ASSESSING THE EFFECTS OF COGNITIVE SECONDARY TASKS AND AUTOMATION TYPE ON CHANGES IN HEART RATE: IMPLICATIONS FOR THE POTENTIAL USE OF NANOTECHNOLOGY

by

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To my family, my advising committee and my friends

To Ye Zhang, for her love and support

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ABSTRACT

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Vehicle automation is developing at a rapid rate worldwide. However, even lower levels of automation, such as SAE Level-1, are expected to reduce drivers' workload by controlling either speed or lane position. At the same time, however, drivers' engagement in secondary tasks may make up for this difference in workload displaced by automation. Previous research has investigated the effects of adaptive cruise control (ACC) on driving performance and workload, but little attention has been devoted to Lane Keeping Systems (LKS). In addition, the influence of secondary cognitive tasks on Level-1 driving performance is also not well understood.

The first goal of this thesis study was to examine the effects of secondary cognitive tasks and driving condition on driving performance. The second goal was to examine the effects of secondary cognitive tasks and driving condition on heart rate related measurements that reflect changes in workload. Both a novel nano-sensor and a commercial ECG sensor were used to measure heart rate. Thus, the third goal was to compare the capability of a nano-sensor in detecting changes in heart rate and heart rate variability with a commercially available ECG sensor. Twenty-five participants drove a simulated vehicle in manual, ACC and LKS driving conditions, while performing a secondary cognitive (N-back) task with varying levels of difficulty.

Results showed that more difficult cognitive secondary tasks were beneficial to driving performance in that a lower standard deviation of lane departure (SDLD) and a lower standard deviation of vehicle speed (SDVS) were both observed. Heart rate and NASA-TLX workload scores were significantly higher in the most difficult secondary task and in the manual driving conditions. However, heart rate variability measures (SDNN, RMSSD, pNN50, LF Power and HF Power) indicated lower variability under more difficult secondary tasks. This thesis suggests that nanotechnological devices may serve as a potential alternative to other heart rate measuring

technology. Limitations in detecting minor heart rate changes between different driving conditions and in heart rate variability measuring were also acknowledged.

CHAPTER 1. INTRODUCTION

This chapter provides an overview of the five aspects key to this thesis: autonomous driving, secondary tasks while driving, cognitive workload, workload assessment techniques, and a brief introduction of the nanotechnology sensor used in this thesis study.

1.1 Autonomous Driving

Nationally, approximately 35,000 fatal car accidents occur each year. According to statistics available, the number of fatal crashes is at an 8-year high (Highway Traffic Safety Administration & Center for Statistics, 2018). Over 94% of crashes had critical reasons that attributed to drivers (Highway Traffic Safety Administration & Department of Transportation, 2015). Naturalistic driving studies showed that driver inattention is believed to potentially contribute to approximately 78% of vehicle crashes (Klauer, 2006). According to a study based on four crash databases in the U.S., lane departure related crashes contribute to 14% of all crashes and 44% of all fatal crashes, whereas that of front collisions make up 30% of all crashes and only 6% of fatal crashes (Kusano & Gabler, 2014). An NHTSA report confirms the significance of unintended lane departure: among all drivers and motorcycle riders who involved in deadly accidents, 7.5% of them failed to stay in the proper lane, which is the third most fatal factor among all, after speeding and influence under drug and alcohol (Highway Traffic Safety Administration & Center for Statistics, 2018).

To make driving safer and help combat these negative accident statistics, several driver-assisted systems have been developed over the past decades (Shaout, Colella, & Awad, 2012). For example, in-vehicle navigation systems, rear cameras, forward collision warning, blind spot monitoring systems, lane departure warning (LDW) systems, and numerous others all support drivers by monitoring the vehicle status and providing alerts and notifications to improve driver's situation awareness. These systems do not take control of any particular driving function and are mostly passive. However, automated-driving systems (ADS) are those that take action for drivers in certain situations. For example, automatic emergency braking systems activate the vehicle's brakes when necessary to avoid potential collisions. Also, lane centering assist systems keep the vehicle centered in the lane during instances when the automobiles drift out of the designated lane.

It is not surprising that both driver-assisted and automated-driving systems may have unintended negative effects on driver behavior, including increasing cognitive workload as a result of the need to monitor and divert attention away from the driving task, both of which may deteriorate driving performance (Bolstad, Cuevas, Wang-Costello, Endsley, & Angell, 2010). Because of this knowledge, auto manufacturers are constantly moving towards assigning more driving tasks, traditionally controlled by a human driver, to the vehicle. In fact, multiple taxonomies have been developed to help understand and classify the capabilities and limitations of various ADS and automation schemes. For example, the Society of Automotive Engineers (SAE) defines six levels of vehicle automation as follow (SAE International, 2018):

- Level-0 is *full manual control*, where the human driver does all the driving.
- Level-1 is *driver assistance*, where a driving assistance system on board will assist the human driver with either steering or speed control.
- Level-2 is *partial automation*, where the automation controls both steering and speed under some circumstances. Here, the driver's full attention in terms of alertness and engagement are both still required at all time.
- Level-3 is *conditional automation*. An ADS handles all aspects of driving task (i.e., speed and lane position control, stopping and starting, and turning corners) under some circumstances. However, the human driver may be required to take over control of the vehicle and perform manual driving tasks, if requested by the ADS.
- Level-4 is *high automation*. The ADS handles the driving task and monitors the environment under certain circumstances; no attention from the driver is needed except for fine maneuvers (such as pulling into a garage).
- Level-5 is *full automation*, where ADS handles all driving tasks, and the human occupant becomes a passenger who does not need to be involved in any driving aspects. In fact, no steering wheel and foot pedals are present at this level.

Although high and full automation has gained much interest in recent years, most current vehicles are only capable of Level-1 or Level-2 automation, where the driver and vehicle share various components of the driving task. Thus, they are referred to as semi-autonomous. At these levels, Adaptive Cruise Control (ACC) and Lane Keeping System (LKS) are two of the common driving assistance features/systems available to the public at the moment. Both ACC and LKS alone are considered as Level-1 automation, but the realization of the technology relies on entirely different approaches.

1.1.1 Adaptive Cruise Control (ACC)

Adaptive Cruise Control (ACC) uses radar or laser distance sensors placed in front of the vehicle to calculate the distance and speed of lead vehicle. It uses this information to adjust its speed equal to or below an initial speed set by the driver. For example, if a slower lead vehicle is detected, the system will reduce its speed to keep a preset distance behind the lead vehicle. Once the lead vehicle accelerates beyond the preset cruise control speed of the subject vehicle, then the subject vehicle (which contains the ACC) will accelerate back to its preset speed. This technology was first introduced as a commercial product in the late 1990s by major automotive manufacturers (Marsden, McDonald, & Brackstone, 2001).

In general, ACC is expected to reduce driving task demands, and thus workload, by freeing up physical, visual, and cognitive resources (Stanton & Young, 1997) involved in perceiving and keeping a preset headway with the lead vehicle. A review article (De Winter, Happee, Martens, & Stanton, 2014) confirms this theory by reporting lower NASA-TLX workload scores when using ACC compared to when not. However, this is not always the case. Some studies (Nilsson, 1996; Rudin-Brown & Parker, 2004; Stanton & Young, 1998) found no change in workload ratings when drivers switched from manual driving to ACC. The reason for these non-conclusive findings is complicated, but the environmental setting, procedure, and even the technique used to obtain workload ratings could affect the results.

Also, the effect of ACC on driving performance has been quantitatively examined in several previous studies and similarly, the findings have not always been consistent. For example, Ma & Kaber (2005) found improved situation awareness when using ACC, which resulted in improved driving performance along multiple dimensions. However, some evidence suggested that this technology may be detrimental to safety and performance. Rudin-Brown & Parker (2004) showed that the use of ACC alone results in significantly higher variability in lane position compared to manual driving and longer response time to lead vehicle braking events (which was out of the margin of safety). The latter study proposed that this counterintuitive result may due to a primary-secondary task engagement shift phenomenon. In other words, participants may have diverted more mental resources away from the primary driving task, towards non-driving related secondary tasks when using ACC. In fact, higher accuracy on the secondary task was observed in Rudin-Brown's study. A treatment to control this shift in engagement will be addressed later in this study. The idea involves asking participants to maintain a certain level of engagement on a secondary task, while its performance is monitored in real-time to assure that this engagement is always maintained.

1.1.2 Lane Keeping System (LKS)

Lane Keeping System (LKS), or automatic steering (AS) system, on the other hand, is a more recent development. An earlier version of automatic lateral control assistance is known as the Lane Departure Warning (LDW) system, which provides passive warnings in different sensory modalities (e.g., auditory or tactile) when a subject vehicle drifts out of a designated lane (LeBlanc et al., 2006). Later iterations of the LDW added automatic interventions in severe circumstances. For example, Lane Keeping Assistance (LKA) steers the subject vehicle back when a substantial lane deviation is detected. A fully functional LKS, however, would actively steer the subject vehicle to keep the vehicle in properly centered in the lane. This technology uses onboard optical sensors that detect the lane markings on the road and is, therefore, able to position the vehicle in the lane with respect to these markings.

LKS may potentially reduce the number accident by freeing up a part or all of the driver's load in steering. Some studies examined the effects of LDW systems. For instance, improved lane-keeping performance (Navarro et al., 2016) and reductions in crash risk (Sternlund, Strandroth, Rizzi, Lie, & Tingvall, 2017) have been observed when using LDW. However, very little work has been done to investigate the effects of LKS on driver's workload and driving performance. It is reasonable to speculate that with the near-complete removal of the steering task, the driving task becomes less manually demanding. But the effect of LKS on driving performance with respect to non-lateral dimensions (as the lateral control is no longer in the driver's control loop) and changes in cognitive demand remains unclear. Miller and Boyle (2018) studied behavioral adaptation to LKS and found shorter time-gaps (Time-To-Collision, TTC) after the introduction of LKS, and it remained low even after the LKS was withdrawn. There are not enough data, and previous studies, to conclude whether this is a beneficial or detrimental effect, but it does confirm that a lateral assistance system has an impact on other dimensions of vehicle control, in this case, longitudinal headway. Given the lack of studies investigating LKS and lack of agreement in ACC-related studies, the current study included both ACC and LKS in the experimental condition settings.

1.2 Secondary Tasks While Driving

While driving, especially when using ADS or other automatic driving assistants, it is common that drivers engage in other tasks. The effect of engagement in secondary tasks depends on the nature of the task. For example, if a driver engages more in a task that is related to driving and supports proper driving practice, such as following a navigation system, then performance may improve. However, engagement in secondary tasks that are unrelated to driving, such as holding a cellphone conversation or texting, may offset the lower task demands brought on by the automatic assistance. In other words, assisted-driving systems may help to lower drivers' workload, but engagement in secondary tasks may bring workload back up, even if not to the same degree at which it initially was in the manual driving condition. In the latter case, these secondary tasks are sometimes referred to as distractions. Driver distraction, a well-studied topic, is generally defined as a diversion of attention away from forward driving to a competing activity (Regan, Lee, & Young, 2009).

To evaluate the effects of secondary tasks while driving, researchers have distinguished two types of secondary tasks to mimic what occurs in the real world. These tasks can be categorized into two types: visual/manual and/or cognitive secondary tasks.

1.2.1 Visual/Manual Secondary Task

Visual/manual tasks involve modality-specific interference with the driving task. It competes with the primary driving task for the concurrent and continuous use of the visual channel (i.e., to monitor the roadway environment) as well as manual resources (i.e., hands on the steering wheel or feet on the brake pedal)(Engström, Johansson, & Östlund, 2005; Engström, Markkula, Victor, & Merat, 2017). For example, using an in-vehicle information system (IVIS) is considered as a classic example of a visual/manual secondary task. Although this type of task also has a cognitive component, its visual or manual aspect dominates and directly competes with the primary task, and thus attentional resources, that could be assigned to the driving task. Other tasks are more cognitive in nature. Cognitive secondary tasks involve little manual interaction with the system (if any). Instead, it refers to a more general shift and re-allocation of attention from the driving task to a different non-driving task. It has been referred to as “mind-off-the-road” (Engström, Markkula, et al., 2017). Using a hands-free mobile device to engage in cellphone conservation is an example of a cognitive secondary task.

