Using Brain-Computer Interfaces to Improve Multitasking in Driving

A thesis submitted by

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Abstract

Previous research has sought to understand and mitigate deteriorating performance during multitasking while driving, but there have not been any proposed solutions. Our system is an adaptive reading interface that builds upon implicit interface work to improve driving performance in multitasking situations – as well as the overall multitasking experience. This thesis demonstrates a proof-of-concept closed-loop solution for multitasking while driving and tests its usability through a preliminary study. Our study involved a functional near-infrared spectroscopy (fNIRS) device, driving simulator, and adaptive reading interface. The fNIRS device monitors brain activity and triggers expansion of the reading interface in response to brain activity evoked by the challenges presented by the driving simulation. While this is preliminary research, future work can build upon our contributions. In doing so, this research will provide insight into how to diminish the effects of task-switching while driving.

Acknowledgements

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My committee members, James Intriligator, Rob Jacob, and Nate Ward. Thank you for your patience and guidance throughout this entire process. You have each helped me with this thesis and with my career in many ways, and I will always be grateful for that.

My interns, who have been nothing short of brilliant and have constantly impressed me. Celebrating the first time our data processing algorithm worked was one of my favorite moments of this thesis.

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USING BRAIN-COMPUTER INTERFACES TO IMPROVE MULTITASKING IN DRIVING

Introduction

Regardless of the dangers involved or the legality of the act, multitasking while driving is a common occurrence. Whether it is changing the radio station or responding to a text, multitasking while driving is on the rise (Pickrell, 2016). The consequences of doing so can vary between minor inconveniences to fatal crashes. Texting and driving related crashes cause roughly 3,000 teen deaths and 300,000 injuries every year (Ricks, 2014). In fact, recently texting while driving has become the leading cause of death for teen drivers (Ricks, 2014).

Previous technological solutions have worked, to some extent, to address this issue. For instance, Apple's Do Not Disturb While Driving feature suspends messaging when the user is driving (Perez, 2017). However, the blocked texts can be circumvented and the feature does not prevent other distractions like music or mapping applications (Perez, 2017). There are a variety of stimuli that divert our attention while we are driving and trying to curtail or block them entirely is impractical and unrealistic. Current solutions looking to completely stop these distractions from happening are ineffective.

Additionally, understanding multitasking while driving is relevant to autonomous driving scenarios, because the driver must be ready to take control of the vehicle even when their engagement is somewhere else

(Horrey et al., 2017). In both present and future cases of driving, multitasking will be involved. Rather than preventing it from happening, we should embrace the phenomenon and try to use it to our advantage. Specifically, perhaps the best alternative is to not try and stop all driving distractions, but instead to begin by understanding the impact that multitasking may have on specific driving-related tasks – and then modify these tasks to make them easier when multitasking is desired. That is the logic employed in this thesis.

Research Questions

In this paper, we present a study that aims to understand the impact of reading while driving and how an adaptive reading interface might lessen these effects. We propose two hypotheses:

> **H1.** The adaptive reading interface will improve driving performance compared to a static interface by lessening the effect of performing a secondary task.
>
> **H2.** The adaptive reading interface will improve the subjective multitasking experience.

With these hypotheses in mind, we hope to explore what role Brain Computer Interfaces (BCI) and adaptive interfaces can have in driving. By utilizing our measurement of a person's brain activity, how can we improve switching between driving and a secondary task?

This study asks participants to drive in a driving simulator while reading information presented on a reading interface (tablet) positioned and configured as an in-dash vehicle display. A functional near-infrared spectroscopy (fNIRS) device monitors brain activity and contributes to a closed-loop solution such that changes in cognitive activity manipulate the reading interface. For instance, elevated fNIRS measurements near the front of the head, which indicates more frontal brain activity, may cause the spacing between lines of text to expand. Because this expanded form comes at the cost of efficiency, we choose to shrink the spacing between lines of text when cognitive activity is below a threshold.

The independent variables of this study were driving difficulty and reading interface state, with easy or hard levels for the former and collapsed text or expanded text for the latter. We included several objective and several subjective measures. The objective dependent variables included: driving performance metrics of velocity and lane offset as well as quantified reading comprehension. The subjective dependent variables were self-reported enjoyability ratings, post-study interviews, and NASA Task-Load Index (Hart and Staveland, 1988) scores.

Main Contributions

This thesis advances driving research through a novel incorporation of a Brain-Computer Interface and an accompanying data processing algorithm that does not use machine learning. To the best of our knowledge, Brain-Computer Interfaces have not previously been used in driving research. This research provides the initial work necessary to explore the advantageous role Brain-Computer Interfaces can have on understanding multitasking while driving behaviors. Additionally, our data processing algorithm is the first to connect NIRX's NIRScout data streaming capabilities to a reading interface. Overall, we built a technically complex interface that integrates different systems to study multitasking behaviors while driving. This thesis provides useful work for future researchers to build upon.

Survey of the Literature

fNIRS and the Prefrontal Cortex

The prefrontal cortex is a well-studied part of the brain, and activity in this region is associated with mental processes relevant to this project. Researchers have found that the prefrontal cortex plays a large role in problem solving and planning (Grafman, 1999; Owen, 1996). In addition, dual-tasking, which involves working memory, was shown to activate specific areas of the prefrontal cortex. For example, in one study (Koechlin et al., 1999) the authors had participants perform tasks that required them to remember information and actively use it while performing a difficult task. Koechlin et al used functional magnetic resonance imaging (fMRI) to show increased brain activity in specific areas of prefrontal cortex while performing this task. Working memory refers to the intake, storage, and processing of information while performing tasks. Working memory is a common processing component employed when performing tasks that require multitasking (D'Espocito, 2000).

Previous work has examined the relationship between activity in the prefrontal cortex and cognitive workload using a variety of methods. Previously, researchers have used functional magnetic resonance imaging (FMRI) and positron emission tomography (PET) to validate this relationship (D'Espocito, 2000; Manoach, 1997). In their study, Manoach et al. (1997) used fMRI to measure participants as they performed tasks requiring high, low, and no working memory. Participants had to remember a set of numbers, then correctly identify them in a series of a random string of numbers. Participants had five numbers to recall for high working memory tasks and two numbers for low working memory tasks. In the no working memory task condition, participants had to press the left or right key to match what was shown on the screen, merely measuring reaction time. They found that there were significant changes in brain activity in the dorsolateral prefrontal cortex when comparing high working memory tasks to the low- and no- working memory tasks.

Recently, functional near-infrared spectroscopy (fNIRS) has been used as a more cost-effective and practical method of measuring brain activity. fNIRS uses hemodynamic monitoring to measure brain activity. The fNIRS process involves shining near-infrared light 3 cm into brain tissue and measuring what is reflected off the oxyhemoglobin in the blood, which is directly related to brain activity (Fox, 1988). In short, fNIRS can measure brain activity and, by extension, cognitive workload.

Studies using fNIRS have specifically focused on the prefrontal cortex (PFC) as a site for probe placement. The PFC oversees several complicated processes including problem solving and multitasking (Koechlin, 1999). More specifically, researchers have shown that specific driving tasks, such as accelerating, decelerating, U-turns, and constant velocity driving, are related to changes in activation levels in Brodmann Area 46 (BA46) and Brodmann Area 7 (BA7) of the PFC (Yoshino, 2013). As a result, in these studies we will focus our probe placement on BA46.

