes of driving. With the effect size of 0.785 at α = 0.05, the power of this analysis was found to be 0.523. Such difference went even worse at 90 minutes of driving for young drivers ($M = -0.396$, $SD = 0.973$) compare with adult drivers ($M = 0.505$, $SD = 0.979$) with $F(1, 24) = 7.07$, $p = .014$. With the effect size of 0.901 at α = 0.05, the power of this analysis was found to be 0.633.

Table 11 ANOVA on Transformed Overall Feeling at 30 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	2.4162	0.3452	0.33	0.930
Linear	3	1.5958	0.5319	0.52	0.675
Group	1	0.8196	0.8196	0.80	0.381
Driving Mode	1	0.1729	0.1729	0.17	0.686
Workload	1	0.6032	0.6032	0.59	0.452
2-Way Interactions	3	0.6350	0.2117	0.21	0.892
Group*Driving Mode	1	0.1834	0.1834	0.18	0.677
Group*Workload	1	0.2877	0.2877	0.28	0.602
Driving Mode*Workload	1	0.1639	0.1639	0.16	0.694
3-Way Interactions	1	0.1854	0.1854	0.18	0.675
Group*Driving Mode*Workload	1	0.1854	0.1854	0.18	0.675
Error	24	24.7357	1.0307		
Total	31	27.1519			

Table 12 ANOVA on Transformed Overall Feeling at 60 Minutes of Driving.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	9.1397	1.30567	1.23	0.324
Linear	3	7.3492	2.44974	2.31	0.102
Group	1	4.9268	4.92677	4.65	0.041*
Driving Mode	1	0.2197	0.21967	0.21	0.653
Workload	1	2.2028	2.20279	2.08	0.162
2-Way Interactions	3	0.5378	0.17927	0.17	0.916
Group*Driving Mode	1	0.1197	0.11971	0.11	0.740
Group*Workload	1	0.3911	0.39109	0.37	0.549
Driving Mode*Workload	1	0.0270	0.02701	0.03	0.874
3-Way Interactions	1	1.2527	1.25265	1.18	0.288
Group*Driving Mode*Workload	1	1.2527	1.25265	1.18	0.288
Error	24	25.4331	1.05971		
Total	31	34.5728			

4.2.2 Young Drivers and Adult Drivers under Manual Driving

Young drivers were expected to develop fatigue faster and more severely under manual driving compared with adult drivers. The Kruskal-Wallis test was conducted to compare the effects of age on the SDNN, pNN50, and perceived fatigue ratings under the manual driving mode.

No significant difference was found in SDNN changes between young drivers and adult drivers at manual high workload $H(1) = 1.10$, $p = 0.294$. Age group yielded an H value of $H(1) =$

6.38, p = .012, indicating that the pNN50 changes were significantly higher for the young group (Mdn = 0.040) than for adult drivers (Mdn = -0.045). Compared between different times of driving, young drivers were not significantly different from adult drivers at 60 minutes of driving $H(1)$ = 1.35, p = 0.245, but they had significantly higher pNN50 changes (Mdn = 0.080) at 90 minutes of driving $H(1)$ = 4.74, p = 0.029 compared with adult drivers (Mdn = -0.045). For the manual low workload, neither SDNN changes $H(1)$ = 1.33, p = 0.248, nor pNN50 changes $H(1)$ = 2.03, p = 0.154, were found to be significantly different between young drivers and adult drivers.

Table 13 ANOVA on Transformed Overall Feeling at 90 Minutes of Driving

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	6192.9	884.70	1.86	0.121
Linear	3	4103.6	1367.87	2.88	0.057
Group	1	3362.0	3362.00	7.07	0.014*
Driving Mode	1	0.5	0.50	0.00	0.974
Workload	1	741.1	741.12	1.56	0.224
2-Way Interactions	3	604.1	201.38	0.42	0.738
Group*Driving Mode	1	435.1	435.13	0.92	0.348
Group*Workload	1	24.5	24.50	0.05	0.822
Driving Mode*Workload	1	144.5	144.50	0.30	0.587
3-Way Interactions	1	1485.1	1485.12	3.12	0.090
Group*Driving Mode*Workload	1	1485.1	1485.12	3.12	0.090
Error	24	11409.0	475.37		
Total	31	17601.9			

Young drivers (Mdn = 2.5) were found to have a significantly higher rating on perceived tense muscles compared with adult drivers (Mdn = 1) under manual driving, with $H(1)$ = 7.19, p = 0.007. Adult drivers (Mdn = 2) were found to have a significantly higher rating on perceived numbness compared with young drivers (Mdn = 0) under manual driving, with $H(1)$ = 5.55, p = 0.018. Adult drivers (Mdn = 1.5) were significantly higher on perceived numbness compared with young drivers (Mdn = 0) at 30 minutes of driving, with $H(1)$ = 5.41, p = 0.020. However, after 60 minutes of driving, no significant difference was found between young drivers and adult drivers, with $H(1) = 0.94$, $p = 0.333$.

Young drivers (*Mdn* = 2) were found to have a significantly higher rating on perceived tense muscles under high workload compared with adult drivers (*Mdn* = 0.5), with $H(1) = 4.13$, $p = 0.042$. No significant difference was found on perceived tense muscles under low workload between young drivers and adult drivers, with $H(1) = 3.26$, $p = 0.071$. However, young drivers (*Mdn* = -29) were found to have a higher rating on overall feelings at low workload compared with adult drivers (*Mdn* = -10). Moreover, adult drivers (*Mdn* = 1.5) were found to have significant perceived numbness at high workload compared with young drivers (*Mdn* = 0), with $H(1) = 5.91$, $p = 0.015$, but no difference was found at low workload, with $H(1) = 0.66$, $p = 0.417$.

When investigating the ratings on different body parts, adult drivers showed significantly higher ratings on left neck and lower arms compared with young drivers. Adult drivers rated discomfort on left neck a median of 2.5, while young drivers rated a median of 0.5 with $H(1) = 6.21$, $p = 0.013$. Adult drivers (*Mdn* = 1, 1) rated 1 point higher than young drivers (*Mdn* = 0, 0) on both left and right lower arm, with $H(1) = 5.02$, $p = 0.025$, and $H(1) = 4.42$, $p = 0.035$. Adult drivers (*Mdn* = 2.5) were found to have a higher discomfort rating on left neck compared with young drivers (*Mdn* = 0). with $H(1) = 7.48$, $p = 0.006$, under high workload; no significant effect was found at low workload, with $H(1) = 0.49$, $p = 0.483$.

4.2.3 Young Drivers and Adult Drivers under Automated Driving

Young drivers were expected to develop fatigue faster and more severely under automated driving compared with adult drivers. Also, their takeover performance was expected to be worse compared with adult drivers. The Kruskal-Wallis test was conducted to compare the effects of age on the SDNN, pNN50, perceived fatigue, and takeover performance under the automated driving mode.

The age group yielded an *H* value of $H(1) = 11.29$, $p = .001$, indicating that the SDNN change was significantly higher for the young group (*Mdn* = 32.45) than for adult drivers (*Mdn* = 9.39). Compared between different times of driving, young drivers (*Mdn* = 28.905) were 21.895 higher than adult drivers (*Mdn* = 7.010) at 60 minutes of driving on their SDNN changes $H(1) = 5.33$, $p = 0.021$. At 90 minutes of driving, they also had a significantly higher SDNN change (*Mdn* = 39.655) $H(1) = 5.33$, $p = 0.021$, compared with adult drivers (*Mdn* = 14.225). No significantly different change in pNN50 was found between young drivers and adult drivers under automated high workload $H(1) = 3.01$, $p = 0.083$. For the automated low workload, neither SDNN changes $H(1) = 2.16$, $p = 0.141$, nor pNN50 changes $H(1) =0.23$, $p = 0.633$, were found to be significantly different between young drivers and adult drivers.

On the perceived fatigue subject ratings, young drivers (*Mdn* = -20) rated higher changes on overall feelings under automated driving compared with the adult group (*Mdn* = -10) with $H(1) =8.05$, $p = 0.005$. Young drivers (*Mdn* = 3) also rated higher on feeling over-drained under automated driving compared with the adult group (*Mdn* = 0), with $H(1) =11.04$, $p = 0.001$. Among the perceived physical fatigue ratings, young drivers rated higher changes on stiff joints and tense muscles. For stiff joints, young drivers (*Mdn* = 3) yielded an *H* value of $H(1) =14.21$, $p < 0.000$, compared with adult drivers (*Mdn* = 0), and for tense muscles, young drivers (*Mdn* = 3) yielded an *H* value of $H(1) =7.68$, $p = 0.006$, compared with adult drivers (*Mdn* = 0). Among the perceived mental fatigue, young drivers rated higher changes on uninterested and drowsiness compared with adult drivers. For uninterested, young drivers (*Mdn* = 4) yielded an *H* value of $H(1) =15.70$, $p < 0.000$, compared with adult drivers (*Mdn* = 0), and for drowsiness, young drivers (*Mdn* = 4.5) yielded an *H* value of $H(1) = 6.17$, $p = 0.013$, compared with adult drivers (*Mdn* = 0.5). Young drivers had a significantly earlier onset of fatigue among over-drained $H(1) = 4.57$, $p = 0.013$, stiff joints $H(1) = 6.70$, $p = 0.010$, uninterested $H(1) = 5.68$, $p = 0.017$, and drowsiness $H(1) = 4.15$, $p = 0.042$, at 30 minutes of driving compared with adult drivers. At 60 minutes of driving, young drivers had a significantly higher rating on numbness $H(1) = 4.35$, $p = 0.037$, and at 90 minutes of driving, young drivers had a significantly higher rating on tense muscles $H(1) = 3.88$, $p = 0.049$.

Under the high workload, young drivers rated higher on overall feeling, tense muscles, uninterested, and numbness compared with adult drivers. For overall feeling, young drivers (*Mdn* = -39) yielded an *H* value of $H(1) = 7.44$, $p = 0.006$, compared with adult drivers (*Mdn* = -10); for tense muscles, young drivers (*Mdn* = 3) yielded an *H* value of $H(1) = 5.97$, $p = 0.015$, compared with adult drivers (*Mdn* = 0); for uninterested, young drivers (*Mdn* = 4) yielded an *H* value of $H(1) = 8.01$, $p = 0.005$, compared with adult drivers (*Mdn* = 0); and for numbness, young drivers (*Mdn* = 3) yielded an *H* value of $H(1) = 6.04$, $p = 0.014$, compared with adult drivers (*Mdn* = 0).

Under low workload, young drivers rated higher on over-drained, stiff joints, uninterested, drowsiness, sleepiness, and numbness. For over-drained, young drivers (*Mdn* = 5.5) yielded an *H* value of $H(1) = 8.37$, $p = 0.004$, compared with adult drivers (*Mdn* = 1); for stiff joints, young drivers (*Mdn* = 1) yielded an *H* value of $H(1) = 4.55$, $p = 0.033$, compared with adult drivers (*Mdn* = 0); for uninterested, young drivers (*Mdn* = 5.5) yielded an *H* value of $H(1) = 7.78$, $p = 0.005$, compared with adult drivers (*Mdn* = 1); for drowsiness, young drivers (*Mdn* = 7.5) yielded an *H* value of $H(1) = 12.42$, $p < 0.000$, compared with adult drivers (*Mdn* = 1) for sleepiness, young drivers (*Mdn* = 6) yielded a *H* value of $H(1) = 7.19$, $p = 0.007$, compared with adult drivers (*Mdn* = 2.5); and for numbness, young drivers (*Mdn* =0) yielded an *H* value of $H(1) = 7.71$, $p = 0.005$, compared with adult drivers (*Mdn* = -0.5).

When investigating different parts of the body, young drivers showed higher changes in ratings of buttocks and right thigh compared with adult drivers. For left buttock, young drivers (*Mdn* = 1.5) yielded an *H* value of $H(1) = 9.27$, $p = 0.002$, compared with adult drivers (*Mdn* = 0), and for right buttock, young drivers (*Mdn* = 2.5) yielded an *H* value of $H(1) = 13.41$, $p < 0.000$, compared with adult drivers (*Mdn* = 0). Young drivers (*Mdn* = 1) also had a higher rating on the right thigh compared with adult drivers (*Mdn* = 0), with $H(1) = 11.19$, $p = 0.001$.