For the past two decades, researchers have examined the effects of visual/manual secondary task demands on manual driving performance. A review paper (Ferdinand & Menachemi, 2014) surveyed 350 studies that evaluated the association between driving performance and engagement in secondary tasks. It found that more than 60% of them used visual/manual secondary task such as mobile phone usage or IVIS operations. According to this review article, in 80% of cases, engagement in secondary tasks had a detrimental effect on driving performance, with the exemption of better driving performance while engaged in secondary tasks (10.3%). Negative effects brought on by more engagement in secondary tasks include an increased number of lane deviations, higher lateral acceleration, longer minimum headway, larger headway variance (Blanco, Biever, Gallagher, & Dingus, 2006), longer reaction time to environmental visual stimuli (Collet, Clarion, Morel, Chapon, & Petit, 2009) reduced speed, and increased lane keeping variation (Engström et al., 2005). However, Beede (2006) found fewer lane position deviations when performing a visual signal detection task, which is an indication of better driving performance under visual secondary task distractions.

Researchers have also begun to investigate the influence of visual/manual secondary on (semi) autonomous driving performance. For example, Miller & Boyle (2018) explained that the similarity in workload found between manual driving and driving with LKS in their study was due, in part, to the increased task demand caused by completing secondary IVIS tasks. Similarly, (Rudin-Brown & Parker, 2004) found subjective workload ratings not to change between no ACC (manual driving) and ACC driving conditions when performing a number search task on an in-vehicle display. Liang & Lee (2010) found visual distractions to dominate driving performance detriments when combined with cognitive distractions when drivers used an in-vehicle IVIS.

Although it is believed that most naturalistic tasks performed while driving includes visual, manual and cognitive components of distraction (Reimer & Mehler, 2013), it is still important to evaluate the cognitive part alone, as other parts usually overshadow its effects.

1.2.2 Cognitive Secondary Task

Unlike visual/manual tasks, fewer studies have explored cognitive tasks. With respect to the effects of cognitive secondary tasks on driving performance, most previous research in this area has been conducted in the context of manual driving and the results are somewhat conflicting. For example, Kubose et al. (2005) found the speed to increase when drivers performed cognitive secondary tasks during manual driving, whereas Son et al. (2010) reported no changes in speed. As mentioned before, detrimental effects of greater engagement in visual/manual secondary tasks were common. For cognitive secondary tasks, depending on the design of the secondary task, it is possible that driving performance may go unchanged or even improve under higher secondary task engagement. Lane departure or lane departure variance decrements were reported during higher cognitive secondary task engagement that did not contain a visual/manual component, such as hand-free interactive verbal task (Atchley & Chan, 2011), cell-phone conversation task (Beede & Kass, 2006), and Auditory Continuous Memory Task (ACMT) (Engström et al., 2005).

Here, this difference in findings may be due to participants' intentional or subconscious re-distribution of task engagement to the primary task and the secondary task during the experiments. In other words, participants may allocate more attention to either driving or secondary task, but not the same to both. However, much less is known regarding the effects of secondary cognitive tasks on partially automated driving performance. To date, few studies have begun to show this re-distribution in drivers devoting more attentional resources towards non-driving tasks. Miller & Boyle (2018) reported improved performance on the secondary task performance at the expense of more inferior headway maintenance when using LKS. This particular re-distribution of engagement, however, is rather difficult to regulate, because even when instructed, participants are usually incapable of fully prioritizing one task over the other (Jamson, Merat, Hamish Jamson, & Merat, 2005). To address this issue, our study explored a method requiring constant engagement in a cognitive secondary task, but where a specified level of performance on the secondary task was required.

The shift of task engagement, especially in cognitive secondary tasks, may lead to a re-allocation of (cognitive) workload. Therefore, the effects of cognitive secondary task on driving performance and levels of automation were examined in this thesis.

1.3 Cognitive Workload

1.3.1 Definition

Workload describes the cost of accomplishing task requirements for the human element of man-machine systems (Tsang & Vidulich, 2002). Generally, the term workload may refer to the actual amount of work being performed or a person's perception of the workload. When performing a task, many factors may affect workload, such as the duration, frequency, difficulty, intensity, or frustration level of the task. Similar to the categories for secondary tasks, workload can be classified as either physical or cognitive. Physical workload involves the activation of muscle force exertion (Mehta & Agnew, 2015). Whereas, cognitive workload refers to the amount of processing resources/effort utilized during information processing to complete a task (Block, Hancock, & Zakay, 2010). It is sometimes referred to as cognitive load (Engström, Victor, Markkula, Victor, & Markkula, 2017), mental workload (Proctor, Zandt, & Zandt, 2018; Stanton & Young, 1998), or simply load (Barrouillet, Bernardin, Portrat, Vergauwe, & Camos, 2007). In driving, both types of the workload are witnessed and, tasks such as monitoring road conditions, steering, and pressing brake/accelerator pedals, all contribute to drivers' workload. However, as vehicle automation takes over any of these particular tasks, the workload, especially the physical workload of the driver is inherently reduced. With higher level automation in the future, the physical workload is not likely to become a challenging aspect of driving. This is not necessarily the case for cognitive workload, as long as human supervision and potential intervention is still required.

1.3.2 Effect of Cognitive Workload

Cognitive workload that is too high or too low may lead to breakdowns in human-machine interaction, which can be inferred by the Yerkes-Dodson inverted U-curve (Yerkes & Dodson, 1908). Although the original setting used in Yerkes-Dodson's study was not related to humans, the idea that task performance increases with arousal level to an optimal region and then declines as arousal level further increase, continues to be proposed as an explanation (Reimer & Mehler, 2011; Wickens, Hollands, Banbury, & Parasuraman, 2015). Specifically, cognitive underload may result in reduced alertness, boredom, and dampened concentration, while cognitive overload could lead to fatigue, anxiety, and misallocation of attention (De Waard & Brookhuis, 1997). These effects may inhibit a person’s decision-making capabilities, as well as their ability to detect alerts and respond to events in an adequate amount of time.

High cognitive workload while driving has been shown to have negative consequences on performance. Blanco (2006) indicated that the higher workload brought on by an increased number of decision-making elements in the secondary task had a substantially negative impact on driving performance, including larger speed and headway variations and longer minimum headway. However, in many cases, cognitive underload may be just as bad as overload. Evidence suggests that being mentally under loaded, could result in declines in performance despite the abundance of attentional resources to carry the task (Young & Stanton, 2002). This detrimental effect has been shown to be more evident when participants feel fatigued, which can lead to increased swerving and reaction times while driving (Du et al., 2015).

However, beneficial effects of cognitive workload while driving has also been reported. A review article (Engström, Markkula, et al., 2017) pointed out a consistent trend: that lower lane-keeping variation (i.e., better lane keeping) was associated with higher cognitive workload conditions. Among the studies mentioned in the review article, a different source of the cognitive workload could lead to different results (i.e., smaller lane variation may not be found for some task design that increases the cognitive workload). Reimer et al.(2011) claimed that the arousal level increased because of the increased workload and was responsible for the improvement in lane keeping performance.

1.4 Assessment of Cognitive Workload

In semi-autonomous driving, especially in Level-1, a certain level of human input is still required to ensure driving safety. It is thus important to have a reliable tool to assess cognitive workload during semi-autonomous driving. Traditionally, there are several methods to assess or predict mental workload, most of which belong to one of three categories: (a) physiological measures, (b) task performance measures, and (c) subjective measures.

1.4.1 Physiological Measures

Researchers have used physiology, i.e., involuntary (chemical) responses in bodily systems, as an indicator of workload. Physiological measurements such as cardiac activity, pupil diameter, skin response, and brain activity have been widely used for this purpose. Each of these measurements is often associated with a separate device, which records continuous data, and have the potential to detect transient changes in cognitive workload.

Heart rate (HR) and Heart Rate Variability (HRV), along with other measures such as blood pressure and blood volume, have been used to evaluate workload, but electrocardiographic activity has shown the most promise (Kramer, 1991). Also, cardiovascular measurements, such as HR and HRV have shown reliable correlations with cognitive workload (Averty, Athenes, Collet, & Dittmar, 2003; Wickens, 2000). HR and HRV measures will be used in this thesis research to assess changes in cognitive workload using different ADS in different cognitive secondary task settings.

1.4.1.1 Heart Rate

Heart Rate (HR) refers to the number of heartbeats within a certain period (usually in a minute) (Wierwille & Eggemeier, 1993). Another metric that reflects heart rate in time-domain is Inter Beats Interval (IBI), which refers to the time in milliseconds between two consecutive beats (Charles & Nixon, 2019). An increased HR will result in a shorter IBI. Heart Rate Variability (HRV) reflects the fluctuation in adjacent IBIs.

The electrocardiograph (ECG) captures the electrical activity of the heart. The structure of a typical cardiac cycle (Figure 1) is labeled P-Q-R-S-T (in order), where the R peak in the QRS complex is the one with the highest magnitude and is used for HR measurements. When using ECG, the time interval between two consecutive R peaks (RRI) reflects IBI, and the number of R peaks per unit time (usually one minute) is used for Heart Rate (HR). All commonly used HR and HRV metrics can be derived from consecutive R-R interval data (in milliseconds). Another widely used metric is Normal-to-Normal (NN) interval, where all abnormal R peaks are removed. Since there is no ubiquitous definition of the term “abnormal”, the two terms are usually used interchangeably.

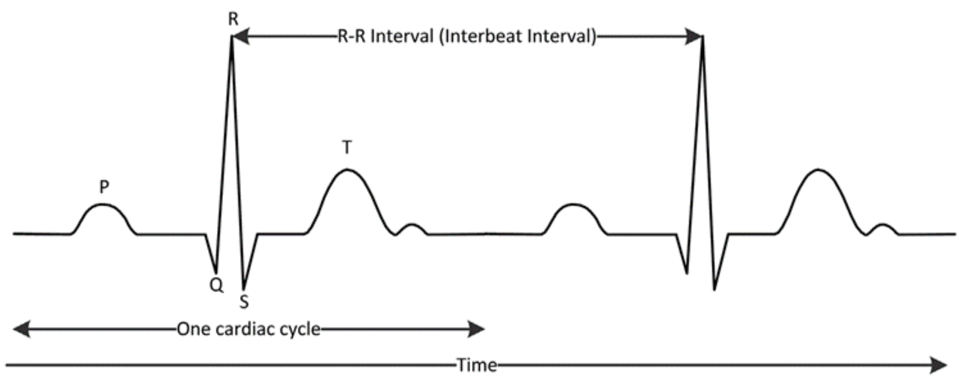

Figure 1 The cardiac cycle

Table 1 Summary of HR and HRV measures for ECG

Measure	**Unit**	**Description**
Time-domain measures		
HR	bpm	Heartbeat count per minute
SDNN (STDRR)	ms	Standard deviation of N-N(R-R) intervals
SDSD	ms	Standard deviation of differences between adjacent NN intervals
NN50		Number of pairs of adjacent NN intervals differing by more than 50 ms in the entire recording
pNN 50	%	Percentage of successive R-R intervals that differ by more than 50 ms
RMSSD	ms	Root mean square of sum of the squares of differences between successive RR intervals
Frequency-domain measures		
LF Power	ms^2	Spectral power in the Low-Frequency range between 0.04 and 0.15 Hz
HF Power	ms^2	Spectral power in the High-Frequency range between 0.15 and 0.40 Hz. This frequency band usually includes the respiratory frequency
Total Power	ms^2	Total Spectral Power over frequencies between DC and 0.40 Hz
LF/HF Ratio	%	Ratio between LF and HF band powers
Non-linear measures		
Approximate Entropy (ApEn)		Approximate entropy (ApEn) measures the complexity or irregularity of the signal
Sample Entropy		Sample entropy (SampEn) is similar to ApEn, but there are two important differences in its calculation

The heart is innervated by the division of the automatic nervous system (ANS): the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS affects the heart by increasing the firing rate of the pacemaker cells and thereby increasing the heart rate; it influences the distribution of the blood throughout the body (Kramer, 1991). The PNS, on the other hand, affects the heart by supplying atrial and nodal muscle through branches of the vagal nerves, and the stimulation of vagal nerves slows the heart rate down; the relaxation of the vagal nerves or less PNS activation could lead to cardiac acceleration (Kramer, 1991; Roscoe, 1992). The stimulation level of the PNS and SNS together dictate the heart rate. The PNS and SNS work together to keep the body under a stable condition. In particular, SNS helps prepare the body for action in response to potential threats, while PNS on the other hand, tends to be more active under unchallenging situations (Choi & Ricardo, 2009). The balance between PNS and SNS infers subject workload by reflecting the voluntary status of the body.