Brain Computer Interfaces

Brain Computer Interactions (BCIs) is a field that uses brain activity as an input to modify overall system performance or operation. A subset of this work utilizes the fNIRS device's cognitive workload measurement capabilities. While BCI's are prevalent in assistive technology, researchers have recently begun to apply them for more general use. Previous work with BCIs has explored using fNIRS to study learning, driving, and multitasking, demonstrating the utility of real-time applications of such data (Ayaz et al., 2012; Solovey et al., 2012; Afergan et al., 2014). However, there has been little research examining how to utilize the advantages of a BCI to improve task performance.

Yuksel et al. (2016) presented BACh, a piano learning interface that adjusts task difficulty according to cognitive workload levels. BACh's interface classifies and adapts to a participant's cognitive workload in real-time. Only once the participant's cognitive workload levels go below a specific threshold does the system deem mastery of the piano piece and that the participant is ready for the next level. In doing so, the timing of introducing increasingly difficult tasks is personalized. As shown in Figure 1, participants performed much better, making fewer errors, taking shorter amounts of time between notes, and taking less time to play the piece under the BCI condition compared to the normal condition. When asked to rate their own performance and enjoyment, participants favored the BCI much more heavily, as shown in Figure 2. This proves that a brain-computer interface that uses brain activity to personalize the learning process is effective in improving learning rate, performance, and subjective experience.

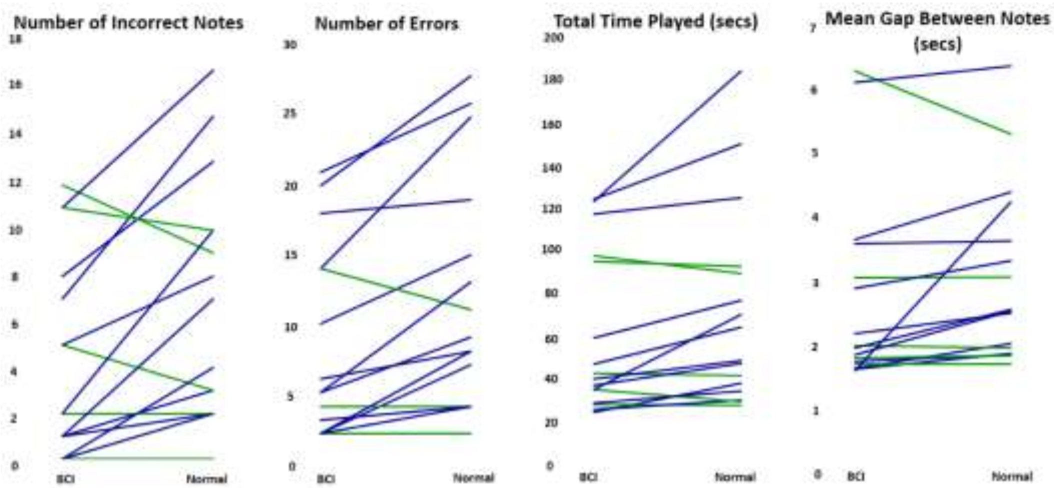


Figure 1. Comparisons of performance with BCI-assisted training and normal methods. Adapted from "Learn Piano with BACh: An Adaptive Learning Interface that Adjusts Task Difficulty based on Brain State," by B. Yuksel et al., 2016, In Proceedings of the 2016 chi conference on human factors in computing systems (pp. 5372-5384). ACM.

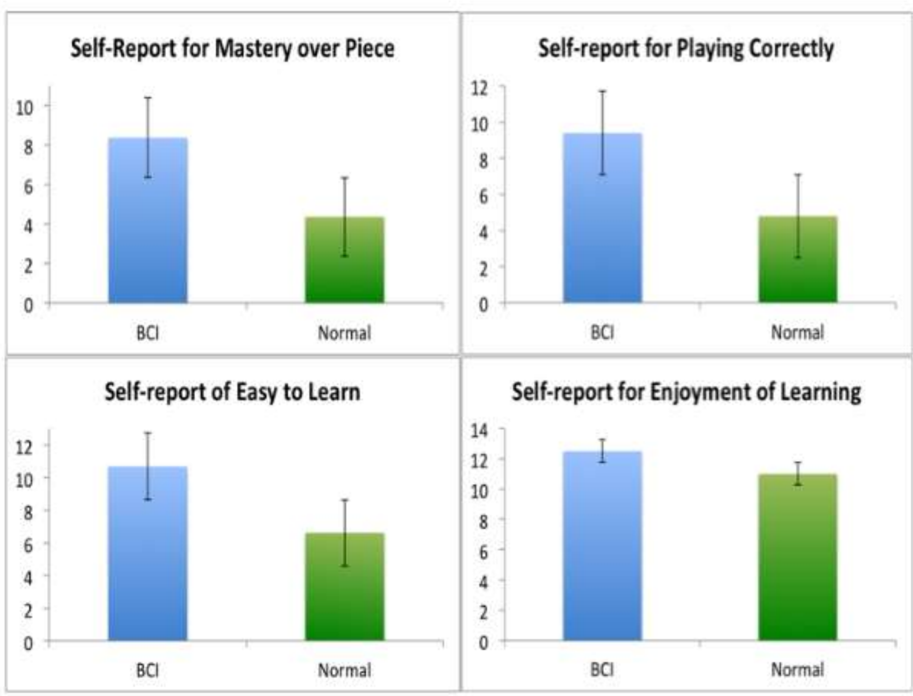


Figure 2. Mean and standard deviation values of self-reported scores comparing BCI and normal conditions. Adapted from "Learn Piano with BACh: An Adaptive Learning Interface that Adjusts Task Difficulty based on Brain State," by B. Yuksel et al., 2016, In Proceedings of the 2016 chi

conference on human factors in computing systems (pp. 5372-5384). ACM.

In addition, Afergan et al.'s (2014) study used brain activity measurements to alter the expansion of a target to improve the usability of bubble cursors. This work provides another example of using fNIRS to classify difficulty levels in real-time leading to fewer errors and improved performance. This paper also presents the concept of dynamic difficulty assessment, which dictates when to add or take away a stimulus according to what and how many mental resources are available (Afergan et al., 2014).

BCI research has also focused on measuring brain activity while driving (Kojima, 2005; Shimizu, 2009). Using fNIRS, we can classify different brain states while driving (Khan & Hong, 2015; Brouwer et al., 2017). BCI work benefits from fNIRS's portability and relatively low cost, which allows for more realistic experimentation. fNIRS is a favorable tool compared to fMRI because it allows participants to sit up while performing driving tasks, as opposed to limiting participants to lying down as is required in most brain-imaging techniques, such as fMRI (Tsunashima, 2009).

Additionally, engaging in a secondary task while driving worsens driving performance (Briem & Hedman, 1995; Patten et al., 2004; Angell et al., 2006). Horrey et al.'s (2017) study points out that the severity of this impact is influenced by how engaging the secondary task is. This thesis works to alleviate this problem by lessening the negative impact multitasking has on driving.

Understanding Multitasking

Researchers have worked to understand how multitasking affects the performance of each task involved (Levine, 2012). Multitasking while reading increases reading time, though it is still unclear how it affects reading comprehension (Subrahmanyam, 2013). Additionally, the medium, either a piece of paper, laptop, or tablet, that the text appears on while multitasking does not matter (Subrahmanyam, 2013). In addition, multitasking also affects driving performance (Brumby et al., 2007). Terken et al. (2011) demonstrated that participants given an additional task put more distance between them and the car in front, or "headway." In addition to increased headway, this study found that people felt safer when driving is the sole task (Terken et al., 2011). Multitasking influences both driving performance and drivers' comfort levels while doing so.