Driving and takeover performance were also studied under the automated driving mode. Overall, young drivers (*Mdn* = 0.75) showed a significantly lower takeover rate compared with adult (*Mdn* = 1) drivers, with $H(1) = 4.71$, $p = 0.030$. Young drivers (*Mdn* = 0.5) also showed a lower successful takeover rate compared with adult drivers (*Mdn* = 1), with $H(1) = 7.83$, $p = 0.005$. During driving, young drivers (*Mdn* = 5.11) also had a significantly higher average eyes off road time in seconds compared with adult drivers (*Mdn* = 2.33), with $H(1) = 7.58$, $p = 0.006$. When looking into different workloads, young drivers performed worse under high workload compared with adult drivers; no significant difference was found between driving and takeover performance under the low workload. During high workload, young drivers (*Mdn* = 0.732) had a lower takeover rate compared with adult drivers (*Mdn* = 1), with $H(1) = 6.27$, $p = 0.012$. For successful takeover rate under high workload, young drivers (*Mdn* = 0.5) were lower, with an *H* value of $H(1) = 11.05$, $p = 0.001$, compared with adult drivers (*Mdn* = 0.875), and for the average eyes off road time in seconds at high workload, young drivers (*Mdn* = 4.36) were higher, with an *H* value of $H(1) = 6.16$, $p = 0.013$, compared with adult drivers (*Mdn* = 2.18).

What the driver was doing before the takeover was requested was also recorded and analyzed. On average, young drivers were found on the phone more often than adult drivers, and adult drivers were found monitoring the simulator more often than young drivers. Table 7 shows the results of the behaviors before taking over. The monitoring rate, on-phone rate, sleeping rate, and looking-away rate were calculated for both adult and young drivers. Detailed behaviors for each participant before taking over can be found in Appendix C.

Table 14 Behaviors before Taking Over for Study Two

	Monitoring rate	On-phone rate	Sleeping rate	Looking-away rate
Adult	85.29%	13.24%	0.00%	1.47%
Young	69.01%	29.58%	1.41%	0.00%

4.2.4 Young Drivers between Manual Driving and Automated Driving

Young drivers were expected to develop fatigue faster and more severely under automated driving mode than under manual driving mode. A Kruskal-Wallis test was conducted to compare the effects of driving mode on the SDNN, pNN50, and subjective ratings under the automated driving mode.

ECG

SDNN was found to be significantly higher under automated driving with high workload (*Mdn* = 32.54) compared with manual driving with high workload (*Mdn* = 14.80) for the young drivers, with $H(1) = 5.83$, $p = 0.016$. When looking into the time of driving, SDNN changes in young drivers under automated driving with high workload (*Mdn* = 28.905) were 25.495 higher than under manual driving with high workload (*Mdn* = 3.410) at 60 minutes of driving, with $H(1) = 4.08$, $p = 0.043$. At 90 minutes of driving, the difference was no longer significant between automated driving and manual driving, with $H(1) = 2.08$, $p = 0.149$. No significant difference in SDNN was found between automated driving and manual driving under low workload, with $H(1) = 0.40$, $p = 0.529$. The pNN50 was found to be not significantly different between automated driving and manual driving at both low workload, with $H(1) = 2.33$, $p = 0.127$, and high workload, with $H(1) = 0$, $p = 1$.

For the perceived fatigue, young drivers rated automated driving (*Mdn* = 3) significantly higher than manual driving (*Mdn* = 0.5) on stiff joints, with $H(1) = 4.79$, $p = 0.029$. Under high workload, young drivers rated higher on physical fatigue such as stiff joints and numbness under automated driving than under manual driving. For stiff joints under high workload, automated driving (*Mdn* = 3) was rated higher, with an *H* value of $H(1) = 12.45$, $p < 0.000$, compared with manual driving (*Mdn* = 0), and for numbness at high workload, automated driving (*Mdn* = 3) was again rated higher, with an *H* value of $H(1) = 4.68$, $p = 0.031$, compared with manual driving (*Mdn* = 0). It was also found that young drivers rated higher on discomfort at the right buttock for automated driving (*Mdn* = 2.5) compared with manual driving (*Mdn* = 0) under high workload, with $H(1) = 4.16$, $p = 0.042$. Under low workload, young drivers rated drowsiness significantly higher for automated driving (*Mdn* = 7.5) than for manual driving (*Mdn* = 3), with $H(1) = 5.15$, $p = 0.023$. No significant difference was found between automated driving and manual driving on overall feeling $H(1) = 0.08$, $p = 0.772$, over-drained $H(1) = 0.12$, $p = 0.724$, tense muscle $H(1) = 0.23$, $p = 0.632$, uninterested $H(1) = 1.98$, $p = 0.159$, and sleepiness $H(1) = 1.02$, $p = 0.134$ for young drivers. No significant difference was found between automated driving and manual driving for discomfort in any part of the body other than the right buttock for the young drivers.

4.2.5 Young Drivers under Manual Driving with Different Workloads

Young drivers were expected to develop fatigue faster and more severely under manual high workload compared with manual low workload. A Kruskal-Wallis test was conducted to compare the effects of workload on the SDNN, pNN50, and subjective ratings under the manual driving mode.

No significant difference on SDNN was found between high workload and low workload under manual driving mode among young drivers, with $H(1) = 0.28$, $p = 0.600$. The pNN50 was also found to be not significantly different between high workload and low workload under manual driving among young drivers, with $H(1) = 0.28$, $p = 0.598$.

Among the perceived fatigue ratings, young drivers rated significantly higher on stiff joints under low workload (*Mdn* = 2) compared with high workload (*Mdn* = 0), with $H(1) = 9.58$, $p = 0.002$. Young drivers also rated significantly higher on discomfort in both left and right fingers at low workload (*Mdn* = 2, 2) compared with high workload (*Mdn* = 0, 0), with $H(1) = 6.05$, $p = 0.014$ and $H(1) = 7.40$, $p = 0.007$. When investigating the time of driving, young drivers rated stiff joints higher at low workload (*Mdn* = 1.5) at 30 minutes of driving compared with high workload (*Mdn* = 0), with $H(1) = 3.94$, $p = 0.047$. The difference for stiff joints went higher at 60 minutes of driving between low workload (*Mdn* = 3.5) and high workload (*Mdn* = 0) among young drivers, with $H(1) = 6.14$, $p = 0.013$. However, the difference was not significant anymore at 90 minutes of driving, with $H(1) = 1.09$, $p = 0.297$. The discomfort in right fingers was found to be significantly higher at 90 minutes of driving under low workload (*Mdn* = 3.5) compared with high workload (*Mdn* = 0), with $H(1) = 3.94$, $p = 0.047$. No significant difference was found between low workload and high workload under manual driving on overall feeling $H(1) = 0.24$, $p = 0.623$, over-drained $H(1) = 0.04$, $p = 0.837$, tense muscles $H(1) = 1.96$, $p = 0.162$, uninterested $H(1) = 0.89$, $p = 0.345$, drowsiness $H(1) = 0.12$, $p = 0.726$, and sleepiness $H(1) = 2.57$, $p = 0.109$ for young drivers. No significant difference was found in any other part of body other than the fingers.

4.2.6 Young Drivers under Automated Driving with Different Workloads

Young drivers were expected to develop fatigue faster and more severely under automated low workload compared with automated high workload. Also, their takeover performance was expected to be worse under the low workload. A Kruskal-Wallis test was conducted to compare the effects of workload on the SDNN, pNN50, subjective ratings, and takeover performance under the manual driving mode.

SDNN was found to be significantly different between high workload and low workload among young drivers under automated driving mode, with $H(1) = 9.28$, $p = 0.002$, which indicates that young drivers have a higher SDNN change at high workload ($Mdn = 32.450$) compared with low workload ($Mdn = -0.115$) under automated driving mode. At 60 minutes of driving, SDNN changes among young drivers under automated high workload ($Mdn = 28.905$) was 30.22 higher than in the young drivers under automated low workload ($Mdn = -1.315$), with $H(1) = 5.33$, $p = 0.021$. At 90 minutes of driving, SDNN changes among young drivers under automated high workload ($Mdn = 39.655$) were still significantly higher than in the young drivers under automated low workload ($Mdn = 7.090$), with $H(1) = 4.08$, $p = 0.043$. No significant difference was found in pNN50 changes between different workloads among young drivers under automated driving mode, with $H(1) = 0.23$, $p = 0.635$.

Young drivers were found to have significantly more drowsiness under low workload ($Mdn = 7.5$) compared with high workload ($Mdn = 1$), with $H(1) = 8.06$, $p = 0.005$. When looking into the discomfort in different parts of the body, young drivers rated significantly lower discomfort in both left and right ankles under low workload ($Mdn = 0, 0$) compared with high workload ($Mdn = 1, 2$), with H values of $H(1) = 4.94$, $p = 0.026$, and $H(1) = 10.94$, $p = 0.001$. No significant difference between low workload and high workload was found in overall feeling

$H(1) = 3.02$, $p = 0.082$, over-drained $H(1) = 1.29$, $p = 0.257$, stiff joints $H(1) = 1.96$, $p = 0.161$, tense muscles $H(1) = 0.20$, $p = 0.657$, uninterested $H(1) = 0.10$, $p = 0.749$, sleepiness $H(1) = 1.78$, $p = 0.182$, and numbness $H(1) = 2.19$, $p = 0.138$.

For the driving and takeover performance, no significant difference was found in average eyes-off-road time in seconds $H(1) = 0.08$, $p = 0.773$, numbers of eyes off road H $H(1) = 2.09$, $p = 0.149$, takeover rate $H(1) = 0.13$, $p = 0.717$, and successful takeover rate $H(1) = 1.01$, $p = 0.315$ between low workload and high workload among young drivers.

Chapter 5 Discussion

5.1 Study One: Are Young Drivers Different from Adult New Drivers?

The purpose of study one was to determine how age and experience contribute to fatigue development and takeover behaviors among young drivers. Adult new drivers were used for comparison with the adult experienced group and the young group to measure the difference between fatigue development and driving behaviors and performance.

Based on the results of the perceived fatigue and discomfort questionnaire, there was a clear trend that young drivers had earlier fatigue onset compared with the other two groups for both mental and physical fatigue. They rated higher on overall feeling, over-drained, drowsiness, sleepiness, stiff muscles, and tense muscles. The onset of their fatigue was also earlier (at 60 minutes) compared with adult groups (at 90 minutes or even having no fatigue onset by the end). No significant difference was observed between adult experienced drivers and adult new drivers. Overall, the results of the subjective ratings confirmed that ages play a more important role in fatigue development compared with experience, as both groups of adult drivers rated lower on perceived fatigue development compared with young drivers

HR reduction can be an indication of fatigue among young drivers. The results of the HR show that compared with both adult experienced drivers and adult new drivers, the young drivers had an earlier onset of HR reduction, which is consistent with the perceived fatigue and discomfort questionnaire results.

For the EEG data, the young driver group showed more increase on the alpha band, which could indicate a more fatigued state for young drivers. However, this increase may have resulted from the lack of data. Due to the failure of the data collection and data cleaning, adult groups had only one set of data left for the EEG. So, the difference in result might be due to the individual difference rather than being some fatigue indicator. Overall. EEG data do not show results as promising as the other measures due to the lack of data.