Although widely used alone or with other measures to assess cognitive workload under transportation setting, the relationship between cognitive workload and ANS activity remain unclear. Most researchers acknowledge a correlation between cognitive workload and HR, but did not detail the underlying mechanisms. Earlier research related many environmental stimuli to the increase of heart rate, many of which are aviation studies. For example, Bateman (1970) concluded that a higher heart rate was observed under higher “mental stress” brought on by high-speed flight. An increased heart rate was also observed with increasing task demand during take-off and landing (Buckley & Hartman, 1969; De Rivecourt, Kuperus, Post, & Mulder, 2008); HR also differentiates between rest and task periods of a flying task (S. G. Hart & Hauser, 1987; Lahtinen, Koskelo, Laitinen, & Leino, 2007). HR has also been used in many driving-related studies. For example, faster heart rate reflected by shorter R-R interval was found during a harder N-back task (Lenneman & Backs, 2009). In a separate study, Mehler (2010) reported that heart rate was significantly impacted by changes in cognitive load during driving.

Although being used as an indicator of workload change, it is also noteworthy that under some circumstances and for some participants, heart rate measures might not change with minor differences in workload (Splawn & Miller, 2013). One reason for this inconsistency relates to the ANS control mechanism. The workload is affected by ANS balance, but HR is regulated by both

PNS and SNS input, which makes PNS and SNS activation indistinguishable solely in the change of HR.

1.4.1.2 Heart Rate Variability

Heart Rate Variability (HRV) is a general term that refers to the variation between heartbeats. Time-domain, frequency-domain, and non-linear measures are used to reflect HRV. According to the length of a recording, HRV can be considered long-term (~24h) or short term (~5 min). Table 1 lists some commonly used HRV measures that are all derived from the R-R interval (RRI) (Camm et al., 1996; Shaffer & Ginsberg, 2017).

For time-domain measures, SDNN reflects the overall variation of RRI, and both SNS and PNS stimulation contribute to SDNN. The NN50 and pNN50 are closely related to PNS activity. Finally, RMSSD reflects variance between successive beats. It is the primary time-domain measure to reflects PNS or vagal nerve stimulation (Camm et al., 1996; Shaffer, McCraty, & Zerr, 2014). For all the time-domain measurements mentioned above, a lower value indicates lower HRV.

For frequency domain measures, researchers use the Fast Fourier Transformation (FFT) or autoregressive (AR) to get a power spectrum density (PSD) for the RRI series. The HRV can thus be separated into very-low-frequency (VLF), low frequency (LF), and high frequency (HF) rhythms according to their respective frequency range. In the case of short-term HRV recordings, LF (0.04-0.15Hz) and HF (0.15-0.4Hz) is generally used. It is believed that the HF component is affected almost solely by PNS, and the LF component is controlled by both SNS and PNS (Berntson et al., 1997). By observing HF power, unlike HR, researchers have a clear-cut measurement that reflects one component of the ANS, thus a better HRV measure that reflects cognitive workload. Higher PNS activation occurs at lower workload conditions, which could lead to lower HF power.

Approximate Entropy (ApEn) was designed to measure the regularity of a time series (Pincus, 1991) in which some noise may be present and makes no assumptions regarding underlying system dynamics (Kuusela, 2013). High values of ApEn imply high fluctuations in heart rate (Zhao, Zhao, Liu, & Zheng, 2012) and low predictability of fluctuation in successive RR intervals (Beckers & Ramaekers, 2001).

It has been confirmed that increased cognitive workload can lower HRV (Kalsbeek & Ettema, 1965; Young, Brookhuis, Wickens, & Hancock, 2015). Cognitive workload was found to have a significant effect on the following HRV metrics: HF component and SDNN (Splawn & Miller, 2013). Mehler (2011) reported that time-domain HRV measures except for SDNN, frequency domain measures except LF/HF provided robust indices of substantial cognitive workload change. Another simulation study found SDNN, LF/HF, pNN50, and ApEn to be sensible to mental workload change, but not between all experimental conditions (Heine et al., 2017). Based on the mechanism mentioned above, we were particularly interested in some of the HRV measures listed in Table 1; these measures will be introduced later in the dependent measure session.

1.4.2 Task Performance Measures

A second way to measure cognitive workload is through the use of task performance measures, which are based on the concept that a human operator has a limited amount of processing resources to be allocated to different tasks (Wickens, 1991). When an operator performs one or more tasks, a set of objectives will be set, and the speed and/or quality of the work to be completed is measured as performance. When workload is increased by the task demand of one or more tasks, the insufficient processing resource allocated to the one more task causes a deterioration in performance, and this relationship is sometimes called the performance-resources function (RPF) (Norman & Bobrow, 1975; Wickens, 1991). This performance cost is often explained by a change in workload.

Performance measurements, for workload assessment, generally have two categories: primary and secondary task measurements. The primary task refers to the task that is of higher importance and should be prioritized (i.e., most attention should be given to); any other tasks are called secondary tasks. In the driving setting, for example, the primary task is often to drive the vehicle safely by controlling speed and lane position. One potential drawback of using a primary task as a measure of workload is that sensitivity can vary depending on the level of the workload imposed by the particular task. A secondary task, on the other hand, is usually required to be conducted while also performing the primary task. As mentioned prior, example secondary tasks while driving would be interacting with an in-vehicle information system (IVIS), holding a phone conversation, or texting, to name a few. To assess workload in this scenario, performance on both the primary and secondary tasks are recorded and poor performance on one or both tasks may indicate high or low workload. However, sometimes, the performance of the secondary task is evaluated as an indicator of “spare capacity” of processing resource when the primary task is not demanding enough (Young, 2002). This approach gives a quantitative measurement of available ‘left-over’ capacity. As previewed earlier in Section 1.2, when setting up secondary tasks, engagement is hard to control and measure. To this end, according to the Multiple Resource Theory (Wickens, 2008), processing stage, coding, and input modality need to be carefully tuned to match that of the primary task if secondary task performance is used as workload indicator.

1.4.3 Subjective measures

Subjective workload measures use numerical ratings from the human that do not directly measure neither task performance nor physiological responses to work. Instead, it reflects the workload perceived by participants or experienced by operators (Annett, 2010). An individual’s subjective experience of the task associated with physical or mental work generally reflects the nature of a task and its demands on physical and mental resources. When measuring workload in a multi-task setting, where more than one task is performed at a time, the participant is usually asked to give a rating based on their feeling of the performance and effort of the combined task.

There are several techniques used to measure subjective or perceived workload. The Cooper-Harper Scale (Cooper & Harper Jr., 1969) was introduced early as a checklist for pilots to subjectively assess the handling quality of the aircraft. The results of this tool infer pilot’s handling task demand and thus their workload while flying. Years later, methods such as the Subjective Workload Assessment Technique (SWAT; Reid & Nygren, 1988), the NASA- Task Load Index (NASA-TLX; Sandra G. Hart & Staveland, 1988), the Subjective Workload Dominance Technique (SWORD; Vidullch, 1991), the Integrated Workload Scale (IWS; Pickup, Wilson, Norris, Mitchell, & Morrisroe, 2005) were introduced to assess the workload of a task. These subjective workload measures are generic and can be used in a variety of domains. Participants are usually asked to complete a questionnaire by giving qualitative and quantitative responses regarding their recent experiences during the experiment or work. One limitation of most subjective measurements is that the results depend on the participants' own understanding of the situation, and it could be interruptive during the experiment. While objective measures of the workload are preferred by many, subjective measures are still valuable, especially when used in combination with task performance and physiological measures (Wierwille & Connor, 1983).

In this study, the National Aeronautics and Space Administration Task Load Index (NASA-TLX) (Sandra G. Hart & Staveland, 1988)was used as the subjective workload measurement. It is a multidimensional assessment tool for perceived cognitive workload and has been widely used in a wide variety of driving-related study that examines the perceived workload (De Winter et al., 2014). It consists of six subscales: mental demand, physical demand, temporal demand, overall performance, effort, and frustration level. The subscales are weighted by each participant according to their understanding of the importance of the combined driving and secondary task after the training session. The perceived global workload is calculated for each experimental condition based on the score for each subscale and the weights assigned.

1.5 Implementation of Nanotechnology for HR Measuring

Traditionally, heart rate is measured using electrocardiography (ECG) sensors, as discussed above, which requires at least two electrodes that have direct contact with skin and are separate. However, wearing ECG electrodes can sometimes be invasive and uncomfortable. Photoplethysmography (PPG) sensors are also used to measure HR. It is widely used in smartwatches and fitness trackers and is a more portable and less intrusive alternative. PPG monitors blood volume changes in the vascular bed of tissue and measures the pulse rate (PR) that reflects heart activity. When compared to ECG, which is usually considered as "the gold standard", PPG readings show better overall precision (Schäfer & Vagedes, 2013). However, different from ECG, the PPG does not have R peaks in its readings. The peaks in PPG readings represent individual pulses detected by the sensors. Though, the peak-to-peak interval (PPI) in PPG readings reflect Inter Beats Interval (IBI) as well. Despite the physical difference between RRI and PPI, the latter was used as an alternative to RRI in calculating HRV measures mentioned in Table 1 that were traditionally been derived from RRI (Vescio, Salsone, Gambardella, & Quattrone, 2018). One study, however, showed that mean heart rate (HR) could be consistently underestimated by mean PR measured using PPG sensors

(Carrasco et al., 1998). When it comes to HRV measurement using PPG, the results become even less promising. In particular, there is a lack of agreement regarding short-term sensitive HRV measures such as RMSSD, LF, and HF between PPG and ECG derived HRV (Rauh, Limley, Bauer, Radespiel-troger, & Mueck-weymann, 2004). These findings show little reliability of pulse-detection based technology such as PPG in measuring HR and especially HRV in a precise manner when compared with the ECG.

Even with the limitations mentioned above, PPG sensors have some other trade-offs. It needs a light source to illuminate body tissue, penetrate the skin to reach the vascular bed; a photodetector is also necessary to measure the small variations in vascular-bed-reflected light intensity associated with changes in perfusion in the catchment volume (Allen, 2007). This means that the external power supply is needed for the sensor to work and the readings could be affected by skin thickness and ambient light. As a result, battery, light emitting, and sensing modules are all inevitable components of the PPG sensor assembly. Also, the limited battery capacity and light intensity can limit the size of the senor as well as the location where the sensor is placed.

To overcome these challenges, advancements in material science engineering have made it possible to employ materials that are on the nanoscale that can be used for PR monitoring. Specifically, a novel piezoelectric sensor made of Zn0 - liquid metal junction, developed by the Wu Group (under the direction of Dr. Wenzhuo Wu) in the School of Industrial Engineering at Purdue University, was explored as a new device that could measure HR (see Figure 2). The novelty of this nano-sensor is the combination of liquid metal and ZnO structure. The oxide layer of the liquid metal helps to form a Metal-Insular-Semiconductor interface (MIS). Under external strain, the MIS allows positive piezo-electric polarization charges to accumulate along the MIS, which attracts negative charges from the ground and helps to generate the electric signal that reflects the intensity of the external strain.

The micro-deformation of the skin on certain locations of the human body caused by pulses provides necessary strain for the piezo-electric nano-sensor to operate. Combining the ZnO nanostructures with a highly deformable liquid metal electrode, the nano-sensor becomes very thin and highly sensitive. The piezoelectric nature of the sensor makes it self-powered and significantly smaller than most of the existing ECG and PPG sensors, which do not have these advantages. Also, the ZnO - liquid metal conjunction is also highly flexible, which makes it possible to apply the sensor onto a broader range of surfaces of the human participant's body.

Similar to PPG, the nano-sensor measures the "product" of heart beats (blood perfusion and skin deformation), instead of the electric signal that "produces" heart beats. PPI derived from the nano-sensor raw readings was calculated and used as an alternative to the RRI derived from ECG sensors in calculating HR and HRV measures. In a previous pilot study, this particular nano-sensor showed good potential in providing similar HR readings as a portable commercial ECG sensor. To date, however, the nano-sensor has not been used to measure HR and HRV in more applied settings, such as simulated driving experiments. In the current thesis, the effectiveness of the nano-sensor in monitoring changes in heart rate during different levels of vehicle automation and various cognitive secondary tasks was evaluated.