Driving Simulators

Driving simulators have long been used in driving research and have contributed greatly to the field (Caird and Horrey, 2011). In addition to furthering our knowledge on driving, driving simulators are used for training and assessment purposes. Using driving simulators in research is beneficial because it allows for physically safe testing of otherwise dangerous driving situations, control over various confounding variables, and a finer understanding of driving performance. However, driving simulators are criticized for being unable to perfectly simulate real world situations, affecting performance because there are little consequences with a simulation, and their inability to assess driving behavior (Caird and Horrey, 2011).

When discussing driving simulators, critics often raise the question of how comparable driving performance in a simulator and in real life are (Caird and Horrey, 2011). This is commonly referred to as simulation validation, which can be further broken down into two terms, relative validity and absolute validity. Relative validity asks if there is a direct relationship between a change of a variable in simulated and real situations. Absolute validity refers to whether metric manipulations in the simulation are the same in real driving. For instance, driving at 60 miles per hour in the simulator is the same as driving at 60 miles per hour in real life. Current research focuses more on relative validity but has had difficulty making any claims about this relationship (Caird and Horrey, 2011).

In their 2011 paper, Caird and Horrey lay out the various dependent measurements that driving simulators can provide. There are eight classifications of variables: longitudinal control, reaction time, lateral control, crash, eye movements, subjective workload, physiological workload, and other measures. From these categories, there are several measurements relevant to this thesis. Longitudinal control variables include speed, speed variability, and time or distance headway. Reaction time includes perception response time, which refers to the time between accelerating and braking, and brake response time, which is the time between a stimulus and braking. Lateral control includes lateral position, lane exceedances, which is the number of times the vehicle goes out of the lane or proportion of time spend outside of the lane, and reversal rate, which is the number of steering wheel changes. Eye movements provide glance, which are all consecutive fixations, eyes-off-road time, which is how often the driver is not looking at the road, and percent dwell time, which is how long the driver is looking at a specific area of interest (AOI). Subjective workload includes NASA TLX scores and a Driving Activity Load Index, an assessment tool specifically for driving. Physiological workload includes heart rate, heart rate variability, skin conductance, EEG, and respiration. Finally, other measurements like navigation are pertinent to this work (Caird and Horrey, 2011).

Readability and Froggy

Improving the readability of online texts is essential given how much work is now being published electronically. Additionally, readers whose native languages are not English struggle with the format of online articles and other texts (Yu & Miller, 2012). To address this, Yu (2013) presents Froggy, a system that increases readability of webpage text by increasing font size and the space between lines. Froggy was built to assist skimmability for non-native speakers (Yu & Miller, 2012). In addition to increasing font size and spacing between lines, Froggy uses a Jenga Format transformation (Yu, 2013). As shown in Figure 3, the Jenga Format transformation separates sentences based on where on the page they begin and end. This format improved reading comprehension for non-native English readers and did not sacrifice reading speed (Yu, 2013).

Cloud computing--the idea of relying on Web-based applications and storing data in the "cloud" of the Internet--has long been touted as a way to do business on the road. Now software companies are making entire Web-based operating systems. Built to work like a whole computer in the cloud and aimed at a wider audience, these browser-based services could help those who can't afford their own computer.

Having the look and feel of Microsoft Windows or other popular desktop programs, the Web-based operating systems bring together a selection of integrated Web-based applications that typically run with Flash or Java.

Users can choose to save data locally or on the Internet.

Joshua Rand,
the CEO of Sapotek, which makes Desktop Two, says that a major goal of an online desktop is to get the collection of applications working together: "It's not a Tower of Babel desktop.

It's entirely fluent."

Desktop Two uses
a number of open-source applications, including Open Office as its productivity suite.

Once a useful group of applications are collected in a familiar format, cloud computing becomes more accessible to people who aren't comfortable tracking down a series of individual Web applications and combining them, Rand says. Desktop Two's service is free for individuals, although a small scroll bar of ads appears at the top of the screen. The company launched its Spanish-language version, Computadora.de, in Mexico in 2003, three years before launching in the United States. Rand says that he and his business partner, Oscar Mondragon, who lives in Mexico, had observed while traveling that in spite of socioeconomic differences that determine whether individuals own computers and how much bandwidth they have, people were

Figure 3. *A sample text with the Jenga Format transformation. Adapted from "Web Page Enhancement on Desktop and Mobile Browsers," by C.H. Yu, 2013, doctoral dissertation, Massachusetts Institute of Technology, Cambridge, Massachusetts.*

Texting while driving is now the leading cause of teenage death (Ricks, 2014). Additionally, DMV.org has reported that texting and driving was responsible for 26% of all car crashes in 2014 (Texting & Driving, 2018). DMV.org states that texting while driving involves visual, manual, and cognitive distractions (Texting and Driving, 2018). One factor of these driving distractions is the readability of the text, as it influences glance frequency and duration (Reimer et al., 2014). To the best of my knowledge, there has been very little work studying the effects of text readability while driving.

Yu's (2012) work discusses solutions for supporting continuous reading as the reading context changes. This system provides the framework for our efforts to improve mobile text readability while driving.

Methodology

Participants

We recruited three participants to participate in pilot studies. All were students at Tufts University and had valid driver's licenses, normal or corrected-to-normal vision, and no history of motion sickness. The procedure was approved by Tufts University IRB office.

Equipment

Driving Simulator

We are using a fixed-base driving simulator with an open-cab mockup (Realtime Technologies, Inc., Ann Arbor, MI). There are five 46-inch widescreen LCD displays, subtending approximately 180 degrees of horizontal visual angle, to display the driving scenario, which is generated with the RTI SimVIsta software and Internet Scene Assembler (Parallel Graphics Ltd.).

Android Tablet

We used an Android Fire tablet with a 6”x3.5” screen to display the reading passages. The tablet was placed on the center console to the right side of the driver.

Reading Questions

Eight passages were randomly selected from Banville’s Breaking News English site, which provides texts and reading comprehension questions of varying reading levels. All eight passages were Level 6, or Upper-Intermediate, difficulty.

NIRX NIRScout

We used the NIRScout (NIRx Medical Technology, LLC.) for measuring brain activity. One source-detector pair was placed approximately 3 cm apart from each other targeting the BA49 of the prefrontal cortex.

Data Processing Algorithm

The adaptive reading interface relies on a post request from the server to trigger the event, collapsing or expanding the text. Our process utilizes a threshold value to determine when to do so; however, this value depends on the individual. So, it is important to normalize each threshold value for each person. The NIRScout streams out raw data processed by a low-pass filter from NIRx's NIRStar software. Upon receiving this data, our machine implements the following algorithm: Because of the sampling rate of 7.81 Hz, there are 7 or 8 readings each second. Each reading is filtered, which acts as a high-pass filter, through the following:

Raw data	Filtered data
x	x
y	(x+y) / 2
z	(x+y+z) / 3
a	(x+y+z+a) / 4
b	(x+y+z+a+b) / 5
c	(x+y+z+a+b+c) / 6
d	(x+y+z+a+b+c+d) / 7

Table 1. Our high-pass filtering.

After taking the average of these 7 or 8 values, we have a mean value for each second. After ten seconds, we average the maximum and minimum values to determine a max slope per ten seconds. We then compare this final value, and if a new value exceeds the current value, it then becomes the new maximum slope value.

Our data processing algorithm is publicly available at https://github.com/kevinbae15/NIRScout-Algorithm-LSL-PUBLIC/tree/master.