The video recording results confirmed that young drivers perform worse during driving compared with adult drivers. Both young drivers and adult new drivers had a higher crash and near-crash rate under manual driving, but adult new drivers performed better than young driver groups on automated driving. During manual driving, inexperience affected both young drivers and adult new drivers; however, when it was automated driving, young drivers were the only ones who performed badly. During the automated driving mode, young drivers had more failures on the takeover. Since both adult new drivers and young drivers lack experience, the bad performance of young drivers could be mostly attributed to their immature brains rather than to the lack of experience. Young drivers' EF has not fully developed, which causes low impulse control and ease of being distracted (Zhang et al., 2020) and thus failure to monitor automated driving and takeover. Moreover, as mentioned earlier, vigilance decrease is a reversed U shape in regard to age; young drivers are more vulnerable to their vigilance decreasing since they are still young and at the beginning of the reversed U shape. When the young drivers were under vigilance decrease, they were less likely to perform well on takeovers compared with the adult new drivers group, even with both being inexperienced.

Although this study has observed that young drivers develop fatigue faster and more severely than adult groups, nothing statistically significant has been confirmed due to lack of data to perform hypothesis testing. This study was a pilot study and had only 2 or 3 repeats for each scenario. After the data cleaning, some of the measures had only one set of data left, which is not enough to do any statistical hypothesis testing. More data were collected in study two to test the differences in fatigue development, driving performance, and takeover behaviors among young drivers and adult drivers.

5.2 Study Two: Young Drivers vs. Adult Drivers

The goal of study two was to test the differences between young drivers and adult drivers under different driving modes and different workloads. Five hypotheses were tested in this study: First, young drivers were expected develop fatigue faster and more severely compared with adult drivers for both automated driving and manual driving. Second, young drivers' fatigue development was expected to be more severe under manual high workload compared with manual low workload. Third, young drivers' fatigue development was expected to be more severe under automated compared with manual driving. Fourth, young drivers' fatigue development was expected to be more severe under automated low workload compared with automated high workload. Last, young drivers' takeover performance was expected to be worse than adult drivers. Young and adult subjects were recruited to perform a driving task on a driving simulator for 1.5 hours, and their self-reported fatigue questionnaire, ECG, and video recording data were analyzed.

The results of the ANOVA test on HR confirmed the first hypothesis. HR reduction can be an indication of fatigue among young drivers (Riemersma et al., 1977). Young drivers' HR reduced significantly more than adult drivers' under different driving modes and workloads, which indicates that young drivers develop the fatigue mode more severely than adult drivers under different driving modes and workloads. Moreover, the difference between young drivers' and adult drivers' HR decrease was 4.63 at 60 minutes of driving and 5.26 at 90 minutes of driving, which indicates that the longer they drove, the more severe the fatigue was for the young drivers.

The analysis of perceived fatigue ratings also confirmed the first hypothesis. Young drivers rated higher on tense muscles compared with adult drivers under manual driving, especially under the manual high workload. However, adult drivers rated higher on numbness than young drivers, but when investigating the time of the drive, although adult drivers rated higher on numbness at the first 30 minutes of driving, no significant difference was found after 60 minutes of driving, which means that young drivers developed more fatigue during the 30 minutes to 60 minutes of driving and had the same perceived numbness at 60 minutes of driving as the adult drivers. Higher ratings on physical fatigue like stiff joints and tense muscles can potentially be explained by the fact that young drivers tend to be more tense during driving (Taubman - Ben-Ari, 2010). They were not able to relax during the driving task and thus caused the fatigue onset to be faster and more severe. The young driver group rated high in stiff joints under high workload conditions, which might be because all the near-crash scenarios and automated failures overwhelmed them. Due to lack of experience (Williams, 2003) and immature brain function (Diamond, 2013; Dumontheil, 2016; Huizinga et al., 2006; Luna, 2009; Walshe et al., 2017), they were not able to adjust well and in turn caused the fatigue.

A similar result was found under the automated driving scenario. Young drivers rated higher on overall feeling, over-drained, stiff joints, tense muscles, uninterested, and drowsiness. Most young drivers' fatigue ratings were found to be significantly different from adult drivers from 30 minutes of driving, which indicates an earlier onset of fatigue among young drivers. Compared with manual driving, young drivers perceived more dimensions of fatigue. While young drivers experienced only significant tense muscles under manual driving, they experienced both mental and physical fatigue under automated driving. Higher ratings on mental fatigue like drowsiness and sleepiness could be caused by the vigilance decreasing under automated driving (Greenlee et al., 2018; Mkrtchyan et al., 2012). Vigilance decreasing has a reversed U shape in regard to age (Davies & Davies, 1975; Seidel & Joschko, 1990), which makes young drivers more vulnerable to vigilance decreasing effects.

Under manual driving mode, adult drivers were found to have higher discomfort in the left neck and lower arms compared with young drivers. Neck pain was found to be related to older age (McLean et al., 2010). Guez et al. (2002) found that adults of working age had more neck pain than other age groups. Thus, a higher rating on neck discomfort could have been caused by pre-existing neck pain in the adult group. Under the automated driving mode, young drivers rated significantly higher on buttock discomforts, especially on the right side. Since the young drivers were expected to be more stressed by the system failure and their inexperience and immature brain were expected to feed back to the stress, they would have been highly tensed under automated driving and had their legs preparing for breaking all the time. Such kinds of stress and tension could lead to fatigue and discomfort for their buttocks.

The second hypothesis was that young drivers' fatigue development was expected to be more severe under manual high workload compared with manual low workload. However, the results pointed in the opposite direction. Young drivers rated higher on stiff joints under low workload compared with high workload. Moreover, they felt more discomfort in the fingers under the low workload compared with the high workload. One potential explanation for young drivers rating higher on the low workload is because the higher workload gives the drivers more simulation and more chance to move around, which decreases the discomfort in their joints and fingers. Under the low workload, young drivers were only required to drive the vehicle, while the high workload required the young drivers to reply to text messages and to break more often. Such tasks may have given the young drivers more chance to move around and thus reduce their discomfort in their joints and fingers.

The third hypothesis was that young drivers' fatigue development was expected to be more severe under automated driving mode compared with manual driving mode. This hypothesis was confirmed by the analysis of the perceived fatigue ratings. Young drivers rated higher on stiff joints and numbness under automated driving compared with manual driving, especially for the high workload. Moreover, young drivers rated higher on buttock discomfort under automated driving compared with manual driving. As mentioned earlier, young drivers have less experience, which means that they need extra effort to take over (Sun et al., 2014), which in turn causes stress and fatigue for them. Moreover, their inexperience could also have made the young divers more stressed when a near crash happened. All these stressors could have increased the fatigue among the young drivers during automated driving compared with manual driving.

The fourth hypothesis was that young drivers' fatigue development was expected to be more severe under automated low workload compared with automated high workload. This hypothesis was confirmed by the perceived fatigue ratings as well. Young drivers rated higher on drowsiness under the low workload compared with the high workload. They also perceived more discomfort in their ankles under the low workload compared with the high workload. Higher ratings on drowsiness could have been caused by the vigilance decreasing. Under the high workload, there were secondary tasks, distractions, and other stimulations, which helped the young drivers be more engaged in the driving environment (Miller et al., 2015), which in turn helped prevent fatigue development. However, under the low workload, young drivers were asked only to monitor the automated driving simulator, which may not have any failure for over 10 minutes; young drivers would then have been fatigued due to the vigilance decreasing.

The last hypothesis was that young drivers' takeover performance was expected to be worse than adult drivers. This hypothesis was confirmed from the video recording analysis. Young drivers were not able to supervise automated driving as they were supposed to, and they were less likely to have remained focused on the road after driving for a while. Before the takeover was needed, young drivers were much less likely to have been monitoring the system but were on their phones or even falling asleep. The rate at which they could successfully take over was also significantly lower compared with the adult groups, and they also had a significantly higher average eyes-off-road time. Young drivers' EF is not fully developed, which makes them more likely to make decision errors and to be distracted during the driving tasks (Diamond, 2013; Huizinga et al., 2006). Walshe et al. (2017) found that young drivers cannot update information at the moment and manage subtasks of driving well. During automated driving, young drivers will be more likely to be distracted by their phones and not able to manage the driving task well. Moreover, young drivers

=[o not have much experience in driving compared with adult drivers, which makes it harder for young drivers to decide when to take over and how to take over when automation failure happens. Thus, their takeover rate and successful takeover rate were low compared with the adult drivers.

Overall, four out of five hypotheses have been statistically tested and confirmed for this study. Young drivers developed more-severe fatigue than adult drivers under all driving conditions. Most of the fatigue measures showed a significant difference between young drivers and adult drivers from 30 minutes of driving, which means that young drivers had their fatigue onset as early as during 30 minutes of driving. Young drivers' fatigue development was more severe under automated driving compared with manual driving, especially under the automated low workload. Moreover, young drivers' driving and taking over performance was much worse than that of the adult drivers under automated driving.

5.3 Limitations

HRV analysis showed opposite results compared with other measurements of the young drivers' fatigue development. Young drivers had an increased SNDD, pNN50, and LF/HF when other indicators showed that they were fatigued. This result is different from the expectation that HRV can decrease when participants become fatigued. A possible explanation for this was that HRV is heavily affected by respiration (Aysin & Aysin, 2006; Bernardi et al., 2000; Yildiz & Ider, 2006), but during the driving task, participants were not guided on how they should be breathing. Thus, different respiration patterns could have affected the HRV analysis results. For example, the participants might have been yawning more when they felt fatigued and the yawn could have led to a different breathing pattern and in turn affected the HRV results.

Due to the data distribution, only HR and LF/HF, SDNN, pNN50, and overall feeling were able to undergo the factorial ANOVA analysis. The nonparametric methods Kruskal-Wallis test was used to test the rest of the data. However, no nonparametric method can perform factorial design. Interactions between the main effects were not tested. Moreover, the sample size of study two was relatively small, and the power of the analysis was not ideal. The result may be more vulnerable to type II error due to relative low power. However, recent evidence indicates that alpha and beta error limits are usually used as a convention, and carefully controlled small studies can provide reliable results at a lower cost (Kaplan et al., 2014).

EEG is considered one of the most reliable measures to detect mental fatigue and drowsiness (Artaud et al., 1995; Erwin et al., 1973; Volow & Erwin, 1973). However, EEG data were not used in study two. Because of the Covid_19 pandemic, it was hard for the EEG equipment to meet cleaning requirements. Moreover, the EEG equipment caused discomfort on the participants' heads, which may have induced discomfort and fatigue simply by its use. Thus, the EEG was not used for study two. However, some valuable measurements and results might have been missed by not looking at the EEG result of the study.

The simulator could not replicate real-world driving. The consequences of crashes are different between simulator driving and real-world driving. The pressure of possible crashes is much less under the simulator driving than real-world driving, which may have an impact on the fatigue development among young drivers. Moreover, simulator driving is similar to car racing games. Participants with racing game experience may find it is easier to drive the simulator than the participants without car racing game experience, which could cause the difference on fatigue development between different participants. Stinchcombe et al. (2017) found that racing game experience was positively associate with simulated crashes and risk-taking behaviors among young drivers. Although the initial screening of the study have excluded the participants who have the intense experience with driving game, but minor difference may still exist between participants. Thus, the gaming experience of the young drivers may have effects on the result of the performance of the participants in this study.

5.4 Future Works

Although the differences between young drivers and adult new drivers was compared in study one, no statistical analysis was performed between them. More adult new drivers should be recruited, and a statistical hypothesis should be performed to test the difference in fatigue development between young drivers and new drivers.