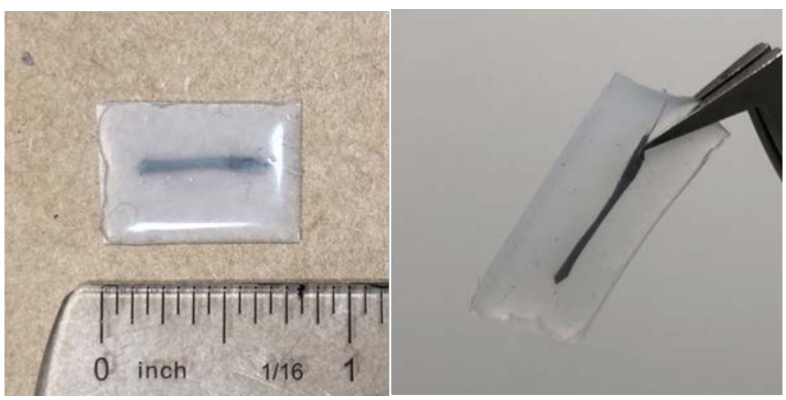

Figure 2 The nano-sensor

1.6 Summary

The preceding sections highlighted several gaps in the literature with respect to (semi)autonomous driving performance, secondary cognitive tasks, physiological measures and workload, and the use of nanotechnological devices. The goals of this thesis are therefore to (a) examine the effects of secondary cognitive task and driving condition (i.e., types of automation) on driving performance (b) examine the effects of secondary cognitive tasks and driving condition on heart rate and heart rate variability, and (c) determine the effectiveness of the nano-sensor in detecting heart rate changes equivalent to that of a commercial EGC sensor.

Chapters 2-5 discuss a large study that compares manual driving (Level-0) to driving with LKS only (Level-1) and driving with ACC only (Level-1). While driving in all conditions, a secondary cognitive task was performed by drivers, and the lateral and longitudinal control performance was measured. Experimental hypotheses were that (1) driving performance would be worse under more difficult secondary tasks as well as in manual driving conditions (with the exception of lane departure variation). It was also expected that (2) heart rate would increase and heart rate variability would decrease under more difficult secondary task and manual driving conditions. (3) The nano-sensor would be as capable as a commercial ECG sensor in identifying changes in HR and HRV measurements under different secondary tasks and driving conditions.

CHAPTER 2. METHOD

2.1 Participants

Twenty-five students from Purdue University (West Lafayette, IN) volunteered to participate in this study (18 males, 7 females). The average age of participants was 22.4 years (SD = 1.3; Range = 21-17). No compensation or incentive was given for participation. All participants were required to have a normal or corrected-to-normal vision, no hearing impairments, and no susceptibility to motion sickness. Fluency in written and spoken English was also required. This study was approved by the Institutional Review Board at Purdue University (IRB Protocol #: 1810021205).

2.2 Apparatus

2.2.1 Driving Simulator

The experiment was conducted using a medium-fidelity fixed-base driving simulator (miniSim developed by the National Advanced Driving Simulator program). This system is equipped with three 48-inch monitors (resolution 1024 x 768), which display the main driving environment and an additional 21-inch screen to serve as the dashboard display. The 48-inch right in front of the participant is referred to as the "center screen." Manual input of the driver is captured by two foot-pedals and a steering wheel. The sampling rate of this system is 60 Hz.

2.2.2 Heart Rate Sensor

This study used the Polar H10 HR monitor (Tarvainen, Lipponen, Niskanen, & Ranta-aho, 2017) to measure the R-R interval series using ECG technology. This device consists of an elastic chest strap and a connector module placed on the middle of the strap (Figure 3). The chest strap has two electrode areas that face the body and is in direct contact with the skin. The connector module is clipped onto the other side of the strap; it processes the ECG signal recorded by the electrodes and sends it to a receiving device via Bluetooth. The sampling Rate of Polar H10 is 130 Hz. Elite HRV was used on a paired cellphone to collect R-R interval series sent from the Polar H10. The chest strap was adjusted to fit snugly, and the connector was centered directly underneath the chest, just above the top of the stomach.

Figure 3 Polar H10 HR monitor

The nano-sensor was placed on the left-front side of the neck (see Figure 4) to allow easy access to experiment equipment. Participants were asked to locate a spot in that area where their pulse is detectable by a fingertip and place the nano-sensor directly onto that location. The nano-sensor would then be fixed and pushed towards the skin using waterproof tape. A copper wire connects the nano-sensor to an amplifier, which had a ground wire and was connected to a National Instrument signal collection module. The electric signal generated by the nano-sensor was then processed and recorded by a program developed using LabView, which served as the graphical user interface and data collection program for the nano-sensor.

Figure 4 Placement of the nano-sensor

2.3 Experimental Setup

2.3.1 Resting Condition

The simulated vehicle was parked in a resting area along the highway, with the engine running in idle. Participants were asked to stay calm, look up and forward, and limit movements. This setting was used to measure resting heart rate, since the background noise and vibration of the driving simulator may affect HR readings on both the ECG and nano-sensor devices.

2.3.2 Driving Task

Participants were asked to complete a simulated driving task on a rural two-lane highway with traffic in each direction. The route consisted of both straight and curved roadway segments. Drivers were also asked to either remain in the center of the lane (in the manual driving condition and ACC driving conditions) and/or maintain a constant headway (i.e., the distance between the back of a lead vehicle and the front of the subject vehicle) with the lead vehicle (in the manual driving condition and LKS driving conditions). While driving, participants would experience wind gusts that caused drifting of the subject vehicle and/or speed changes to the lead vehicle. The same route map was used in all experimental conditions, but the locations of wind gusts and lead vehicle speed change dials were different in each condition and were pseudo-randomized. There were six wind gust events and six speed-change events in both the first and second halves of the drive. There were three possible speeds for speed-changes of the lead vehicle (i.e., 50mph, 55 mph, 60 mph), whereas the wind gust events had a constant speed of 60mph. The direction of the wind was perpendicular to the road, either from the left or from the right. There were wind gusts and speed-change events in all experiment conditions, but the driver could not feel drifting caused by wind-gusts in LKS condition and did not need to react to speed-change events in ACC conditions. We employed wind gust events and random speed changes to produce equivalent task demand levels in both the ACC s and LKS conditions.

At the beginning of each simulation session, there was an adaptation zone of 0.5 miles. When driving in this zone, the lead vehicle started from a complete stop and accelerated as the subject vehicle started to move. The lead vehicle would adapt its speed to the subject vehicle, such that a 150 feet headway was maintained regardless of the speed of the subject vehicle. The lane position of the subject vehicle was also maintained in the adaptation zone in all experimental settings. After

0.5 miles, the message "experiment starts" would appear in the middle of the center (main) simulator display, and the driver would need to control the vehicle as each condition demanded.

2.3.3 Auditory Delayed Digit Recall Task (N-back Task)

An n-back task was used as the secondary cognitive task in this study, which has been used for the same purpose in multiple prior driving-related studies (e.g., Mehler, Reimer, and Wang, 2011; Reimer and Mehler, 2011). This task makes use of auditory perception, memorization, and verbal responses, which draws some of the same cognitive resources utilized in common real-life tasks, such as cellphone calls, inter-person conversations, and audio navigation. In general, for this task, participants are asked to hold a specified amount of numbers they have heard in the working memory and determine if the number given later appeared before. The task presents multiple computer-generated, randomized sets of numbers ranging from 0 to 9, which are played in a random sequence at a constant interval of 2.5 seconds.

For this particular implementation of the task, participants need to press a button attached to their index finger either right after each verbal presentation of the target number or with some delay to indicate the identification of a target number. Once the participant pressed the button, both the participant and experimenter would hear "yes." In the 1-back case (**Easy** task condition), the target number is the one that has the same number right before it. However, in the case of 3-back (**Difficult** task condition), the target number is the one that was the same as the number that was presented three numbers previously (see Table 2). The 3-back task was chosen to be a **Difficult** task condition based on the results of a pilot study when 2-back was compared to 3-back. In particular, most participants in the pilot study reached a 100% correct rate on the 2-back task, but approximately 85% on the 3-back task. In our experiment, the word "Next" was used to indicate the start of the second number set in a block, and thus, participants would stop keeping numbers in mind get ready for a fresh start. In this study, there were four numbers sets in each drive, two sets for each block. Between blocks, there was a separation interval; other details will be explained in the method chapter. For the 1-back task, each number set has 21 numbers, and for the 3-back task, each number set has 23 numbers. Such the time participants devoted to the memory task remained the same. There were seven target numbers in each number set; they were put in a pseudo-randomized way to assure even distribution and unpredictability. For both 1-back and 3-

back tasks, 12 pre-recorded, computer-generated number set audio files were randomly assigned to different conditions. Participants were instructed to respond as accurately as possible. The experimenter could monitor the correct rate in real-time by comparing the answer given by the push-button responses to the expected answer sheet of the corresponding number set. Before the experiment, participants were trained on this task until an 80% minimum correct rate was reached on the 3-back task.

Table 2 Example of a number set in the 3-back task used in this study (N: No Response; Y: Press Button)

Number Played	8	7	5	4	0	5	0	0	6	0	8	8	7	8	8	5	8	6	5	4	6	8	0
Correct Response	N	N	N	N	N	Y	N	Y	N	Y	N	N	N	Y	Y	N	N	N	Y	N	Y	N	N

2.4 Experimental Conditions

This study employed three types of driving conditions: **Manual**, **Adaptive Cruise Control (ACC),** and **Lane Keeping System (LKS)**. In the **Manual** driving condition, participants needed to control both speed and lane position. In the **ACC** driving condition (Level-1 automation), headway was controlled by the automation, but the driver was required to control steering. In the **LKS** driving condition (also Level-1 automation), lateral lane position was controlled by the automation, but the participant was required to control the speed. There were also three types of secondary tasks: **No-Task** (used as a baseline), **Easy** (0-back), and **Difficult** (3-back). All combinations of driving conditions and secondary tasks were tested for a total of 9 experimental conditions: **Manual + No-Task, Manual + Easy, Manual + Difficult, ACC + No-Task, ACC + Easy, ACC + Difficult, LKS + No-Task, LKS + Easy,** and **LKS + Difficult.** Here we use a 3x3 matrix to show all the combinations of experimental conditions (Table 3)

Table 3 Experimental Conditions

		Secondary Tasks		
		No-Task	**Easy (0-back)**	**Difficult (3-back)**
Driving Conditions	**Manual**	Manual + No-Task	Manual + Easy	Manual + Difficult
	ACC	ACC + No-Task	ACC + Easy	Difficult + Difficult
	LKS	LKS + No-Task	LKS +Easy	LKS + Difficult

2.5 Procedure

2.5.1 Experiment Preparation

Participants were first asked to complete a pre-experiment demographic questionnaire that asked about their driving experiences, caffeine consumption history, and susceptibility to motion sickness. After confirming the eligibility, participants signed a consent form outlining the purpose of the study. Then, the researcher would answer any questions about the consent form, and the experimental setting, task requirements, and expectations. Afterward, the ECG and nano-sensor devices were then placed on the participant, heartrate data were collected simultaneously by the two sensors.

Then, they completed a training session to become familiar with both the driving and secondary tasks. The training session used the same route map as those used in experiment sessions. Real-time instructions were given during the training session, the training was at least 10 minutes, or until all driving and secondary task requirements are met. A 'run' was defined as from the start of a session to the end of that session. In the training session, in the first half of the run, the lead vehicle would adapt its speed to the subject vehicle to maintain a 150 feet constant headway, and random wind gusts would be experienced. If the speed of the subject vehicle was greater than 80 mph or the vehicle deviated from its lane position, a message "too fast" or "please stay in your lane" would present on the main display screen. In the second half of the training session, the lead vehicle would activate its LKS, and would no longer adapt its speed to the subject vehicle. Participants were also asked to perform several sets of 0-back and 3-back tasks, until an 80% correct rate was reached.