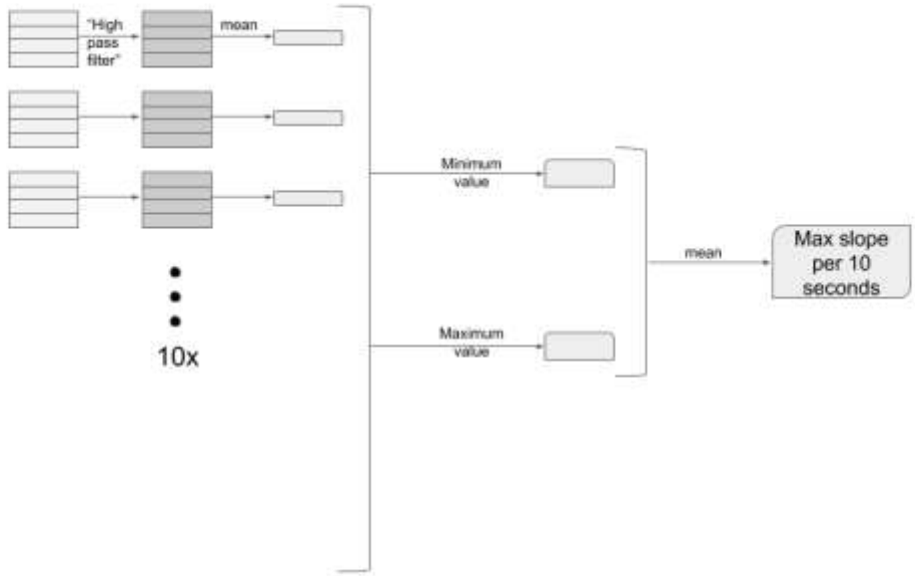


Figure 4. Overview of our data processing algorithm.

Figure 5. The experimental setup.

Figure 6. An additional view of the experimental setup.

Procedure

This was a 2x2 within-subjects design. Participants performed various tasks involving reading, driving, or reading and driving in a single session lasting for one hour and a half. The experiment reflected the following outline:

Condition #	**Task**
0	Driving Training
1	Easy reading
2	Hard reading
3	Easy driving
4	Hard driving
5	Easy driving + easy reading
6	Easy driving + hard reading
7	Hard driving + easy reading
8	Hard driving + hard reading

9	Easy → Hard driving
10	Easy → Hard driving
11	Easy → Hard driving
12	Easy → Hard driving
13	Easy → Hard driving
14	Easy driving + BOTH reading
15	Hard driving + BOTH reading

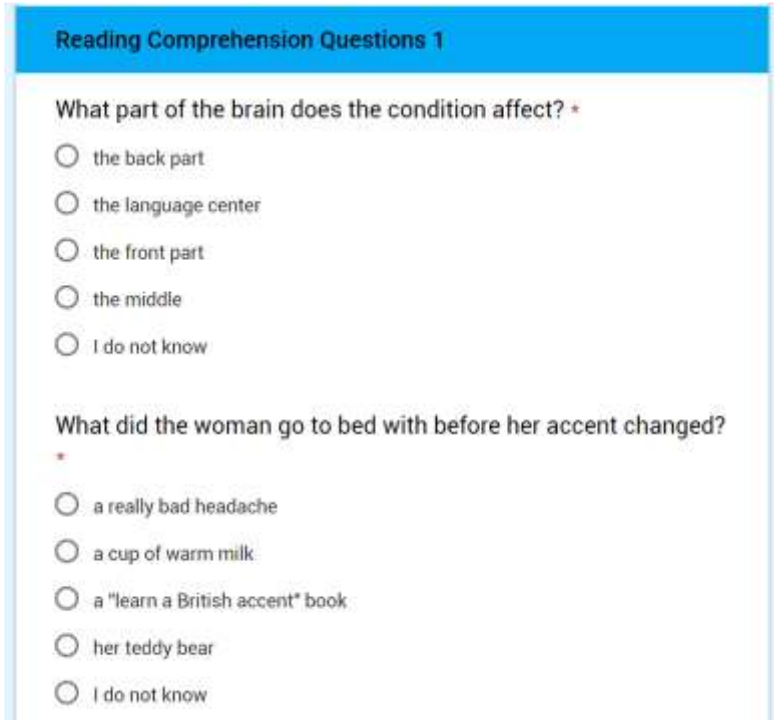
Table 2. An overview of the experimental procedure.

The first four conditions served as baseline measurements, isolating each level of each independent variable, while conditions 5-8 examined the interactions of each. Conditions 9-13 provided training data for our data processing algorithm, determining the maximum threshold for triggering an event. Finally, conditions 14 and 15 tested the implementation of our adaptive reading interface.

We asked participants to perform tasks involving reading, driving, or reading while driving. In conditions where the participant was just reading, they read a passage while seated and answered reading comprehension questions and completed a NASA TLX form. In conditions with solely driving, participants were given two minutes to drive freely. In conditions where participants both drove and read, participants were given thirty seconds to reach the speed limit before the text appeared on the tablet. After two more minutes of driving, we asked participants to pull over and answer a reading questionnaire and a NASA TLX form. There were three driving scenarios: easy driving, hard driving, and one that transitioned from easy to hard driving. In hard driving conditions, wind gusts pushed the vehicle at randomized rates, requiring participants to actively adjust the steering wheel. In easy driving conditions, the wind was absent. For tasks involving driving, we asked participants to stay in the right lane, not pass any vehicles, follow the 65 miles per hour speed limit, and drive as safely as they normally would.

Questionnaires

In conditions involving reading, we gave participants questionnaires and an online NASA TLX form (Grubert, 2014). The questionnaire involved four reading comprehension questions and a Likert-scale of how enjoyable the task was. The scale ranged from 1 to 5 with 1 being very unenjoyable and 5 being very enjoyable. Figure 7 shows sample reading comprehension questions. Figure 8 shows the subjective rating question. Figure 9 shows the online NASA TLX form.



Reading Comprehension Questions 1

What part of the brain does the condition affect? *

- the back part
- the language center
- the front part
- the middle
- I do not know

What did the woman go to bed with before her accent changed? *

- a really bad headache
- a cup of warm milk
- a "learn a British accent" book
- her teddy bear
- I do not know

Figure 7. Sample reading comprehension questions.

On a scale of 1 to 5, with 1 being very unenjoyable and 5 being very enjoyable, how enjoyable was the task? *

	1	2	3	4	5	
Very unenjoyable	○	○	○	○	○	Very enjoyable

Figure 8. The subjective rating question.

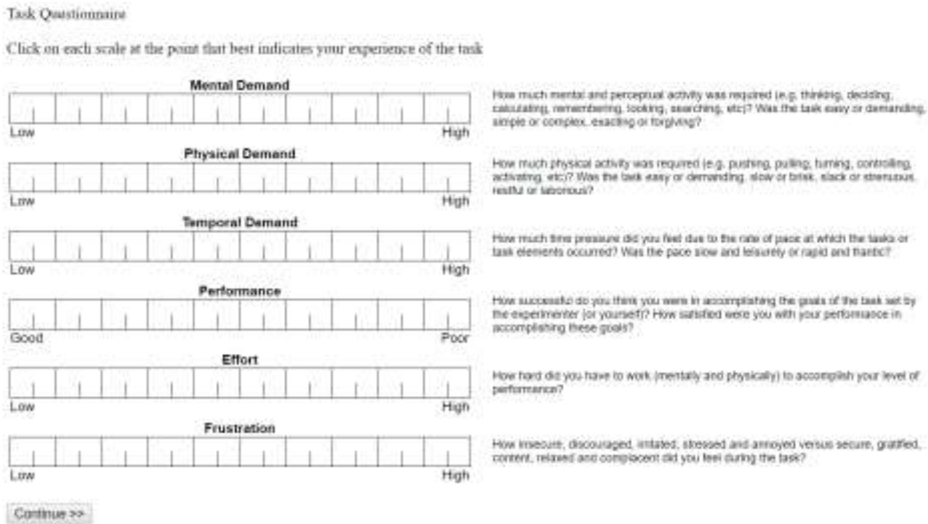


Figure 9. The online NASA TLX form.