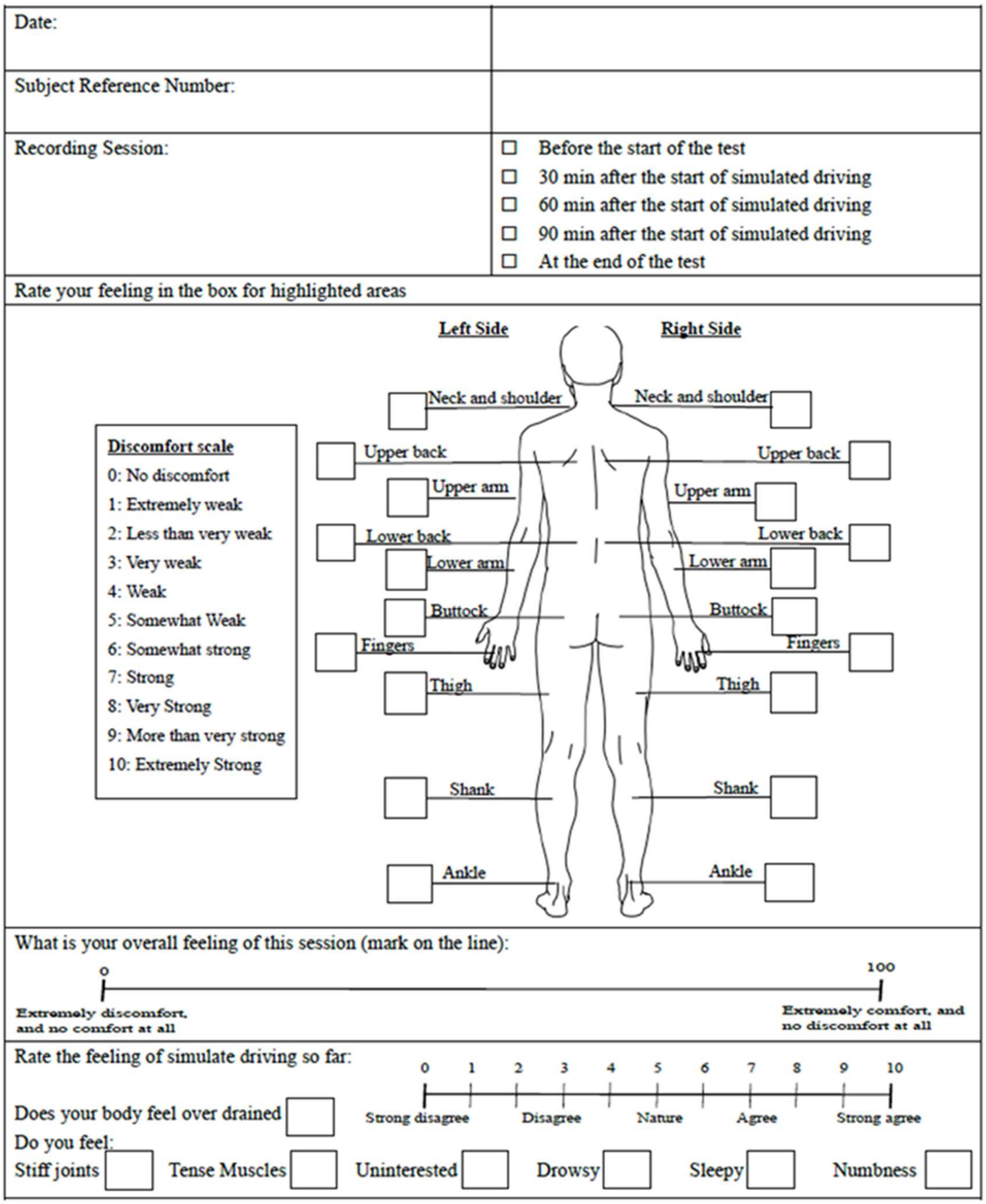
Most of the conclusions were drawn from the perceived fatigue questionnaire. HR was the only objective measure used in this study. HRV analysis was not included since the breathing could have affected the results of HRV, and the results of HRV were indicating opposite results to the other measures. More subjective measurements should be used. For example, participants should be guided on how they are breathing to facilitate use of the HRV to analyze the fatigue. EEG should be also used, since it is considered one of the most reliable measurements for driving fatigue. Moreover, eye tracking information should be used as an objective measurement as well. Lal & Craig (2001) found that eye blinking will be faster and eye movement will be slower when people are fatigued. Eye fixation can also be used to detect the attention of the participants and their distractions.

More participants could be recruited for this study. Based on the central limit theorem (Fischer, 2011), the independent variable will have a normalized distribution when there are 30 or more repeats in each group. Once the normal distribution can be assumed, factorial ANOVA can be performed for all the measurements and the interactions between different main effects can be tested. Also, older adult group could be recruited to test if more difference could be found between young drivers and older adult drivers.

It was worth to mentioned that the vigilance decrement may be a contributing factor for fatigue under the level 2.5 automated driving scenario. However, when the automated driving technic develops to the higher level, vigilance decrement should not be considered any more. As the vigilance tasks refers to the tasks that require a person to maintain alertness for a long period of time to detect signals that are not frequent and predictable (Hancock, 2017; Warm et al., 2015), monitoring the level 2.5 automated driving can be considered as a vigilance task. However, the level 3 or above automated driving does not need the driver to monitor the road all the time, thus, sit in a level 3 automated vehicle cannot be considered as a vigilance tasks, and vigilance decrement should not be considered as factors contribute to the fatigue under any more.

Appendices

Appendix A. Perceived Fatigue and Discomfort Questionnaire



Date:	
Subject Reference Number:	
Recording Session:	☐ Before the start of the test ☐ 30 min after the start of simulated driving ☐ 60 min after the start of simulated driving ☐ 90 min after the start of simulated driving ☐ At the end of the test

Rate your feeling in the box for highlighted areas

Discomfort scale

0: No discomfort
1: Extremely weak
2: Less than very weak
3: Very weak
4: Weak
5: Somewhat Weak
6: Somewhat strong
7: Strong
8: Very Strong
9: More than very strong
10: Extremely Strong

What is your overall feeling of this session (mark on the line):

0 — Extremely discomfort, and no comfort at all
100 — Extremely comfort, and no discomfort at all

Rate the feeling of simulate driving so far:

0 1 2 3 4 5 6 7 8 9 10
Strong disagree — Disagree — Nature — Agree — Strong agree

Does your body feel over drained ☐

Do you feel:

Stiff joints ☐ Tense Muscles ☐ Uninterested ☐ Drowsy ☐ Sleepy ☐ Numbness ☐

Figure A.1. Perceived Fatigue and Discomfort Questionnaire

Appendix B. Normality Test for the Measurements

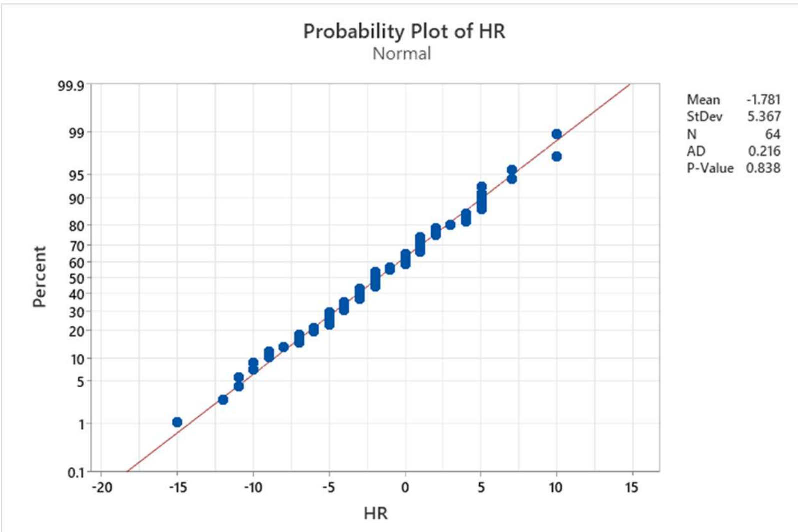


Figure B.1. Normality Test for HR

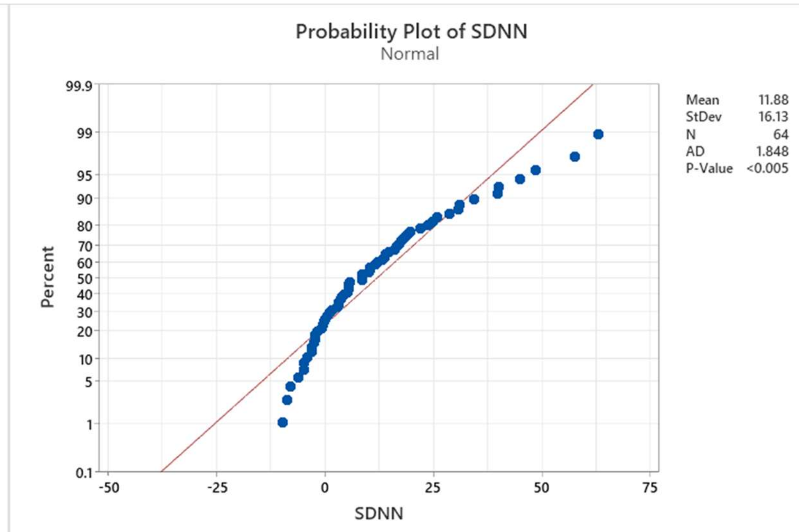


Figure B.2. Normality Test for SDNN

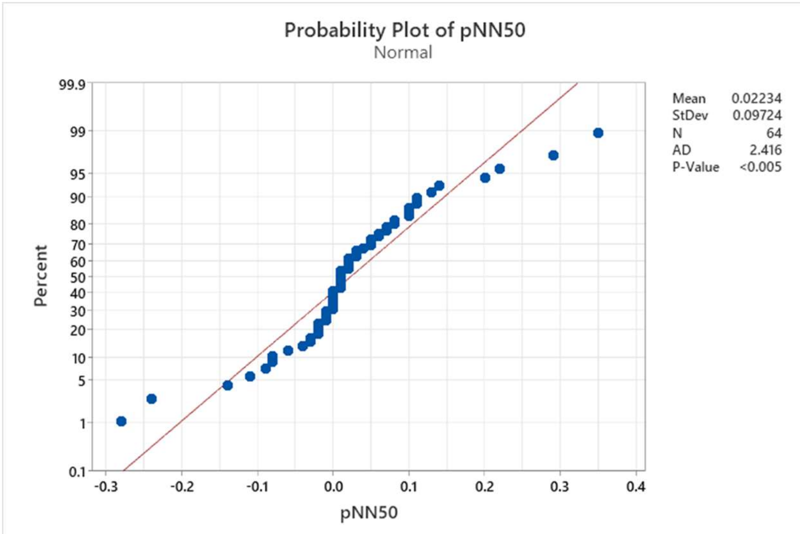


Figure B.3. Normality Test for pNN50

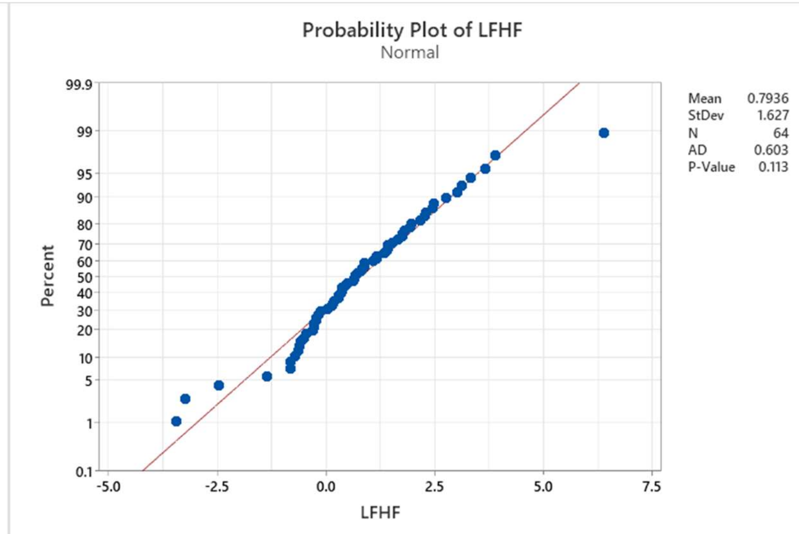


Figure B.4. Normality Test for LF/HF

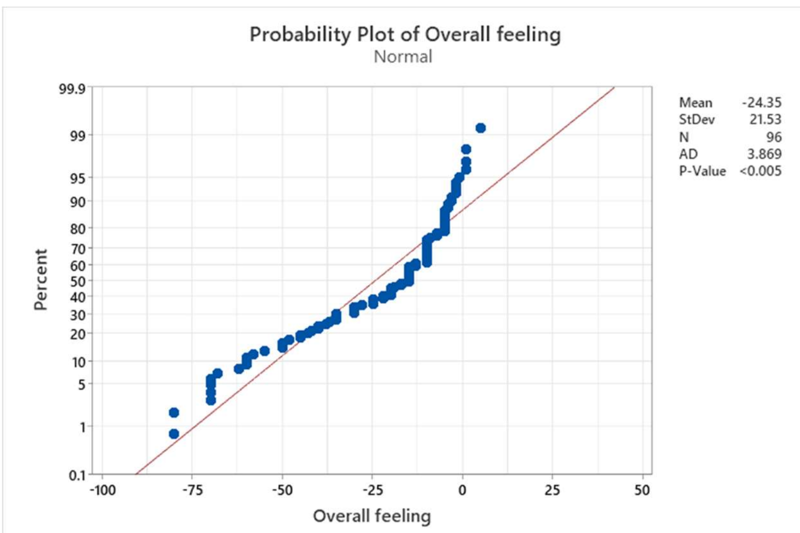


Figure B.5. Normality Test for Overall Feeling

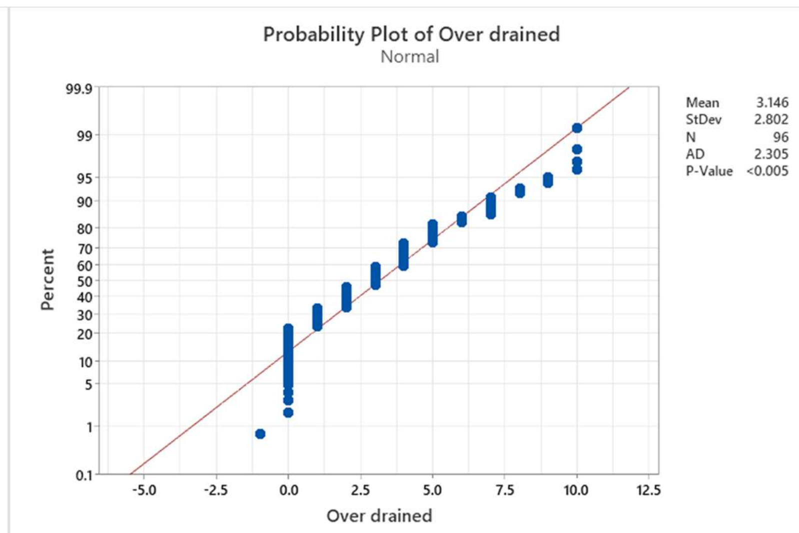


Figure B.6. Normality Test for Over Drained

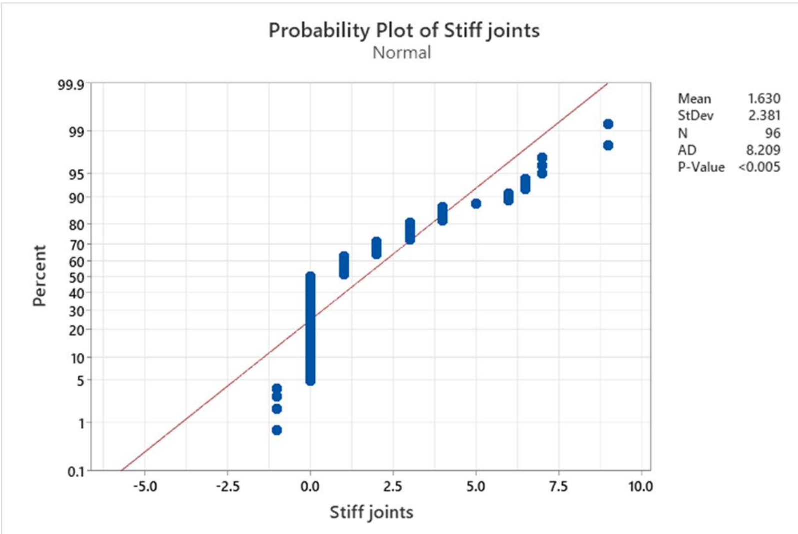


Figure B.7. Normality Test for Stiff Joints

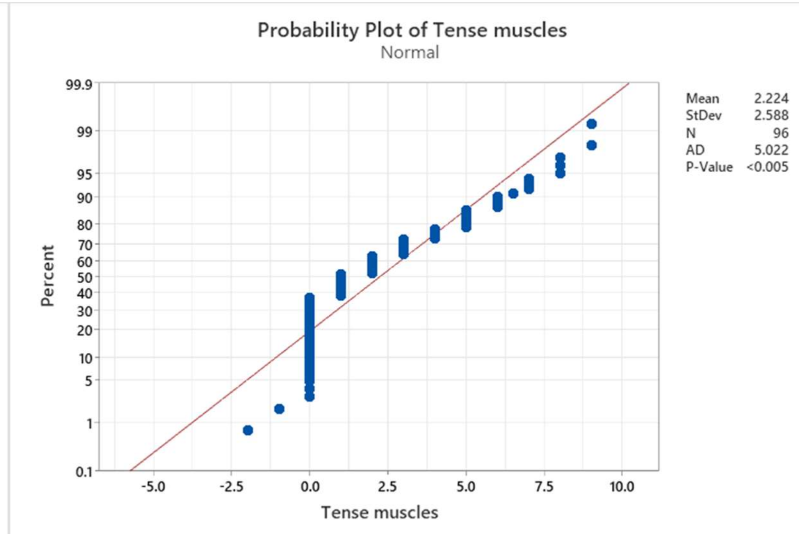


Figure B.8. Normality Test for Tense Muscles

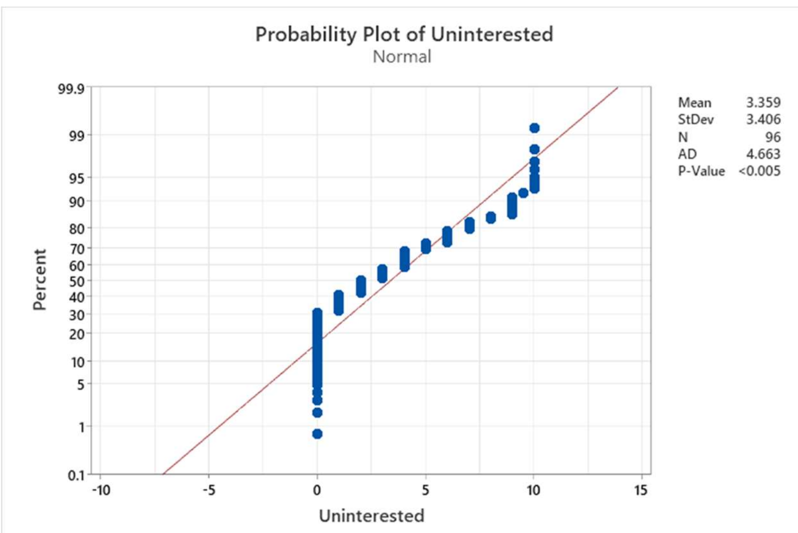


Figure B.9. Normality Test for Uninterested

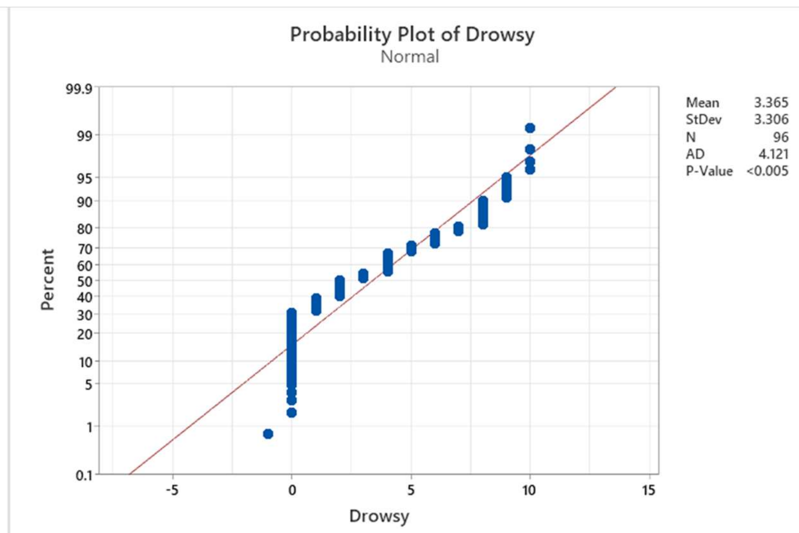


Figure B.10. Normality Test for Drowsy

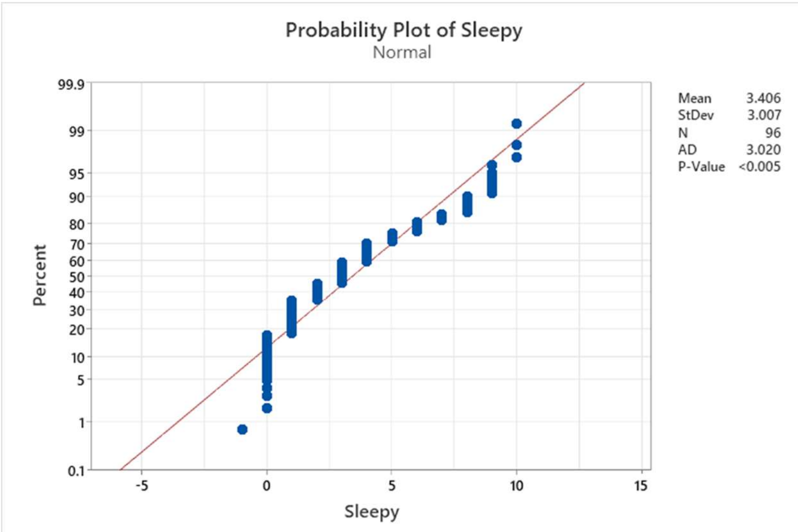


Figure B.11. Normality Test for Sleepy

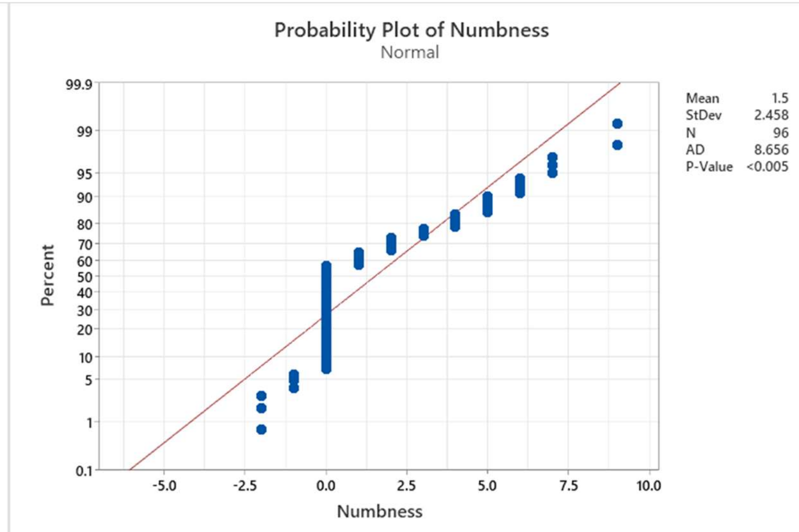


Figure B.12. Normality Test for Numbness

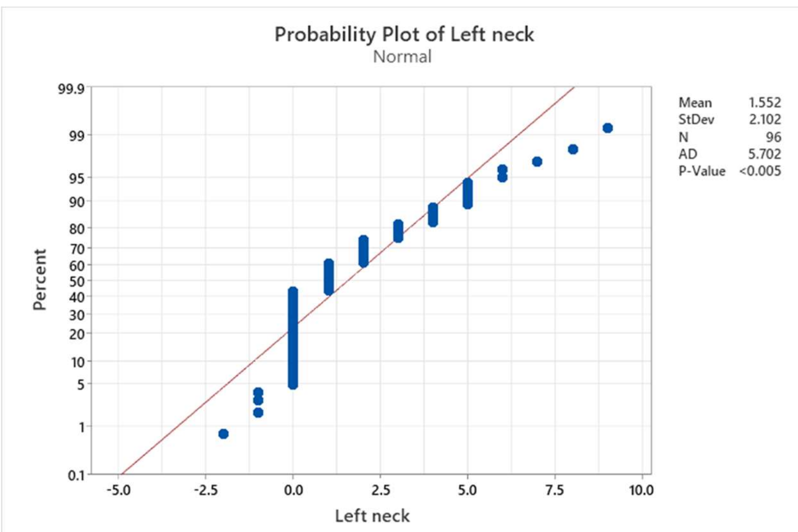


Figure B.13. Normality Test for Left Neck

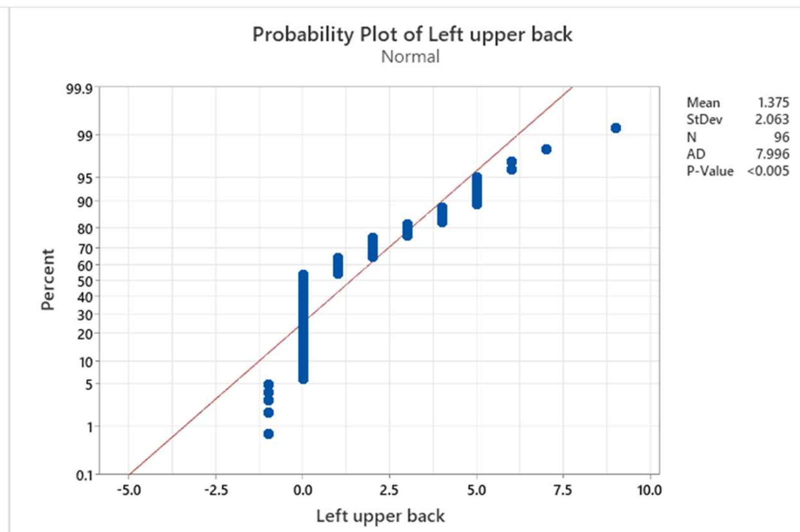


Figure B.14. Normality Test for Left Upper Back

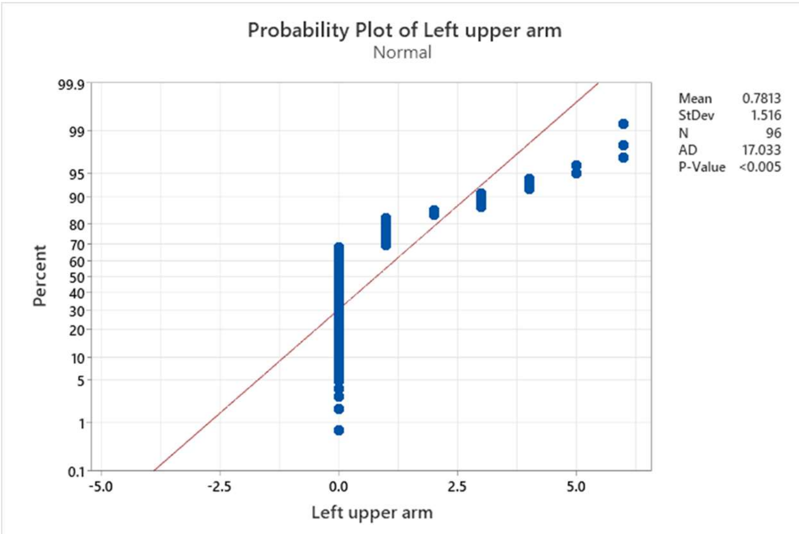


Figure B.15. Normality Test for Left Upper Arm

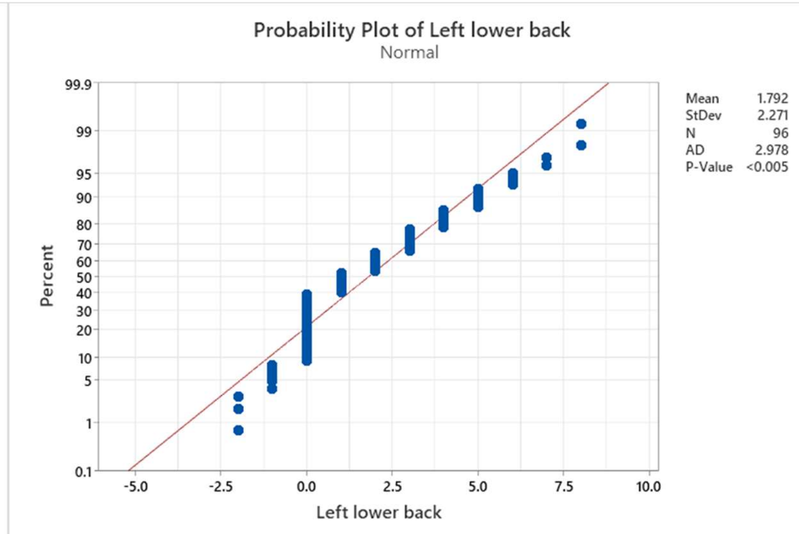


Figure B.16. Normality Test for Left Lower Back

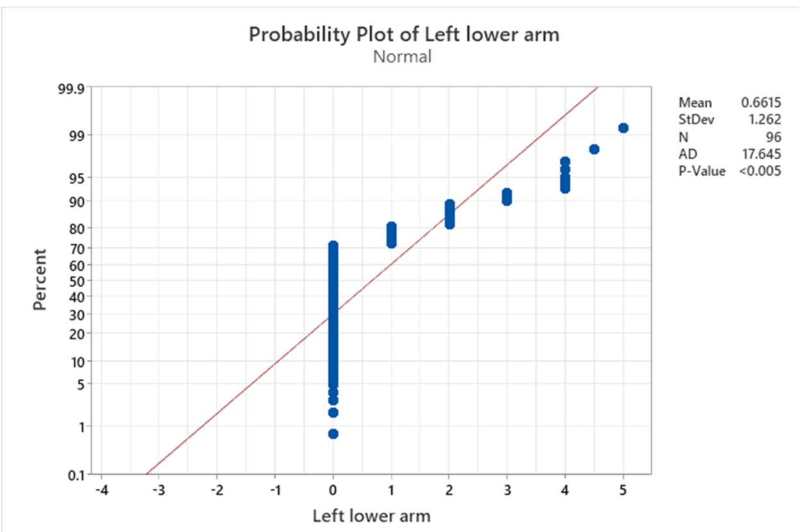


Figure B.17. Normality Test for Left Lower Arm

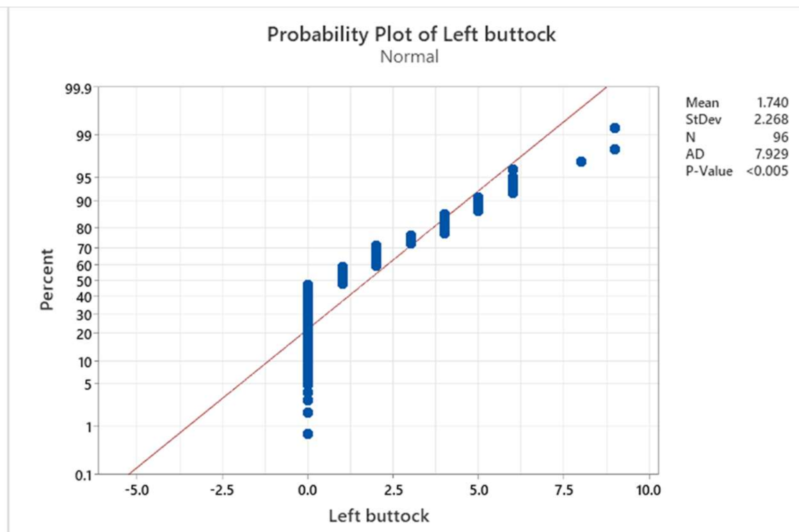