2.5.2 Experiment Execution

For each participant, there were 9 runs (one for each of the 9 experimental conditions) plus 2 resting heart rate collection sessions: one immediately after training and the other after the 9th run. Each resting heart rate session lasted 5 minutes. For the resting heart rate session, there was only one block, which was 5 minutes long (top image in Figure 5). However, there were two blocks for all other experimental conditions (bottom image in Figure 5). In this case, these two blocks were separated by an approximately 30-second interval for which no data was collected during the time. Each block lasted approximately 2.5 minutes and consisted of two number sets; each contains about 20 numbers. A typical run would take about 6 minutes. If an N-back task was included in an experimental condition, the experimenter monitored the real-time correct rate of the N-back task. Data collected during the number set that has a correct rate of lower than 80% would be excluded from the experiment.

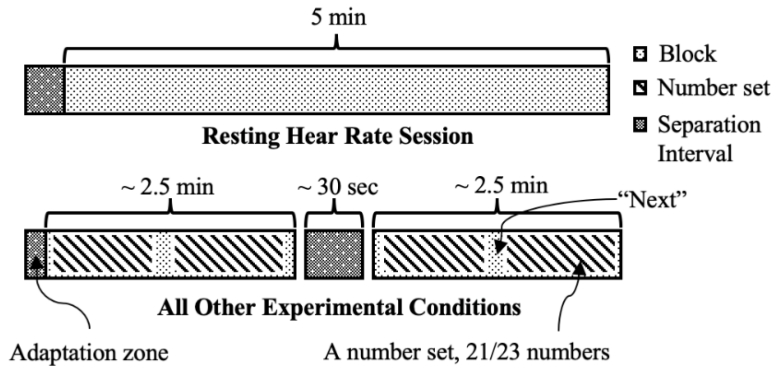

Figure 5 Diagram of experimental blocks for both secondary task conditions

2.5.3 Subjective Workload Assessment

After the completion of each run, participants rated their cognitive workload of performing both driving and secondary tasks at the same time. Participants would be asked to complete a weighing session indicating their subjective preference for certain NASA-TLX scales. A series of pairwise comparisons among multiple NASA-TLX subscale pairs was performed, and for each pair, the participant would indicate the more important one, meaning this subscale contributes more to her/his overall cognitive workload. The weighted scores obtained during this process were used to adjust the raw scores of each subscale to get an overall cognitive workload score.

2.6 Dependent Measures

Three classes of dependent measures were used in this study: (a) driving performance measures, (b) heart rate-related measures, and (c) subjective workload measures.

2.6.1 Driving Performance Measures

Driving performance measures included: Mean Headway (MHW; feet), Standard Deviation of Headway (SDHW; feet), Standard Deviation of Lane Departure (SDLD; feet), and Standard Deviation of Vehicle Speed (SDVS; feet). The headway readings (HW_i) were obtained from the driving simulation software; it was defined as the distance between the front bumper of the subject vehicle and the rear bumper of the lead vehicle. There were 60 readings (frames) per second. MHW and SDHW were defined, respectively, as:

$$MHW = \frac{1}{N}\sum_{i=1}^{N} HW_i\,; SDHW = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|HW_i - MHW|^2}$$

$$N = E - S$$

E: $ending\ frame\ of\ a\ block$

S: $starting\ frame\ of\ a\ block$

HW_i: $heaway\ at\ frame\ i$

Similarly, the offset of the subject vehicle from the center of the lane (LD_i ; feet) was used as the lane departure measurement in this study. Similarly, SDLD were defined, respectively, as:

$$SDHW = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left||LD_i| - \frac{1}{N}\sum_{i=1}^{N}|LD_i|\right|^2}$$

$$N = E - S$$

E: $ending\ frame\ of\ a\ block$

S: $starting\ frame\ of\ a\ block$

LD_i: $lane\ offset\ at\ frame\ i$

The speed of the vehicle (VS; miles per hour) was recorded by the driving simulation software. In this study, since in the headway maintenance task VS is heavily constrained by the varying velocity of the lead vehicle, VS is not a meaningful measurement of driving performance in this particular case. SDVS was defined as:

$$\mathrm{SDVS} = \sqrt{\frac{1}{\mathrm{N}-1}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left|VS_i - \frac{VS_i}{N}\right|^2}$$

E: $ending\ frame\ of\ a\ block$

S: $starting\ frame\ of\ a\ block$

$\mathrm{VS_i}$: $vehicle\ speed\ at\ frame\ i$

2.6.2 Heart Rate Related Measures

In this study, mean inter beat interval (MIBI) was used as heart rate measure. For HRV measurement, SDNN, RMSSD, pNN50, HF Power (HF) and LF Power (HF) were used because these measures were believed to have clear relationship with automatic nervous system (ANS) activities. ApEn was used because it is less sensible to linear data loss, which was expected in data from the nano-sensor because of the limitation of the signal processing technique used. Peak-to-peak interval (PPI) obtained from the nano-sensor's raw data was used as an alternative to the R-R interval (RRI) in HR and HRV measure calculations, when evaluating the effectiveness of the nano-sensor. Kubios HRV (Tarvainen et al., 2017) software was used for HRV analysis. RRI or PPI sequence files obtained from Polar H10 and nano-sensor were used for time-domain (MIBI, SDNN, RMSSD, pNN50), frequency-domain (HF,LF) and non-linear (ApEn) HR and HRV measurement calculations as described in international guidelines (Melillo, Formisano, Bracale, & Pecchia, 2013; Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996).

2.6.3 Subjective Workload Measures

The global workload score of NASA-TLX (NASA-global) was used to measure the perceived workload for each experimental condition. NASA-TLX scores were recorded by the experimenter during the simulated driving and manually typed into an excel file for data analysis.

2.7 Data Reduction

Driving performance data were obtained directly from the driving simulation software. A MATLAB program was used for raw data extraction and performance measurement calculation.

All heart rate related measures were calculated based on the RRI sequence obtained from the ECG sensor or the PPI sequence obtained from the nano-sensor. The RRI sequence file was obtained directly from the Polar H10 ECG sensor. However, a specific filtering process was needed to extract PPI from the raw nano-sensor recordings. A program inspired by a clinical physiology study (Storck, Ericson, Lindblad, & Jensen-Urstad, 2001) was written specifically for this purpose.

In a previous pilot study, the parameters involved in this process were adjusted and fixed such that major outliers and noise could be filtered out. The details of the process are as follow:

1. Apply a Butterworth bandpass filter with the following parameters: lowcut = 0.4 Hz, highcut = 2Hz, sample rate = 500 Hz, order = 3;
2. A normal distribution of IBI length was assumed, IBI that was more than $\pm 2SDs$ away from the mean was removed from the data set;
3. Apply a IBI rejection region: min IBI = 600 ms, max IBI = 1200 ms;
4. Linearly interpolate the data to replace any IBI that was removed in step (3)
5. Apply an ectopic beats filter to get normalized IBIs;
6. Perform linear interpolation to replace any IBI that was removed in step (5)

2.8 Experimental Design and Data Analysis

2.8.1 Experimental Design

The study used a 3 (driving condition: **Manual, ACC**, or **LKS**) X 3 (secondary task: **No-task**, **Easy**, or **Difficult**) full factorial design. Driving condition and secondary task were both within-subject variables. For driving-related measures, a 2 (driving condition) X 3 (secondary task) full factorial designs were used. However, specifically when the analysis focused on speed-control measures (i.e., MHW, SDHW, SDVS), **Manual** and **LKS** were included, and when the analysis focused on steering-control measures (i.e., MLD, SDLD), **Manual** and **ACC** were included. Since speed control in the **ACC** condition and steering control in the **LKS** condition were controlled by the automation, they no longer reflect driving performance of the driver, thus were excluded from data analysis.

To determine if the nano-sensor and the ECG sensor had similar capabilities in differentiating HR and HRV changes caused by different experimental conditions, first the same 3 X 3 design used to analyze the ECG data was applied to HR and HRV measures derive from the nano-sensor readings. Then, a 10 (experimental condition: : **Resting**, **Manual + No-Task, Manual + Easy, Manual + Difficult, ACC + No-Task, ACC + Easy, ACC + Difficult, LKS + No-Task, LKS + Easy,** and **LKS + Difficult**) X 2 (sensor: **Nano-sensor and ECG sensor**) two-way repeated measures (Analysis of Variance) ANOVA was performed on measures that was found to have been significantly affected by driving or secondary task conditions.

2.8.2 Data Analysis

A two-way repeated measures ANOVA was used. For driving performance and heart rate related measures, data from the two blocks of a drive were averaged, so each participant had one average value for a dependent measure for each experimental condition. Data from all 25 participants were included in the analysis of driving performance.

When analyzing HR data, the two-way repeated measures ANOVA was first performed on ECG derived HR data, to determine the effect of both driving condition and secondary task on HR and HRV measures. Data from both ECG and nano-sensor were used. Then a 10 X 2 two-way repeated measures ANOVA was used to determine whether the differences in HR and HRV measures collected from both sensors were indistinguishable. Data from all 25 participants were included in the analysis for the ECG. However, for analysis that involved the nano-sensor, data from only 17 of these 25 participants were included, due to the availability of the nano-sensor.

For subjective workload measurement, only one score was recorded for each experiment condition. For this, the 3 X 3 repeated measures ANOVA (factors: driving condition and task difficulty) was used, which is the same analysis used for ECG data analysis.

For all tests, statistical significance was set at $p < 0.05$ and Bonferroni corrections were used in post-hoc comparisons to account for multiple statistical tests.

CHAPTER 3. RESULTS

This chapter summarizes the findings from the thesis study described in Chapter 2. ANOVA results, indicating significant main and interaction effects, are organized in tables, with associated F-value, p-value, and partial η^2 (effect size). Driving performance measures, HR and HRV measures derived from inter beats interval (IBI) readings from both the Polar H10 and nano-sensors, and subjective workload measures were analyzed.

3.1 Driving Performance

The effect of within-subject factors (driving condition and task difficulty) on driving performance measures are listed in Table 4. Among all speed-control measures ($A \in \{MHW, SDHW, SDVS\}$), no significant main effect of driving condition was found on driving performance measures, with the exception of a marginally significant effect on SDHW and SDLD.

However, secondary task type had a significant effect on both speed control ($A \in \{MHW, SDHW, SDVS\}$) and steering control ($A \in \{SDLD\}$). Specifically, the standard deviation of vehicle speed (SDVS) and standard deviation of lane departure (SDLD) was significantly affected by the secondary task condition. SDVS was lower in the **Difficult** condition when compared with the **No-Task** (*MD* = .562, *SE* = .193, *p* =.024) (see Figure 7). Also, SDLD was significantly lower in the **Easy** and **Difficult** conditions when compared with the **No-Task** condition (Easy vs. No-Task: *MD* = -.065, *SE* = .024, *p* =.041; Difficult vs. No-Task: *MD* = -.071, *SE* = .193, *p* =.028) (see Figure 6). There was no difference in SDLD between **Easy** and **Difficult** conditions. Finally, no significant driving condition x secondary task interaction was found.

Table 4 Within-subject factor effect on driving performance measures

	Driving Condition			**Secondary Task Condition**			**Interaction**		
Driving Performance Measures	***F¹***	***p***	***partial*** $\boldsymbol{\eta^2}$	***F²***	***p***	***partial*** $\boldsymbol{\eta^2}$	***F³***	***p***	***partial*** $\boldsymbol{\eta^2}$
MHW	.789	.384	.035	.509	.605	.023	1.214	.307	.052
SDHW	3.287	.084*	.140	.153	.858	.007	.511	.580	.024
SDLD	3.423	.078*	.135	5.736	***	.207	.924	.404	.040
SDVS	1.487	.236	.063	3.958	.026**	.152	.583	.562	.026

[1] F (1,22) degrees of freedom before correction; repeated measure GLM model. Corresponding significance levels are marked with * (*: marginally significant, $1 > p \geq 0.05$; **: significant, $0.05 > p \geq 0.01$;***: $0.01 > p$).
[23] F (2,44) degrees of freedom before corrections.