Study Design Iterations

The following outlines how the study design evolved over time. Development of the adaptive reading interface and data processing algorithm drove many of the changes.

Iteration 1: The original study used the Hamamatsu NIRO fNIRS machine to measure brain activity. Participants would read different texts on a static and dynamic interface. Afterwards, they would perform two more reading tasks on static and dynamic interfaces while driving. We had to change this study design to gather baseline data and training data for the adaptive interface.

Iteration 2: This study design featured two sessions. In the first, we would gather baseline measurements as well as study the interaction between easy or hard driving and easy or hard reading. In the second session, participants would interact with our dynamic adaptive reading interface in both easy and hard driving conditions. Our motivation for splitting the study into two sessions was because of technical constraints of our data processing algorithm. However, we were able to build a process that could process training data rapidly, leading to our final iteration.

Iteration 3: The final iteration is outlined in the above section. It combines the previously separated sessions into one and adds five conditions for gathering training data.

Results

Proof-of-Concept of a Closed-Loop Driving Solution

We successfully built a system that alters the text presentation of a reading interface in response to brain activity. In all three pilot tests, our adaptive reading interface triggered a response, expanding the text when the participant was exerting mental energy.

In order to evaluate our solution, we interviewed each participant after their respective studies. Participant one stated that their emotional state remained the same throughout the study. They noted that they felt comfortable even as tasks got harder. Additionally, they thought that the steering wheel was malfunctioning when the driving task got more difficult. Participant two stated that they got more comfortable switching between driving and reading as the study went on. For the conditions featuring our adaptive reading interface, they thought that the tablet had malfunctioned and did not see it as an aid. However, they did point out that they felt that reading the expanded version of the text was easier than reading the collapsed version. When asked about the timing, both participant two and three pointed out that the change in display happened too late, saying that it was only after they had finished reading that the text finally expanded. Participant three also stated that they expected the interface to change, so they waited until it expanded to read the passage. Finally, they stated that they were more focused on the driving task than the reading task.

The following table displays some key quotes gathered from our interviews:

Participant 2: "The difference between the easy and difficult driving was not big enough."
Participant 2: "Finding my place on the text after looking away was the stressful part. I think the expanded part helped with that."
Participant 3: "The change just happened and I thought something went wrong, but I just kept going." Participant 3: "The timing changed too late."
Participant 3: "[The expanded text] absolutely made it more enjoyable to read."
Participant 1: "The first time, I had already read it so it wasn't so helpful. If the timing was correct, it probably would have been better."

Table 3. Quotes from Post-Experiment Interviews.

Reading Performance

Table 4 summarizes the number of reading comprehension errors each participant made for each condition. For instance, participant 1 made one mistake in the easy reading condition and no mistakes in the hard reading condition.

subject_id	task	errors
1	easy reading	1
1	hard reading	0

1	easy driving, easy reading	0
1	easy driving, hard reading	1
1	hard driving, easy reading	4
1	hard driving, hard reading	1
1	easy driving, adaptive reading	0
1	hard driving, adaptive reading	2
2	easy reading	0
2	hard reading	0
2	easy driving, easy reading	0
2	easy driving, hard reading	0
2	hard driving, easy reading	1
2	hard driving, hard reading	1
2	easy driving, adaptive reading	0
2	hard driving, adaptive reading	0
3	easy reading	3
3	hard reading	1
3	easy driving, easy reading	1
3	easy driving, hard reading	0
3	hard driving, easy reading	0
3	hard driving, hard reading	2
3	easy driving, adaptive reading	0
3	hard driving, adaptive reading	0

Table 4. Error rate for each participant.

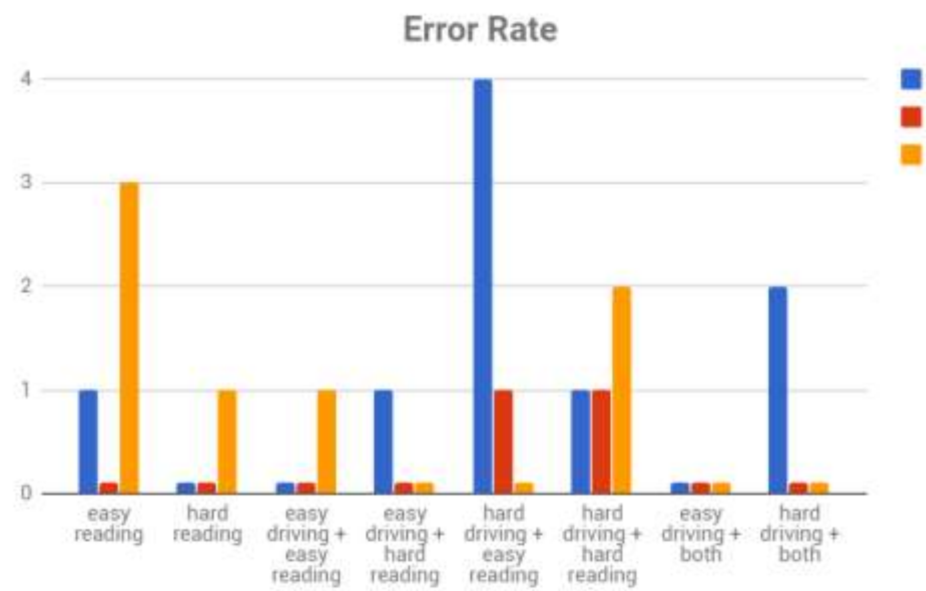


Figure 10. A bar chart showing error rate for each participant.

Driving Performance

Driving performance was evaluated based on velocity, measured in meters per second, and lane offset, measured by meters. Lane offset refers to the vehicle's distance from the center of the lane. The data from the first pilot study and the first two conditions of the second were unusable due to a technical error. We were unable to time-lock data between the simulator and the fNIRS.

Task	Velocity mean (m/s)	Velocity standard deviation	Velocity Mean (mph)	Velocity standard deviation (mph)	Lane offset mean (m)	Lane offset standard deviation
easy driving	n/a	n/a	n/a	n/a	n/a	n/a
hard driving	n/a	n/a	n/a	n/a	n/a	n/a
easy driving, easy reading	26.531	6.843	59.349	15.307	0.375	0.298
easy driving, hard reading	27.917	5.735	62.448	12.830	0.377	0.333
hard driving, easy reading	27.727	5.923	62.023	13.249	0.389	0.385
hard driving, hard reading	27.905	5.747	62.421	12.855	0.375	0.333
easy driving, adaptive reading	27.933	5.717	62.485	12.788	0.378	0.334
hard driving, adaptive reading	27.915	5.703	62.443	12.757	0.390	0.346

Table 5. Mean and standard deviation for velocity and lane offset for pilot 2 with data excluded from the easy and hard driving tasks due to a technical error.