Figure B.18. Normality Test for Left Buttock

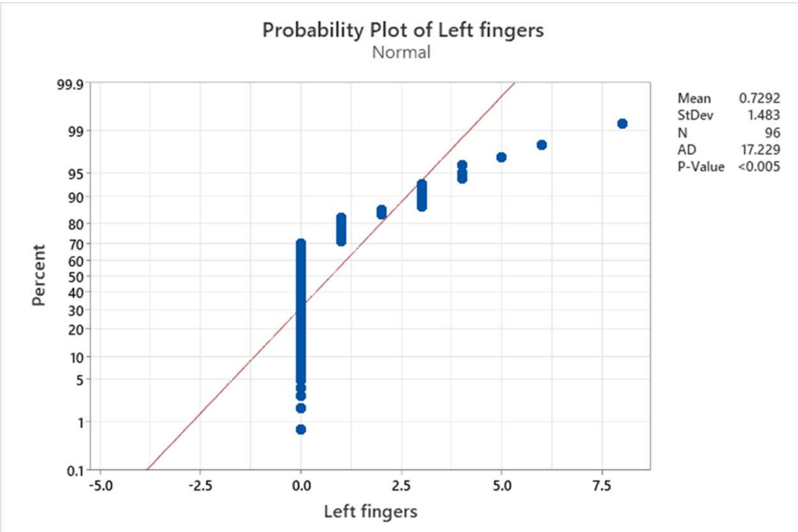


Figure B.19. Normality Test for Left Fingers

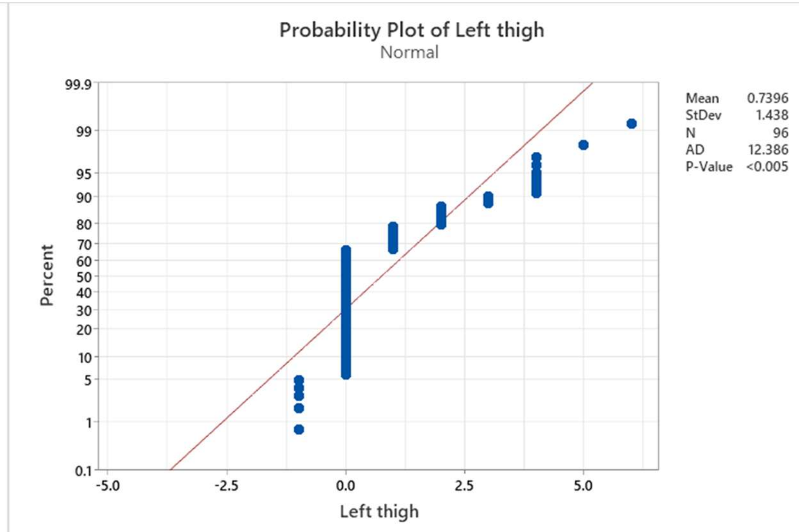


Figure B.20. Normality Test for Left Thigh

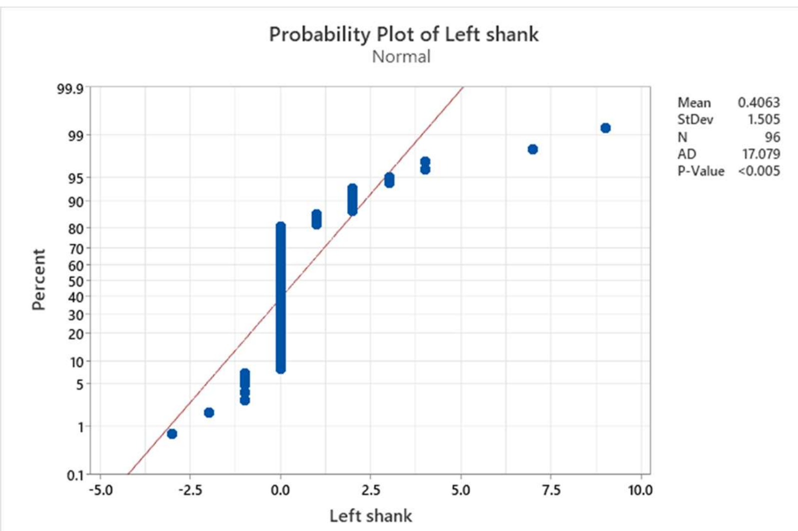


Figure B.21. Normality Test for Left Shank

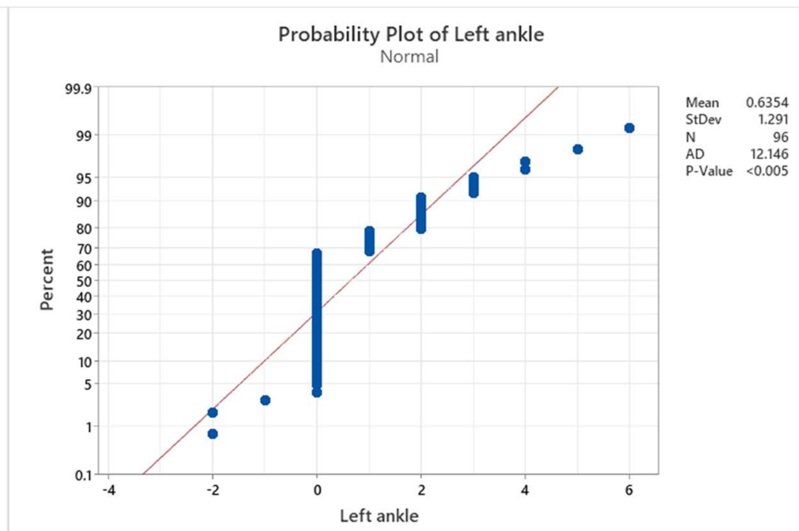


Figure B.22. Normality Test for Left Ankle

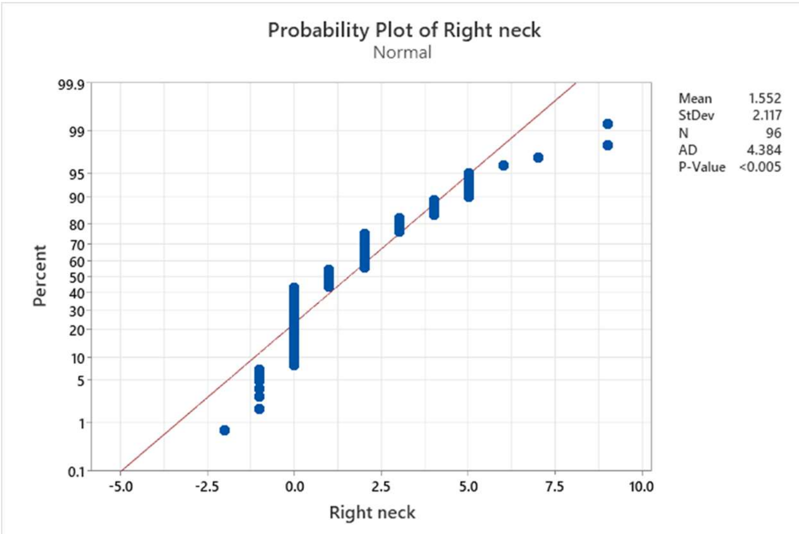


Figure B.23. Normality Test for Right Neck

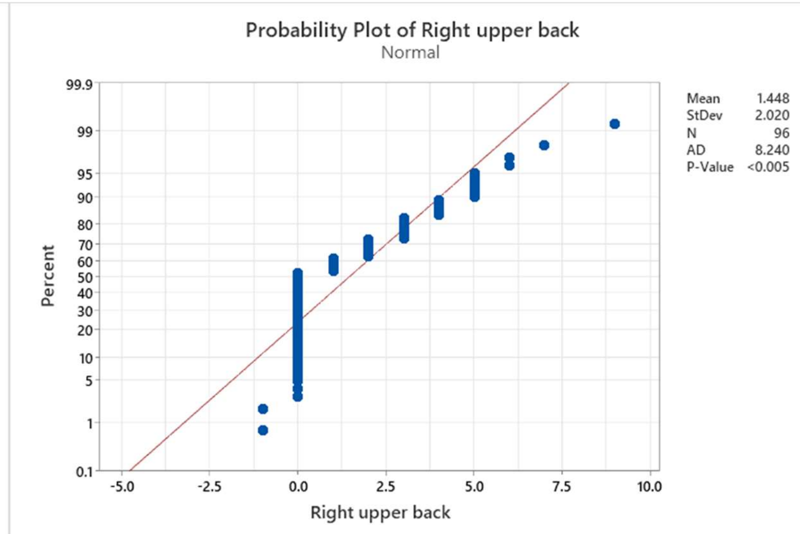


Figure B.24. Normality Test for Right Upper Back

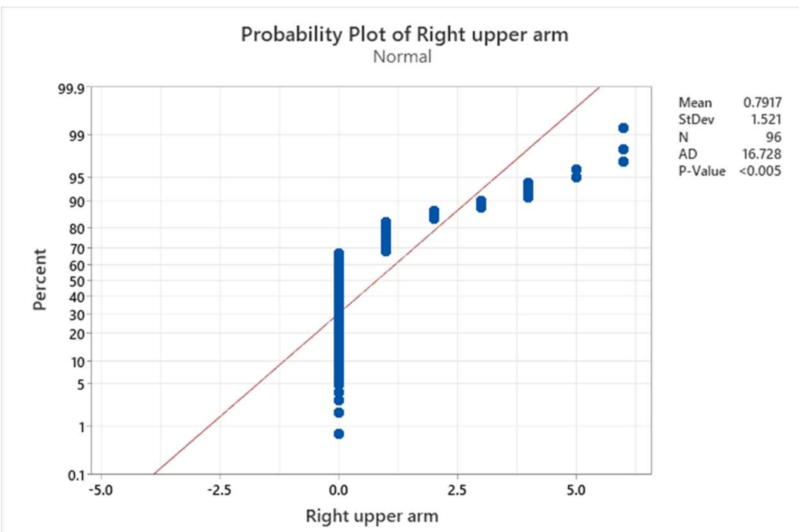


Figure B.25. Normality Test for Right Upper Arm

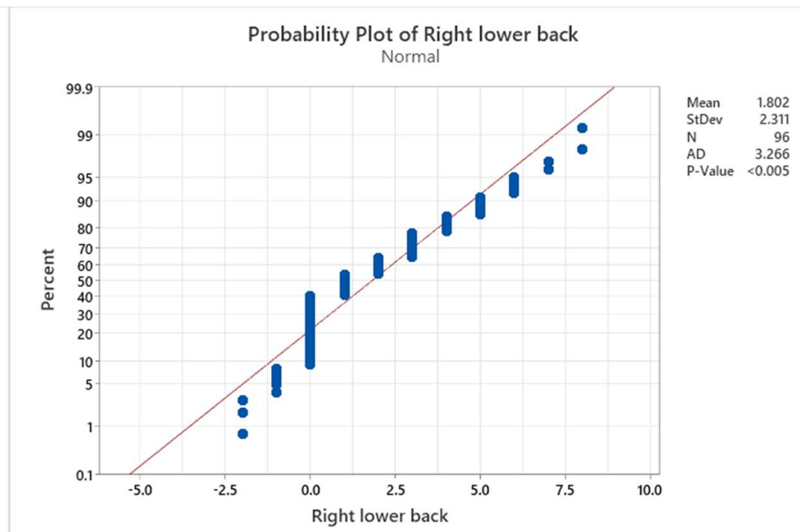


Figure B.26. Normality Test for Right Lower Back

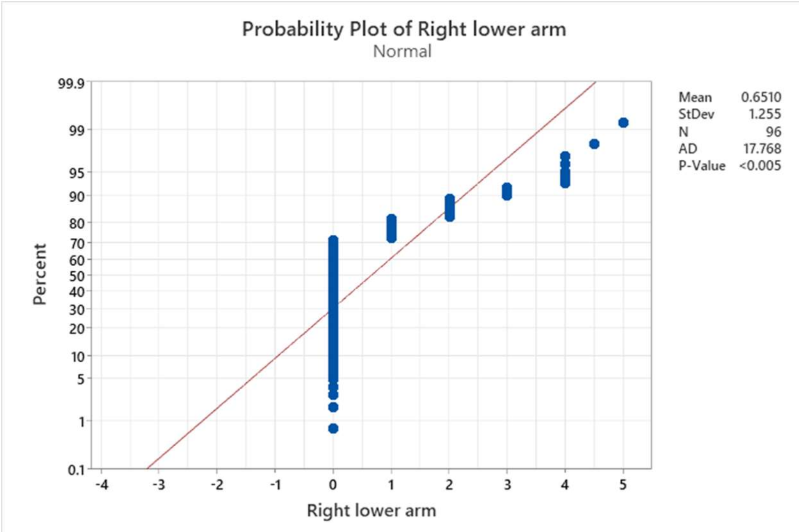


Figure B.27. Normality Test for Right Lower Arm

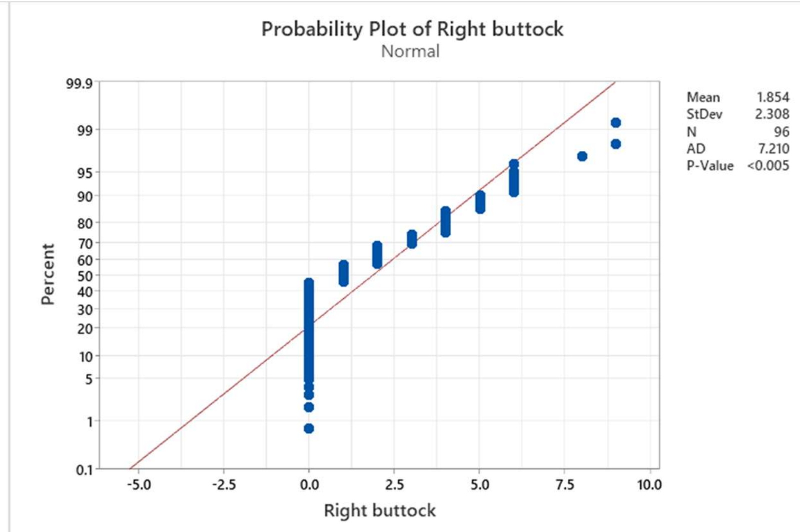


Figure B.28. Normality Test for Right Buttock

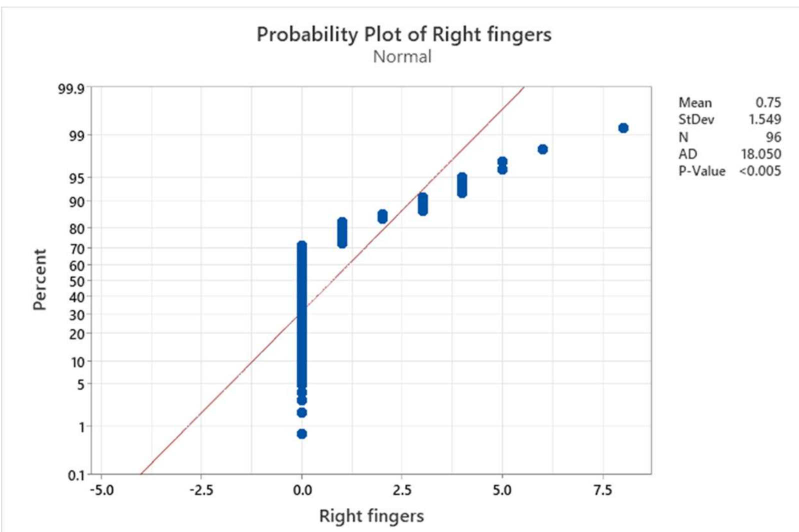


Figure B.29. Normality Test for Right Fingers

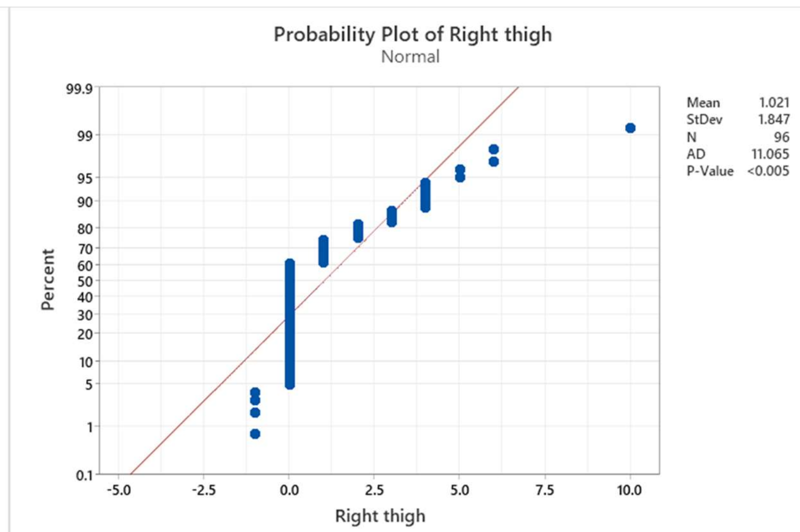


Figure B.30. Normality Test for Right Thigh

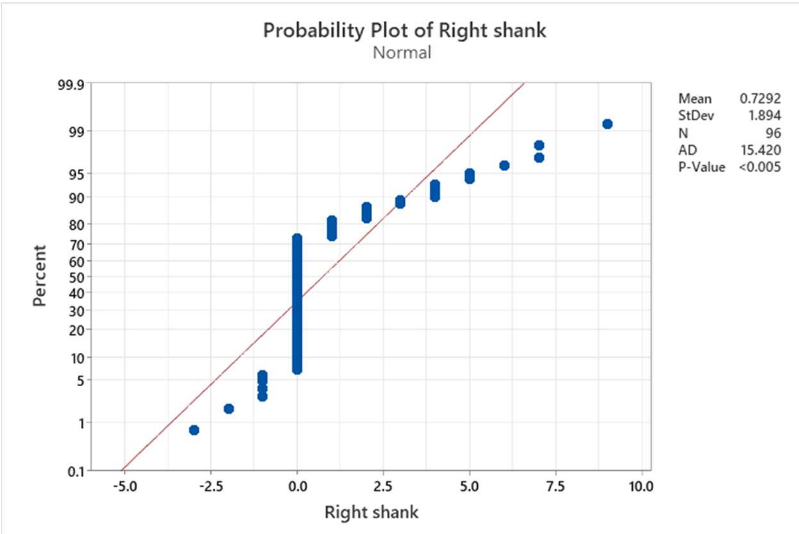


Figure B.31. Normality Test for Right Shank

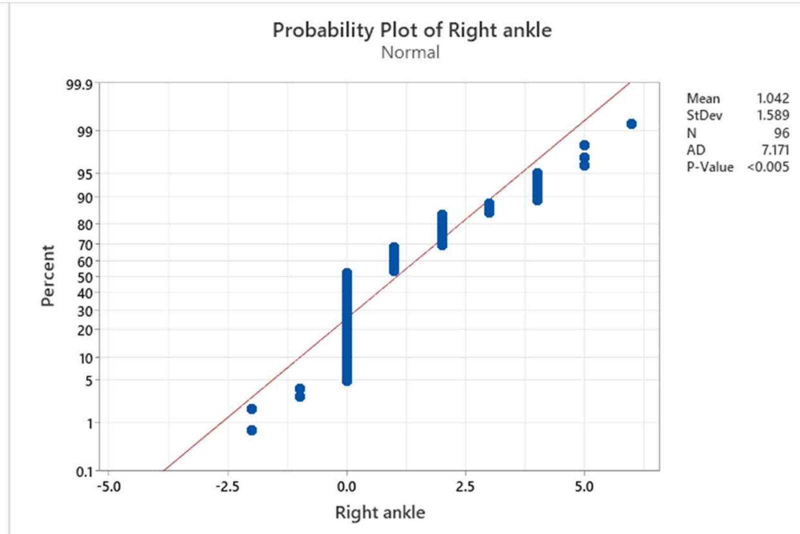


Figure B.32. Normality Test for Right Ankle

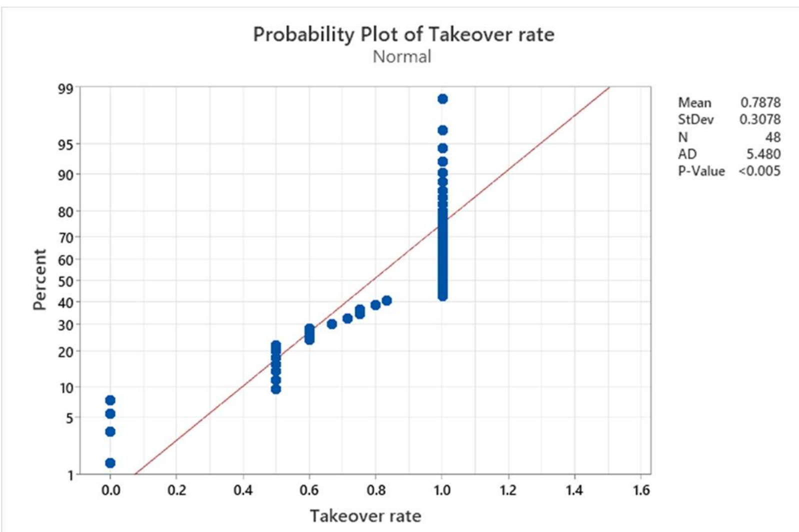


Figure B.33. Normality Test for Takeover Rate

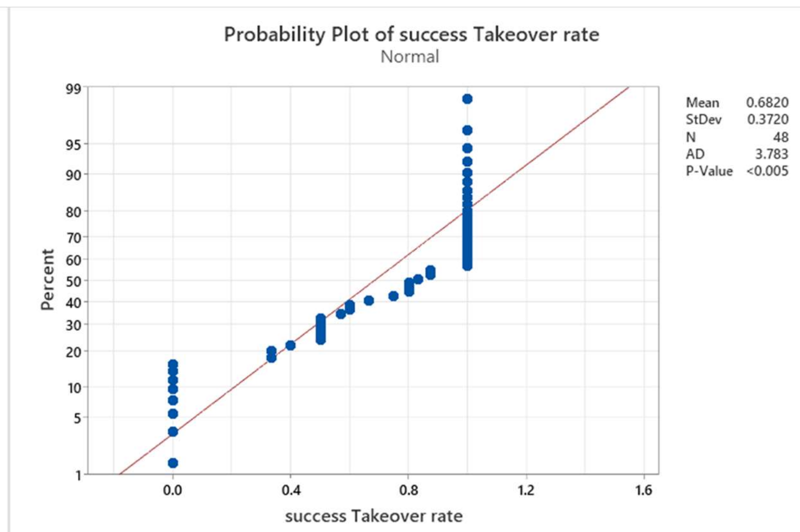


Figure B.34. Normality Test for Success Takeover Rate

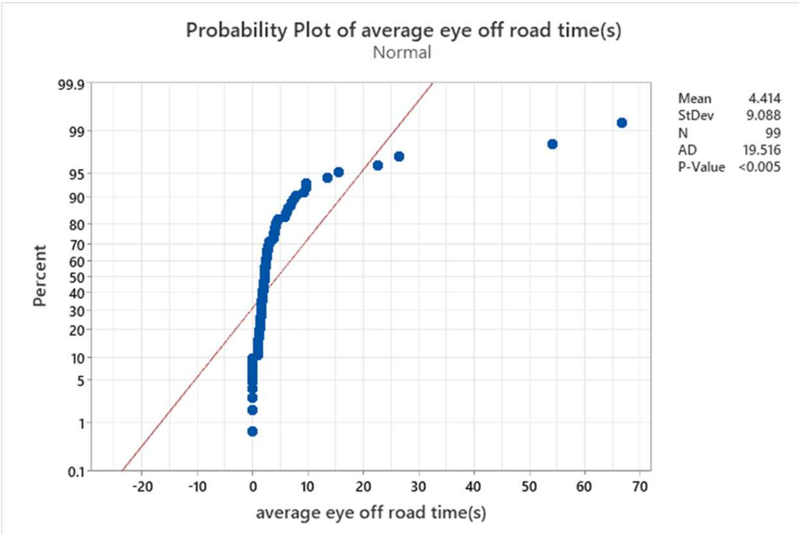


Figure B.35. Normality Test for Average Eye Off Road Time

Appendix C. Behaviors before Takeover for Study Two

Time	Participant	Group	Workload	Takeover 1	Takeover 2	Takeover 3	Takeover 4	Takeover 5	Takeover 6	Takeover 7	Takeover 8	Takeover 9