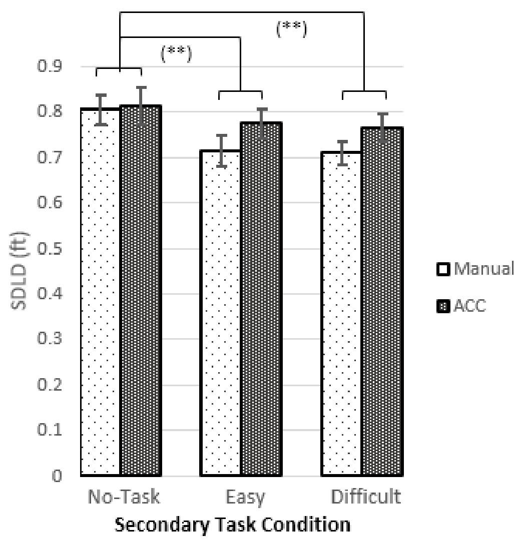

Figure 6 Standard Deviation of Lane Departure (SDLD) as a function of secondary task type and driving condition (error bars represent standard error of the mean)

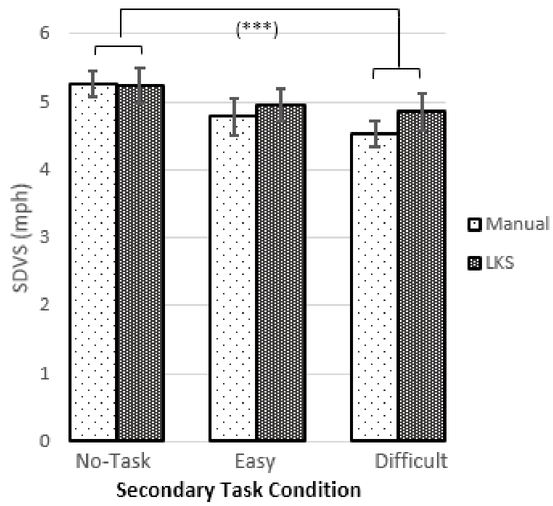

Figure 7 Standard Deviation of Vehicle Speed (SDVS) as a function of secondary task type and driving condition (error bars represent standard error of means)

3.2 Heart Rate (HR)

The effect of the within-subject factors (driving condition and task difficulty) on HR measures are listed in Table 5. Due to violation of sphericity assumption according to the epsilon value, Huynh-Feldt (epsilon > .75) or Greenhouse-Geiser (epsilon <.75) corrections were applied (Girden, 1992). For HRR, both p-values are affected, Huynh-Feldt corrections were applied in case a and b (see Table 5), causing a change in the degree of freedom (a: F (1.51, 36.249); b: F (1.667, 40.019)) and increase in p-value.

A significant main effect of driving condition was found on HR (see Table 5). Specifically, mean IBI (MIBI) was significantly larger (i.e., slower HR) in the **ACC** when compared with the **LKS** (ACC vs. LKS: MD =13.495, SE = 4.888, p =.033) condition. No other HR measurement was affected by the driving condition.

Similarly, a significant effect of secondary task type was found (See Table 5). Mean IBI was significantly smaller in the **Difficult** task condition compared to the **No-Task** and **Easy** conditions (Difficult vs. No-Task: MD = -20.526, SE = 7.191, p =.026; Difficult vs. Easy: MD = -20.618, SE = 5.247, p =.002)(see Figure 8). No other HR measurement was affected by secondary task condition and no significant interaction between driving condition and secondary task condition for any driving performance measures.

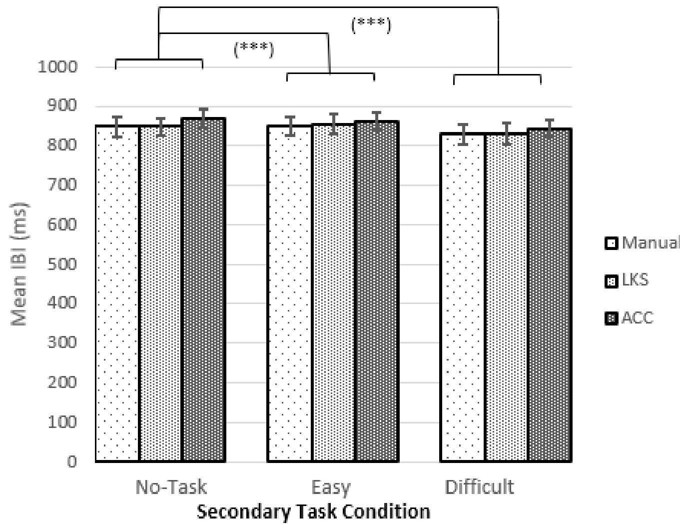

Figure 8 Mean Inter Beats Interval (IBI) as a function of secondary task type and driving condition (error bars represent standard error of means)

3.3 Heart Rate Variability (HRV)

The effect of the within-subject factor (driving condition and task difficulty) on HRV measures are listed in Table 5. Due to the violation of the sphericity assumption, Huynh-Feldt correction was applied in cases c and d (see Table 5).

No significant main effect of driving conditions was found on any HRV measure. However, all HRV measures were significantly affected by the secondary task condition. In particular, SDNN was significantly lower in the **Difficult** condition compared with the **No-Task** (*MD* = -7.852, *SE* = 1.360,*p* <.001) and the **Easy** (*MD* = -5.845, *SE* = .781, *p* <.001) conditions (Figure 9). Similarly, RMSSD was significantly lower in the **Difficult** condition compared with the **No-Task** (*MD* = -5.443, *SE* = 1.450, *p*=.003) and the **Easy** (*MD* = -5.951, *SE* = 1.124, *p* <.001) conditions (Figure 10). LF was significantly lower in the **Difficult** condition compared to the **No-Task** (*MD* = -444.021, *SE* = 93.906, *p* <.001) and the **Easy** (*MD* = -285.427, *SE* = 84.931, *p* = .008) conditions (Figure 11). HF was significantly lower in the **Difficult** condition compared to the **No-Task** (*MD*

= -224.459, *SE* = 63.420, *p* =.005) and the **Easy** (*MD* = -220.995, *SE* = 61.081, *p* = .004) conditions (Figure 12). Finally, the effect of secondary task condition on ApEn was different than all others. Lower ApEn was found in the **Easy** condition when compared with the **No-Task** (*MD* = -.067, *SE* = .009, *p*<.001) and the **Difficult** (*MD* = -.068, *SE* = .068, *p* <.001) conditions.

Table 5 Within-subject factor effect on HR and HRV measures (using the ECG sensor)

	Driving Condition			**Secondary Task Condition**			**Interaction**		
HR and HRV Measures	***F*[1]**	***p***	***partial*** η^2	***F*[1]**	***p***	***partial*** η^2	***F*[2]**	***p***	***partial*** η^2
MIBI	5.587[a]	.013**	.189	8.260[b]	***	.256	.234	.918	.010
SDNN	2.190	.123	.084	24.452[c]	***	.505	1.038	.392	.041
RMSSD	2.553	.088*	.096	13.192	***	.355	.665	.618	.027
pNN50	1.674	.198	.065	8.651[d]	***	.265	.866	.487	.035
LF	1.106	.339	.044	11.963	***	.333	1.285	.281	.051
HF	2.524	.091*	.095	8.059	***	.251	1.467	.218	.058
ApEn	1.157	.323	.046	37.253[e]	***	.608	.799	.529	.032

[1]F(2,48) degrees of freedom before correction; repeated measure GLM model. Corresponding significance levels are marked with * (*: marginally significant, $1 > p \geq 0.05$; **: significant, $0.05 > p \geq 0.01$;***: $0.01 > p$)
[2] F(2,96) degrees of freedom before the correction
[a] correction applied due to violation of sphericity assumption

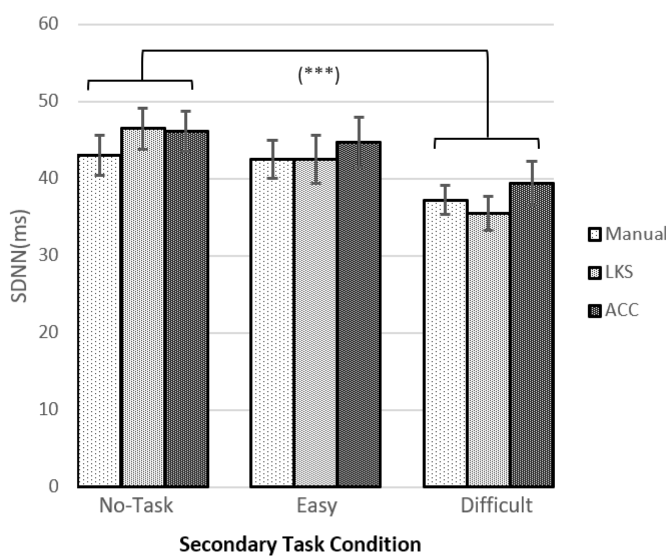

Figure 9 SDNN as a function of secondary task type and driving condition (error bars represent standard error of means)

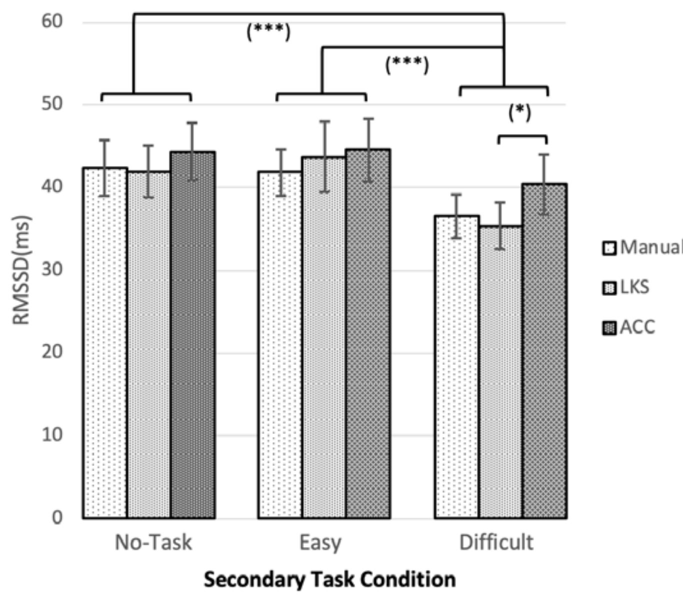

Figure 10 RMSSD as a function of secondary task type and driving condition (error bars represent standard error of means)

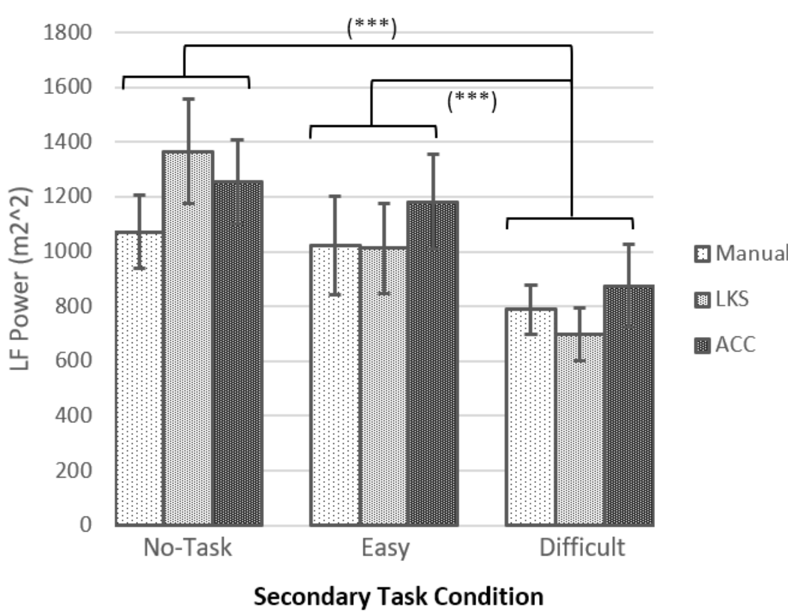

Figure 11 LF Power as a function of secondary task type and driving condition (error bars represent standard error of means)