Task	Velocity mean (m/s)	Velocity SD	Velocity Mean (mph)	Velocity standard deviation (mph)	Lane offset mean (m)	Lane offset standard deviation
easy driving	26.25	6.57	58.73	14.71	0.49	0.41
hard driving	27.28	4.62	61.02	10.33	0.51	0.33
easy driving, easy reading	27.28	4.62	61.02	10.33	0.51	0.33
easy driving, hard reading	27.06	4.96	60.54	11.09	0.51	0.36
hard driving, easy reading	27.25	4.64	60.95	10.37	0.51	0.34
hard driving, hard reading	27.28	4.61	61.02	10.32	0.51	0.33

easy driving, adaptive reading	27.28	4.62	61.03	10.33	0.51	0.33
hard driving, adaptive reading	27.28	4.62	61.02	10.32	0.51	0.33

Table 6. Mean and standard deviation for velocity and lane offset for pilot 3.

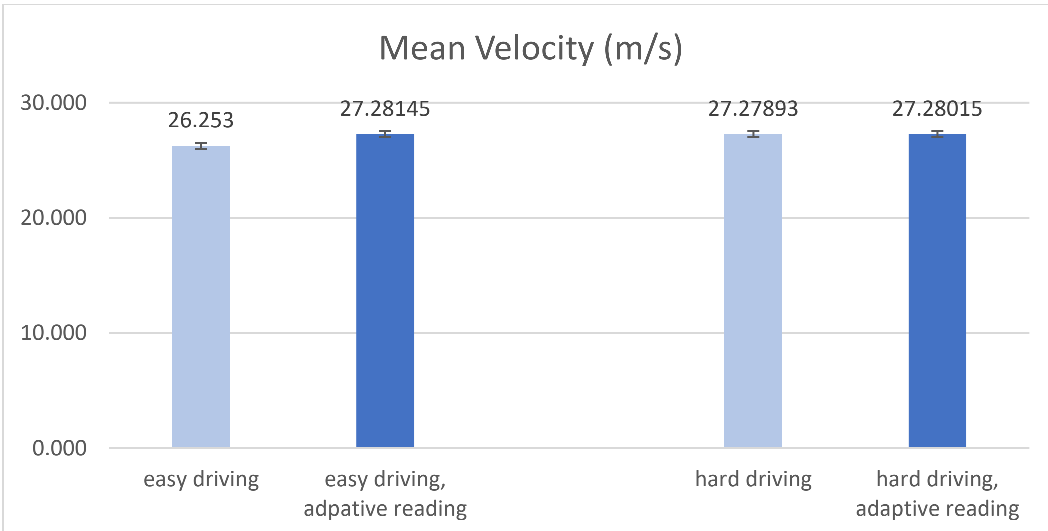


Figure 11. Mean velocity for pilot 3 comparing easy driving with easy driving and adaptive reading and hard driving with hard driving and adaptive reading.

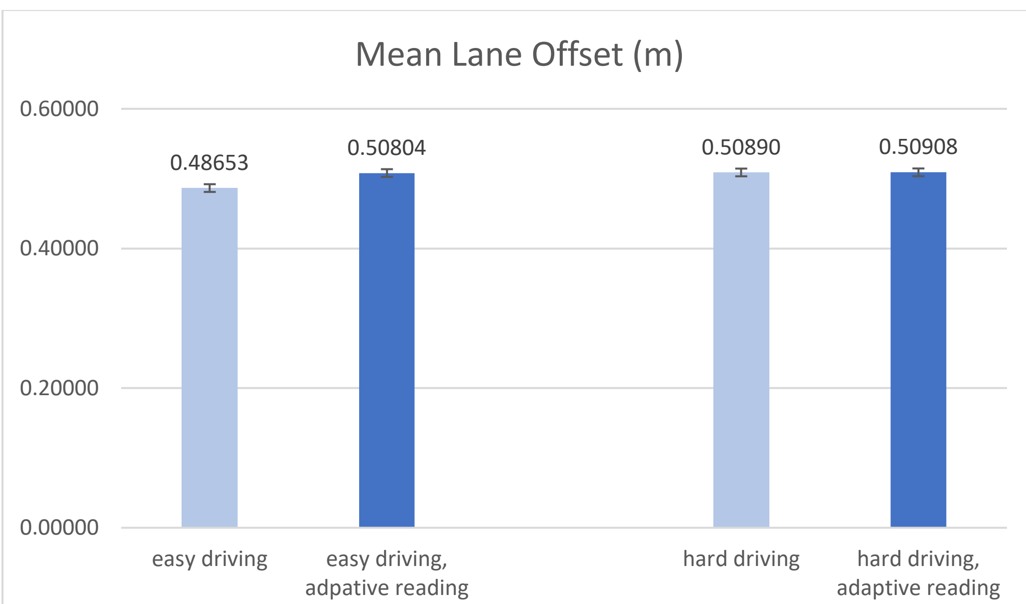


Figure 12. *Mean velocity for pilot 3 comparing easy driving with easy driving and adaptive reading and hard driving with hard driving and adaptive reading.*

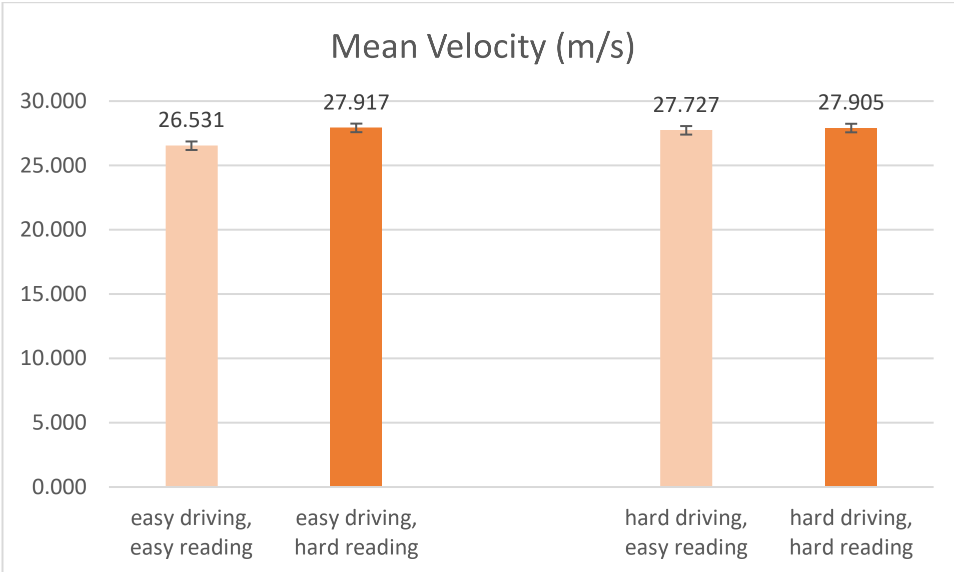


Figure 13. *Mean velocity for pilot 2 comparing easy driving, easy reading condition with easy driving, hard reading conditions and hard driving, easy reading with hard driving, hard reading conditions.*