30 min	A02	Adult	Low workload	monitoring								
60 min	A02	Adult	Low workload	monitoring	monitoring	monitoring						
90 min	A02	Adult	Low workload									
30 min	A07	Adult	Low workload	look away								
60 min	A07	Adult	Low workload	monitoring								
90 min	A07	Adult	Low workload	monitoring								
30 min	A10	Adult	Low workload	monitoring								
60 min	A10	Adult	Low workload									
90 min	A10	Adult	Low workload	monitoring								
30 min	A11	Adult	High workload	monitoring	monitoring	monitoring	monitoring	monitoring				
60 min	A11	Adult	High workload	monitoring	monitoring	monitoring						
90 min	A11	Adult	High workload	on phone	on phone	monitoring	monitoring	monitoring	monitoring	monitoring		
30 min	A12	Adult	High workload	monitoring	monitoring	on phone	monitoring	on phone				
60 min	A12	Adult	High workload	monitoring	monitoring	on phone						
90 min	A12	Adult	High workload	monitoring	on phone	on phone	monitoring	monitoring				
30 min	A13	Adult	High workload	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring	
60 min	A13	Adult	High workload	monitoring								
90 min	A13	Adult	High workload	monitoring	monitoring							
30 min	A14	Adult	High workload	monitoring	monitoring	monitoring	monitoring	monitoring	monitoring			
60 min	A14	Adult	High workload	monitoring	monitoring	monitoring	monitoring					
90 min	A14	Adult	High workload	monitoring	monitoring	monitoring	on phone	on phone	monitoring	monitoring	monitoring	
30 min	A15	Adult	Low workload	on phone	monitoring							
60 min	A15	Adult	Low workload									
90 min	A15	Adult	Low workload									
30 min	C04	Young	Low workload	monitoring	monitoring	monitoring						