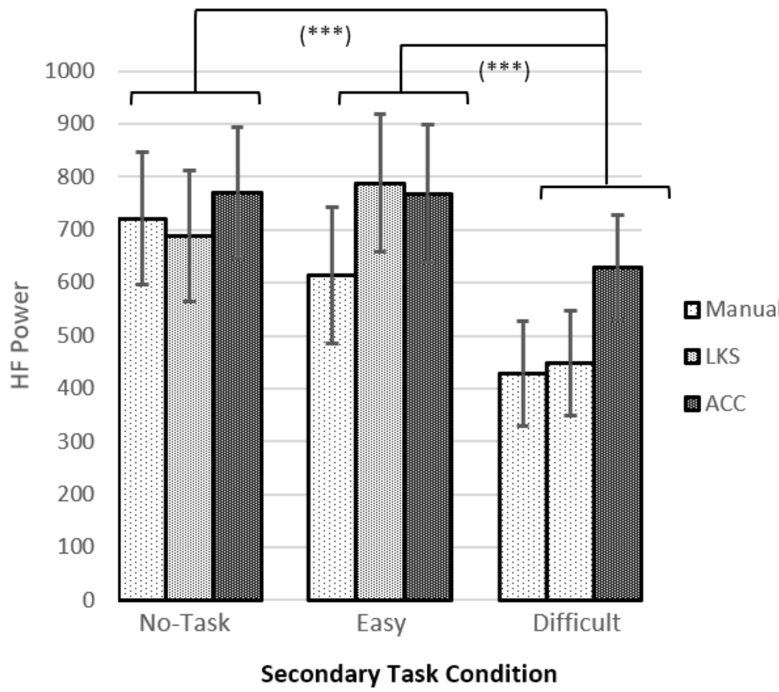

Figure 12 HF Power as a function of secondary task type and driving condition (error bars represent standard error of means)

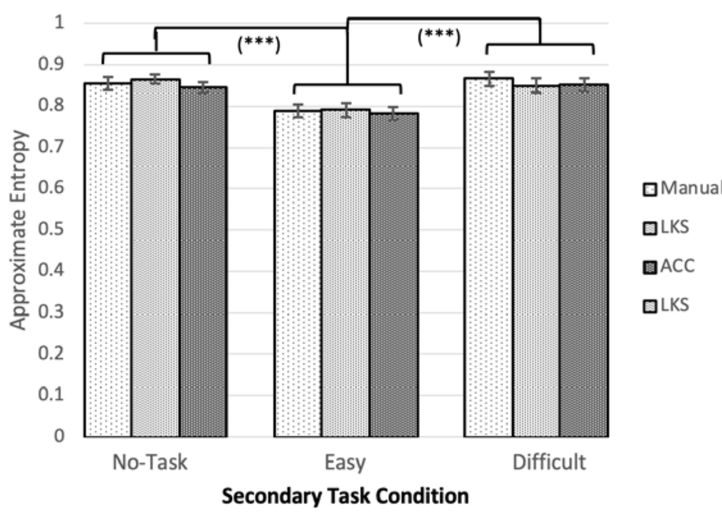

Figure 13 Approximate Entropy (ApEn) as a function of secondary task type and driving condition (error bars represent standard error of means)

3.4 Nano-sensor HR and HRV readings

First, the same 3 X 3 repeated-measures ANOVA was performed using the HR and HRV data derived from the nano-sensor readings (N=17). The results were listed in Table 6.

Table 6 Within-subject factor effect on HR and HRV measures (using the nano-sensor)

	Driving Condition			**Secondary Task Condition**			**Interaction**		
HR and HRV Measures	F^1	p	partial η^2	F^1	p	partial η^2	F^2	p	partial η^2
MIBI	.391	.690	.108	4.788	.015**	.230	1.257	.296	.073
SDNN	.279	.759	.017	1.020	.372	.060	2.405	.059	.131
RMSSD	.037	.963	.002	1.457	.248	.083	1.076	.376	.063
pNN50	.075	.928	.005	1.563	.225	.089	2.032	.100	.113
LF	3.481	.043**	.179	.044	.957	.003	1.184	.326	.069
HF	.077	.926	.005	.272	.763	.017	.593	.669	.036
ApEn	.010	.990	.001	123.972[a]	***	.886	1.102	.363	.064

[1]F (2,32) degrees of freedom before correction; repeated measure GLM model. Corresponding significance levels are marked with * (*: marginally significant, $1 > p \geq 0.05$; **: significant, $0.05 > p \geq 0.01$;***: $0.01 > p$)
[2] F (4,64) degrees of freedom before correction.

Overall, mean IBI (MIBI) and ApEn were significantly affected by secondary task condition (see Table 6). MIBI was significantly higher, indicating slower HR in the **Easy** condition when compared with the **Difficult** (*MD* = 13.538, *SE* = 4.405, *p* = .022) condition. Likewise, ApEn was significantly higher in the **No-task** condition when compared with the **Easy** (*MD* = .367, *SE* = .032, *p* < .001) and **Difficult** conditions (*MD* = .336, *SE* = .027, *p* < .001). LF was found to be significantly affected by driving condition, with lower LF power in the **LKS** condition when compared with the **Manual** condition (**MD** = -549.176, *SE* = 155.111, *p* = 0.008).

Next, the 10 X 2 two-way repeated-measures ANOVA was performed to compare the differences between ECG and nano-sensor readings on those particular measures that were identified as significant (i.e., MIBI, LF, ApEn). For MIBI, no significant effect of sensor type was found. However, LF and ApEn, were significantly affected by sensor type (see Table 7). In particular, LF were found to have much higher readings on the nano-sensor than on the ECG sensor (*MD* = 6491.516, *SE* = 284.497, *p* < .001). Also, a significant interaction between sensor type and experimental condition for MIBI and ApEn was found.

Table 7 With-subject effect of sensor type and experiment condition on MIBI, LF and ApEn

	Sensor Type			**Experiment Condition**			**Interaction**		
HR and HRV Measures	***F*[1]**	***p***	***partial η^2***	***F*[2]**	***p***	***partial η^2***	***F*[2]**	***p***	***partial η^2***
MIBI	.220	.645	.014	3.361	***	.174	2.520	.037**	.136
LF	.520.640	***	.970	1.391	.197	.080	1.769	.079	.100
ApEn	5.290	.035**	.248	84.762	***	.841	38.889	***	.709

[1] F (1,16). Corresponding significance levels are marked with * (*: marginally significant, $1 > p \geq 0.05$; **: significant, $0.05 > p \geq 0.01$;***: $0.01 > p$)
[2] F (9,144)

3.5 Subjective Workload

Global NASA-TLX scores were significantly affected by driving condition (*F* (1.558, 37.3,92) = 10.532, *p* = 0.001, *partial* $\eta^2 = .305$) and secondary task condition (*F* (1.513, 36.324) = 39.738, *p* < 0.001, *partial* $\eta^2 = .623$) (see Figure 14). Due to violation of sphericity assumption, Huynh-Feldt corrections were applied, causing changes in the degree of freedom (originally F (2, 48)) and p-value, but did in a detectable level. No significant effect of interaction was observed.

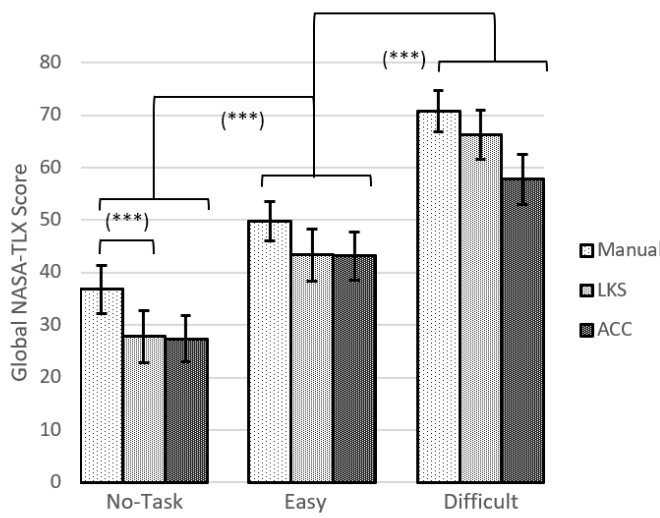

Figure 14 Global NASA-TLX Score as a function of secondary task type and driving condition (error bars represent standard error of means)

Particularly, NASA-Global scores were significantly higher in the **Manual** condition when compared with the **LKS** (MD = 6.902, SE = 1.832, p = .003) and the **ACC** (MD = 9.178, SE = 1.668, p <.001) conditions. However, NASA-Global differences were not distinguishable between the **LKS** and **ACC** conditions. In general, NASA-Global differences are different for all three secondary task conditions. Lower NASA-Global scores were observed in easier secondary task conditions (No-task vs. Easy: *MD* = -6.067, *SE* = 1.731, *p* =0.005; No-task vs. Difficult: *MD* = -23.47, *SE* = 3.276, *p* <.001; Easy vs. Difficult: *MD* = -17.4, *SE* = 2.945, *p* <.001).

CHAPTER 4. DISCUSSION

This chapter explains the results found in Chapter 3. The goal of this thesis was to examine the effects of cognitive secondary task and driving performance and heart rate, as well as validate the capability of a nano-sensor in distinguishing these changes in heart rate and heart rate variability. Overall, driving performance was found to be better during the more difficult secondary task, but appears to be unaffected by driving condition/automation type. Heart rate was found to be significantly slower when drivers did not perform a secondary task and when drivers used the adaptive cruise control (ACC) system. Also, all heart rate variability (HRV) measures were significantly affected by secondary task condition, with less variability during more difficult tasks, but were not affected by driving condition. The nano-sensor was capable of distinguishing differences in mean Inter Beats Interval (MIBI) brought by different secondary tasks. Finally, the Global NASA-TLX scores indicated that perceived cognitive workload was higher in **Manual** condition and when performing more difficult secondary tasks.

4.1 Driving Performance Measures

As expected, the standard deviation of lane departure (SDLD), and standard deviation of vehicle speed (SDVS) were found to be significantly affected by secondary task conditions. Lower SDLD was observed in the **Easy** and **Difficult** secondary task conditions when compared with the **No-tack** condition. The difference between **Easy** and **Difficult** condition was not significant. Engagement in cognitive secondary tasks improved lane-keeping performance by reducing lateral position variation (lower SDLP). This finding is consistent with previous work (Engström et al., 2005) and, according to Reimer's physiological arousal theory (2011), more difficult secondary tasks increased arousal level during the mundane driving task, which improved performance on the driving task (Wiener et al., 1984). Surprisingly, however, this beneficial influence of increased cognitive workload was evident on speed-control as well. It has been discussed that normally the beneficial effects of increased cognitive workload on driving performance were only observed as a reduction of lane-keeping variation. This is because when is ACC activated, the driving task demands become too low (thus a lower arousal level), resulting in a negative driving performance. However, when the secondary task as added, arousal level is brought back upward towards the optimal region, which lead to gains in driving performance. This could be the case here in our study; the driving task in the LKS condition may be as mundane as in the ACC condition, so this beneficial effect of secondary task can be observed as well.

SDVS followed the same trend as SDLD as described above: significantly more stable speed control performance was found in the **Difficult** secondary task condition when compared with the **No-task** condition. In the post-hoc comparisons, mean SDLD was marginally lower in the **Manual** condition under **Difficult** task condition, which agrees with Rudin-Brown's theory (Rudin-Brown & Parker, 2004) regarding **ACC.** Given that this finding was observed for the **Difficult** task condition, one could speculate that higher cognitive demands can result in an involuntary shift in task engagement and a re-allocation of attentional resources towards a secondary task. Although the engagement of secondary task in this study was managed by requiring a certain correct rate, this does not prevent the driver from engaging more in secondary tasks. The Malleable Attentional Resource Theory (MART) (Young, 2002) supports this interpretation. Although the total amount of attentional resources needed is reduced as a result of the automation, the spare resource (in this case visual resource needed for lane-keeping) may temporarily diminish because of a lack of demand for that particular resource.

In our study, no other driving performance measures were found to be significantly affected by automation nor secondary task condition. However, in contrast in previous work (Miller & Boyle, 2018) that examined the effects of LKS and secondary task on workload and driving performance, found shorter mean headway (MHW) times using the LKS and in the Manual driving condition without a secondary task. In another study, Kubose (2005) reported longer headway times in the dual-task condition (driving with a speech task) compared to the single-task condition. In Miller and Boyle (2018), drivers were asked to keep a 'safe' following distance behind the lead vehicle, and thus, participants had the freedom to choose a preferred headway. In Kubose (2005) study, a 2-second headway was required. In this case, a headway time might be much harder to perceive compared to a headway distance, especially with the non-constant speed of a lead vehicle and with only a single training session prior to the experiments. This likely allowed for greater variation in following distances to begin with. But, in our study, participants were required to maintain a constant specified distance headway in all conditions. At the beginning of each drive, the perception of headway was reinforced by having the lead vehicle to adapt its speed to the subject vehicle and keep the required headway until data collection starts. This may have led to less variance in headway.