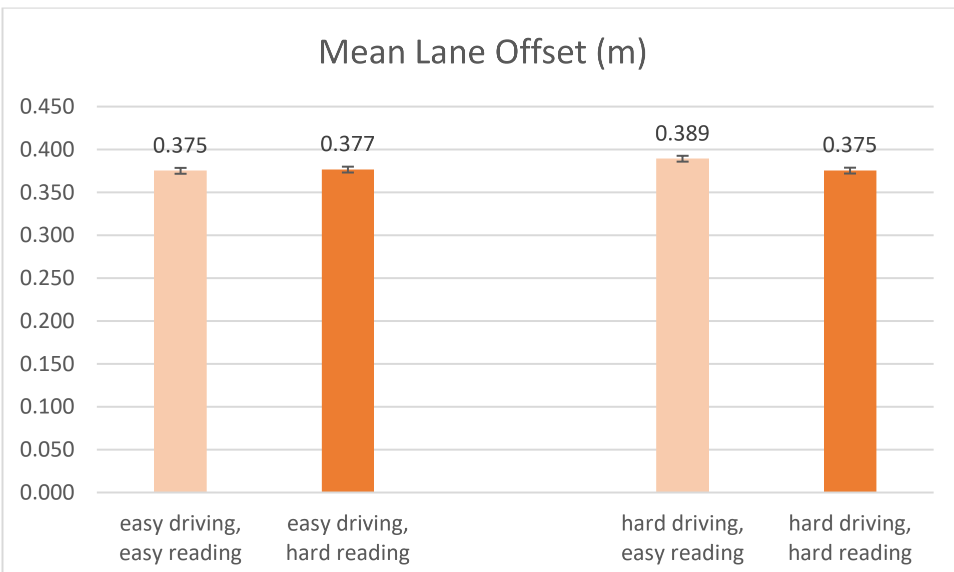


Figure 14. *Mean lane offset for pilot 2 comparing easy driving, easy reading condition with easy driving, hard reading conditions and hard driving, easy reading with hard driving, hard reading conditions.*

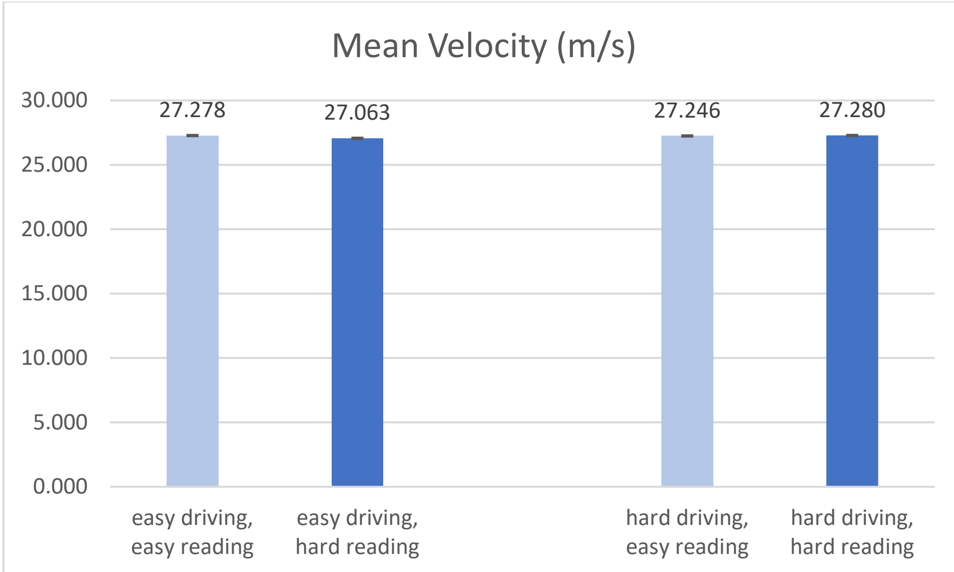


Figure 15. Mean velocity for pilot 3 comparing easy driving, easy reading condition with easy driving, hard reading conditions and hard driving, easy reading with hard driving, hard reading conditions.

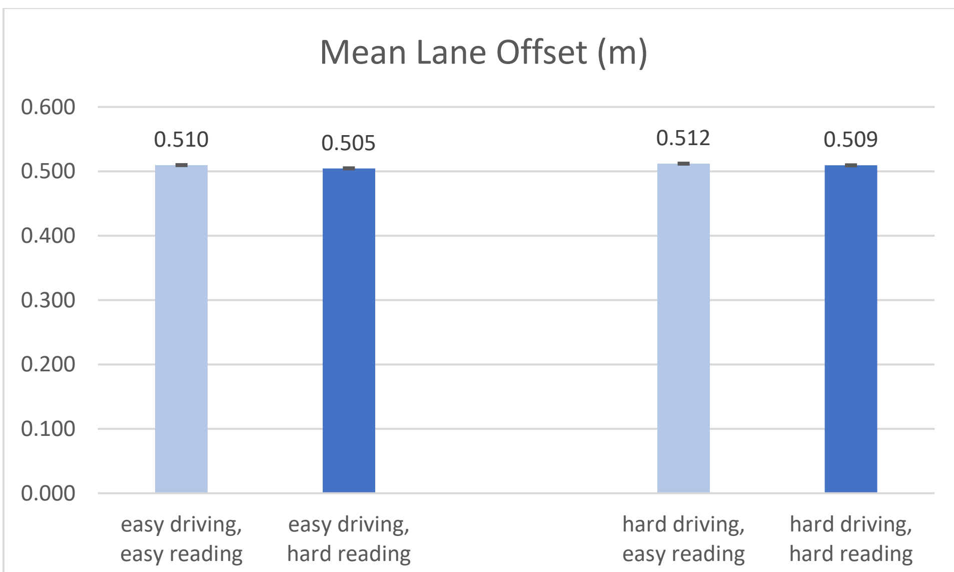


Figure 16. Mean lane offset for pilot 3 comparing easy driving, easy reading condition with easy driving, hard reading conditions and hard driving, easy reading with hard driving, hard reading conditions.

NASA Task Load Index

We asked participants to complete a NASA Task Load Index (TLX) form after each condition to confirm differences in difficulty levels of each task. Two-sided t-tests performed on overall mental workload for each condition had no significant results. Table 7 shows the self-reported NASA TLX scores for two participants. The data from the first pilot was not collected.

Subject id	Condition #	Mental Demand	Physical Demand	Temporal Demand	Performance	Effort	Frustration	Overall
pilot2	1	60	20	35	5	65	5	31.66
pilot2	2	70	20	25	5	55	5	30
pilot2	3	80	50	15	30	55	30	43.34
pilot2	4	75	70	10	30	70	40	39.17
pilot2	5	85	80	60	35	85	40	64.17
pilot2	6	75	70	45	25	70	20	50.83
pilot2	7	85	75	50	30	75	50	60.83
pilot2	8	80	75	45	30	80	40	58.33
pilot2	14	70	70	55	15	60	15	47.5
pilot2	15	85	80	60	35	70	35	60.83
pilot3	1	45	25	25	85	60	60	50
pilot3	2	40	20	55	50	50	55	45
pilot3	3	40	25	50	45	50	40	41.67
pilot3	4	50	35	25	45	35	45	39.17
pilot3	5	60	70	55	40	65	45	55.83
pilot3	6	60	60	40	45	45	45	49.17
pilot3	7	45	35	40	45	55	55	45.83
pilot3	8	45	55	40	50	55	65	51.67
pilot3	14	45	40	30	45	65	70	49.17
pilot3	15	40	55	45	45	45	60	48.33

Table 7. Self-reported NASA TLX scores for pilot 2 and pilot 3. The data from pilot 1 was not collected.

Subjective Ratings

In our post-task surveys, we asked participants to rate how enjoyable they found the task on a scale of 1 to 5 with 1 being very unenjoyable and 5 meaning very enjoyable. Figure 17 shows how the average enjoyability ratings changed for each condition.