60 min	C04	Young	Low workload									
90 min	C04	Young	Low workload									
30 min	C06	Young	High workload	monitoring	on phone	on phone	monitoring	monitoring				
60 min	C06	Young	High workload	monitoring	monitoring	on phone	monitoring	sleeping				
90 min	C06	Young	High workload	monitoring	monitoring	monitoring	monitoring					
30 min	C08	Young	High workload	monitoring	on phone	monitoring	monitoring	on phone	monitoring	monitoring		
60 min	C08	Young	High workload	on phone	monitoring	on phone	on phone	on phone	on phone			
90 min	C08	Young	High workload	monitoring	monitoring	on phone	monitoring	monitoring	monitoring	monitoring	monitoring	
30 min	C09	Young	Low workload	monitoring	monitoring							
60 min	C09	Young	Low workload	monitoring	monitoring							
90 min	C09	Young	Low workload	on phone								
30 min	C12	Young	High workload	monitoring	monitoring	on phone	on phone	on phone	monitoring			
60 min	C12	Young	High workload	monitoring	on phone							
90 min	C12	Young	High workload	monitoring								
30 min	C14	Young	Low workload	on phone								
60 min	C14	Young	Low workload	on phone	monitoring						Successfuly take over	
90 min	C14	Young	Low workload									
30 min	C16	Young	High workload	monitoring								
60 min	C16	Young	High workload	monitoring	monitoring	monitoring	monitoring	monitoring			fail to take over, crash	
90 min	C16	Young	High workload	monitoring	monitoring	monitoring	monitoring					
30 min	C18	Young	Low workload	monitoring	monitoring	on phone						
60 min	C18	Young	Low workload	monitoring	on phone						fail to take over, but no crash	
90 min	C18	Young	Low workload	on phone								

Figure C.1. Behaviors before Takeover for Study Two

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