4.2 Heart Rate and Heart Rate Variability Measures

4.2.1 Heart Rate Measures

The heart rate (HR) measure, MIBI was significantly affected by both driving and secondary task conditions. In post-hoc comparisons, significantly faster HR (i.e., lower MIBI) was found in the **Difficult** secondary task condition when compared with the **No-task** and **Easy** conditions. This is consistent with other previous driving studies that used the N-back task as a secondary task (e.g., Lenneman & Backs, 2009; Mehler et al., 2010) and shows that increasing task difficulty or workload does increase heart rate. The insignificant difference in MIBI between the **No-task** and **Easy** conditions is also consistent with Splawn & Miller (2013). In this study, the **Easy** condition was used to isolate the factor of task difficulty, and the cognitive demands of No-task and Easy task were similar. On the other hand, HR was significantly slower (higher MIBI) in the **ACC** driving condition when compared with both the **LKS** and **Manual** conditions. This finding is consistent with the conclusion made in a review article that explored the effect of ACC on HR (De Winter et al., 2014).

4.2.2 Heart Rate Variability Measure

All heart rate variability (HRV) measures were significantly affected by secondary task condition. Also, time-domain (RMSSD, pNN50) and frequency-domain measures (HF power and LF power) were significantly lower in the **Difficult** conditions when compared with the **No-task** and **Easy** conditions. These findings point to the potential of higher cognitive workload in more difficult secondary tasks and are supported by explanations in previous research (Heine et al., 2017; Mehler et al., 2011; Splawn & Miller, 2013). The time-domain measure, SDNN, was significantly affected by secondary task difficulty. However, unlike other time-domain HRV measures, its difference between **Easy** and **Difficult** was not significant, which is similar to Mehler et al. (2011). This study indicated the limitation of SDNN in reflecting substantial increases in cognitive workload.

The non-linear HRV measure, Approximate Entropy (ApEn), was also significantly affected by secondary task condition. Surprisingly, ApEn was the lowest in the **Easy** task condition and higher for both the **No-task** and **Difficult** conditions. Higher ApEn indicates higher variability in heart rate activities during driving-only **No-task** condition, which is understandable given that ApEn reflects similar characteristics of HRV as time- and frequency-domain measures. However, one past driving-related research study showed that lower ApEn revealed a reduction of slow variations and an increase of complexity of the RR interval series. This measure was once observed to increase as the task condition changed from *resting* to *low-workload*, which was companied by a decrease in SDNN (Heine et al., 2017). In this study, SDNN decreased between **Easy** and **Difficult** task. Thus, the unexpected increase in ApEn when the secondary task changed from **Easy** to **Difficult** in our study could be in line with Heine's findings. However, the change did not apply to all task conditions in Heine et al. (2017), and as such, this rather abnormal trend could not be supported by other facts. As it stands, no conclusion can be drawn about the influence of secondary task difficulty on ApEn.

On the contrary, none of the HRV measures were significantly affected by the driving condition/mode. Few studies have compared HRV measures between manual driving and different types of autonomous driving conditions. One study that is remotely similar compared HRV measures between normal driving and driving in a platoon of vehicles in an Automated Highway System (AHS)(Dick de Waard, van der Hulst, Hoedemaeker, & Brookhuis, 1999). Here, 0.1 Hz component (which falls in LF band) of HRV was significantly affected by driving conditions. Lower values were found in the manual driving condition when compared with other AHS (automated driving) conditions. This LF power result in the manual driving condition was accompanied by the highest subjectively rated metal effort. In the post-hoc analysis of LF power, we found that under the **No-task** (baseline) condition, LF power was significantly lower in the **Manual** condition when compared with the **ACC** condition by a very small margin ($p = 0.049$), which is consistent with de Waard's study.

4.3 Nano-sensor Data

In previous pilot studies conducted prior to this thesis work, the nano-sensor showed good potential in given similar HR readings as the ECG sensor. In the actual experiment, the nano-sensor succeeded in distinguishing the differences in MIBI and ApEn brought on by different secondary task conditions, which was nearly identical to that of the results from the ECG sensor. However, other significant differences caused by different secondary task conditions on HR and HRV measures detected by the ECG sensor were not detected by the nano-sensor. In particular, SDNN, RMSSD, pNN50, LF Power, and HF Power were not significantly affected by the change of secondary task conditions with the nano-sensor.

Surprisingly, a significant main effect of driving condition on LF power was found in nano-sensor data. The difference was not detected by the ECG sensor. The LF power measure was found lower in the **LKS** condition than in the **Manual** condition, which was contrary to our expectations since lower LF power was expected to be witnessed in more cognitively demanding conditions, and **LKS** condition was not designed to be more demanding than the **Manual** condition. By further analysis, we found that LF power readings were significantly affected by sensor type, with readings being as high as 600% different than those from the ECG sensor.

Here, we do not make any conclusions regarding the effect of secondary task difficulty on ApEn because of the unexpected increase of ApEn between the **Easy** and **Difficult** conditions in the ECG data analysis. When analyzing ApEn derived from the nano-sensor readings, ApEn in both the **Easy** and **Difficult** conditions were found to be lower than ApEn in the **No-task** condition, different from the ECG analysis. Although the changes in ApEn observed from the nano-sensor data were much consistent with our expectations, considering the novelty of the technology and the possible lack of sensitivity with respect other HRV measures, more work is needed to make strong inferences regarding the use of this technology. The nano-sensor did, however, show some potential for detecting HRV changes in less linear-sensitive situations.

No significant difference in MIBI was found between the EGC and nano-sensors. However, the observed power of the sensor type factor was .073, and thus we caution the reader not to over interpret the findings. In the post-hoc comparisons, the nano-sensor tended to have higher MIBI readings with lower standard error (ECG: mean = 835.794, SE =29.139; nano: mean = 850.269, SE=4.441). This overestimation of IBI (or underestimation of HR) tended to be even larger in the **Easy** condition. Though not significant, the difference in MIBI indicates an underestimation of heart rate or pulse rate, which is consistent with previous working using a PPG sensor (Carrasco et al., 1998). It is possible that the nano-sensor has similar limitations in detecting HRV as the PPG discussed in this study.

Overall, the nano-sensor was capable of detecting HR (MIBI) changes in a comparable fashion to that of the ECG sensor, but not time- and frequency-domain HRV changes. This indifference may have been caused by the limitation of the data processing technique. The signal picked up by the nano-sensor was based on skin deformation produced by blood profusion induced vessel expansion. Environmental noise, such as vibrations from the driving simulator or minor physical maneuvers that have similar frequencies as heart rate can easily mask the true deformation signal of the heart beats. In data processing, those covered HR signals could not be recovered and was removed with the noise detection. HRV measures generally rely heavily on comparing successive IBI variations, but with some of the IBI data extracted out of the sequence, the HRV calculation becomes inaccurate. No matter if linear interpolation is applied, the MIBI is not heavily affected since it is the arithmetic average of IBIs over time. This could potentially explain why differences in MIBI were detected, but not other time-domain and frequency-domain HRV measures. As a non-linear HRV measure, ApEn is less sensitive to data loss in a time sequence.

4.4 Subjective Workload Measure

As expected, both driving and secondary task conditions had a significant influence on global NASA-TLX scores. For driving condition, NASA-global was significantly higher in the **Manual** condition, which is consistent with most of the similar driving-related studies, according to the findings in a previous review article (De Winter et al., 2014). This also suggests that the effort we made to control secondary task engagement was successful in preventing subconscious changes of task engagement, and thus led to a different result than a previous study (Rudin-Brown & Parker, 2004).

With respect to secondary tasks, NASA-global was found to be the lowest in the **No-task** condition (Mean = 32.0, SE = 3.401), higher in the **Easy** condition (Mean = 38.0, SE = 3.368), and even higher in the **Difficult** condition (Mean = 55.467, SE = 3.029). We can conclude that the cognitive secondary task used in this thesis successfully increased perceived mental workload (Chong, Mirchi, Silva, & Strybel, 2014; Neumann, 2002; Wu, Miwa, & Uchida, 2017).

4.5 Summary

Overall, our first hypothesis that driving performance would be worse under more difficult secondary tasks as well as in manually demanding driving conditions was not accepted. Driving performance was not significantly affected by driving condition and, in contrast, SDLD and SDVS were better in the more demanding secondary task conditions.

Our second hypothesis that heart rate would be faster and heart rate variability would be lower under more difficult secondary task and manual driving conditions was not rejected.

Our third hypothesis that the nano-sensor would be equally capable as a commercial ECG sensor in identifying changes in HR and HRV measurements under different secondary tasks and driving conditions was partially supported. The nano-sensor can potentially measure heart rate changes as reliably as the ECG sensor, but did not detect the correct changes in heart rate variability measures.

CHAPTER 5. LIMITATIONS AND FUTURE WORK

There are several limitations of this thesis, which could serve as the basis for future work. First, we did not focus on the performance of the secondary task an indicator of workload. Instead, our goal was to use the secondary task to influence driving performance. However, future work may need to evaluate secondary task performance, especially if higher levels of automation are employed for which no driving performance measurements can be collected.

In the discussion chapter, the observed beneficial effect of workload on certain driving performance was explained by increased arousal level. However, this could be effectively reflected by other physiological measures as well, such as skin conductance level (SCL) and pupil dilation. Future work should include more physiological measures in more naturalistic driving settings.

Finally, with respect to the nano-sensor, more work is needed to explore its capabilities for monitoring heart rate during non-cognitive, physical tasks. Data loss during data processing was believed to be the cause of limited accuracy of the HRV measures for the nano-sensor. Data loss associated with Inter Beats Interval (IBI) values is difficult to avoid considering the nature and developmental stage of the sensing technology. Since the HRV measures used in this study were originally designed for ECG data, a specific set of HRV measures that are customized for nano-sensor data may be needed, which should contain similar information about the irregularity of heart activities. Once developed, the establishment of a method for calculating differences in measures between the two sensing approaches should soon follow.

CHAPTER 6. CONCLUSION

This thesis examined the effects of cognitive secondary tasks and driving condition (automation type) on changes in driving performance, heart rate measurements, and perceived workload. It also sought to determine the capability of a new nano-sensor for measuring heart rate and heart variability.

Chapter 1 (Introduction) introduces several theoretical concepts, including autonomous driving and its classification system, different types of secondary tasks used in driving-related studies and their potential impact on driving performance, and the concept of cognitive workload and workload assessment techniques. Then, the strengths of the nanotechnological device used in this thesis study was briefly introduced. Finally, the goal of this study and some corresponding hypothesis were proposed. Chapter 2 (Methods) details the experimental setup, materials, and procedures used to carry out the simulated driving study used a part of this thesis. Chapter 3 (Results) presents the data analysis methods and findings from the experiment explained in Chapter 2 and Chapter 4 (Discussion) discusses the meaning of those findings. Chapter 5 (Limitations and Future Work) discusses limits of the thesis project and suggests multiple areas for future work. Finally, Chapter 6 (Conclusion) reflects on the overall meaning and broader implications of the findings of this work.

The work described in this thesis may contribute to theories and advance the knowledge in the areas of human-automation interaction, driving human factors, and physiological sensing and monitoring. In summary, we found that certain driving performance measures (SDLD and SDVS) appear to be better during more difficult secondary tasks. The results highlight the potential performance costs and benefits associated with the introduction of Level-1 (semi)autonomous driving systems. It can also be used to regulate drivers’ behavior through educational or technological interventional strategies. The knowledge produced regarding differences in HR and HRV measures in varying workload conditions may be used to develop more robust physiological monitoring systems, as well as to create prediction models about how drivers might behave while driving. These predictions could, in turn, also result in the development of adaptive technology that mediate physiology. Finally, the nano-sensor used in this thesis study shows good potential to serve as an alternative to current heart rate technologies in measuring heart rate changes caused by workload changes. This offers a potentially less intrusive solution for physiological response measuring in wide range of laboratory and applied research studies, and in real-world conditions.

Ultimately, this work may help to better understand how and why humans use and perceive different types of automation/automated features, as well as their choice of engagement in various in secondary tasks. To this end, this work has broader implications across several application domains beyond driving, including aviation, healthcare, manufacturing, and military.

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