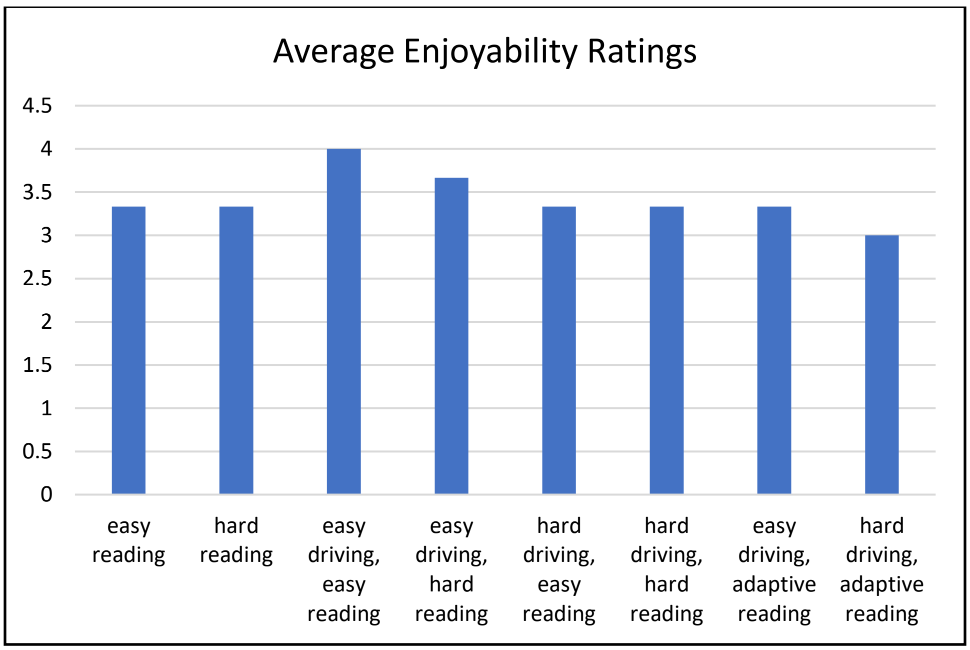


Figure 17. Average enjoyability ratings across all participants for each condition.

Discussion

While we are unable to make any definitive claims due to the small sample size, the following section discusses observations and patterns revealed through preliminary testing.

Proof of Concept

Our adaptive reading interface serves as a proof of concept of a closed-loop driving solution. When the participant reaches a specific threshold of brain activity, the interface adjusts accordingly. Our current system is only capable of expanding the space between lines and therefore is only relevant to situations where a person faces a more difficult task. It is not equipped to handle the scenario where the participant has available mental resources and can manage a higher level of difficulty. In this case, the interface would then reduce the line spacing and perhaps the font size.

Our interviews with participants revealed opportunities for improvement to our adaptive reading interface. While our system was successful in triggering the text expansion, the timing did not meet expectations. For one, the timing was too sudden and surprised them, disrupting their reading experience. All three participants pointed out that the text expanded too late. They had already finished reading the text before expansion, making our system moot.

According to user feedback, our system improved certain parts of the multitasking experience. Participants agreed that the expanded text was preferable and easier to read than the collapsed version. Our system also helped one participant feel more comfortable switching between the driving and reading tasks.

From this feedback, our adaptive reading interface can evolve in various ways. While our system is successful in expanding, we would suggest implementing finer degrees of expanding and shrinking text to create a more fluid experience. The current system changes too suddenly, which negatively impacts the overall experience. The next version of this system should also address the timing of the change. Changes to our data processing algorithm would lessen this weakness. One suggestion would be to focus on deoxygenated hemoglobin instead of oxygenated hemoglobin, as it appeared to be more stable in our preliminary studies. Additionally, increasing the training data trials would make our algorithm more robust and enhance the timing.

Reading Performance

One participant made a mistake for each static reading task while under hard driving conditions, but scored perfectly for the dynamic reading task under hard driving conditions. Similarly, for another participant, they made few mistakes with static reading tasks but also scored perfectly when the reading interface was dynamic. It is possible that this occurred because of a learning effect and the participants got accustomed to the format of the study. However, from this, we can speculate a pattern of improved reading performance with the dynamic interface, and this should be explored further.

Driving Performance

Examining the driving performance data allows us to understand how driving metrics changed for different conditions and our system's efficacy.

We chose to examine the interactions of each independent variable to understand how effective our manipulation of the variables was. Figure 13 and Figure 15 compare easy and hard reading tasks for both easy and hard driving in terms of mean velocity. We might expect that the harder reading task would negatively impact driving compared to the easier reading task, but the change is minimal. This is also seen in Figure 14 and Figure 16, which depict lane offset. Our manipulation of the reading task difficulty might not have been strong enough, and the data from both pilot studies supports this.

Figure 11 and Figure 12 compares one condition with just driving to another that involves driving with the use of our adaptive interface. We expected to see that the integration of our system and a secondary reading task would have some impact on driving performance, but the difference was minimal. In terms of both mean velocity and mean lane offset, values neither improved or decreased. Instead, participants maintained a similar speed and distance from the center of the lane even when performing a secondary task. This might imply that the use of our adaptive reading interface negates the harmful effects of performing a secondary task while driving. It is also possible that the task difficulty was not hard enough, allowing the participant to perform well even in conditions that we considered to be difficult. While we are only able to support this claim with one participant's data, it provides an interesting direction for future work to examine.

NASA TLX

Our manipulation was ineffective, and there was no significant difference in perceived difficulty across the conditions. This is a major limitation of the study. Future studies should increase the difference in difficulty for each condition. We might accomplish this by introducing a different difficult driving scenario such as limiting visibility by asking participants to drive at night or with intense fog. Additionally, adjusting font size or other text variables might widen the difference in reading task difficulty.

Subjective Ratings

Participants reported that their enjoyability for conditions skewed positively, ranging from neutral to very enjoyable. None of our participants had a negative experience with the task. This might be due in part to the wording of our question, but this would also mean that the multitasking experience was overall not negative.

Conclusion

The issue of multitasking while driving will not disappear, even with the emergence of autonomous vehicles. Rather than working around the problem, our solution hopes to take advantage of our knowledge of a person's brain state to make task switching a safer and more comfortable experience. In this thesis, we presented an adaptive reading interface that expands text spacing and size in response to increased levels of cognitive workload, thereby showing a proof-of-concept for a closed-loop solution.

In our preliminary studies, we were unable to confirm our two hypotheses that our system would improve driving performance and subjective ratings. However, this thesis provides the framework for a future study that might accomplish this with improvements to our system.

Future Work

Future iterations of this work can improve by increasing the difficulty of driving and reading tasks, make changes to the reading interface, and redesign the actual experiment.

Further iterations of this work should increase the difference in difficulty levels, both with the reading and driving tasks. We might increase driving difficult through manipulating the current wind condition or introducing a new driving task altogether. Our pilot studies revealed an issue with the wind. It was not apparent that it was wind pushing the vehicle, but rather there was a problem with the study. For instance, participants thought that there was a technical malfunction with the steering wheel. Increasing the fidelity of the wind by either including windy sound effects or visual cues such as tree leaves moving or visual gusts would better communicate the wind's impact on the vehicle. Wind is just one driving manipulation found in previous literature. Traffic density, visibility, or a car-following task are additional options for increasing driving difficulty. Traffic density would have low traffic and high traffic conditions. There might also be a night and day condition to alter visibility. Finally, asking participants to follow a car that involves both easy and hard driving maneuvers is another option.

Improvements to the reading task might address the lack of difficulty we found through our study. Using a tablet with a larger screen would fit longer texts, increasing the reading duration and creating more opportunities to correctly time the text expansion. The adaptive reading interface could become more continuous with finer degrees of expansion, responding to smaller increments of brain activity changes. Also, a future study should implement the jigsaw formation found in previous work (Yu, 2013).

Future work could also explore various other metrics that we chose not to focus on in this thesis. For reading performance, we did not measure reading duration, but another study might find that our system affects how long it takes for a driver to read a text rather than how well they understand it. There are many other driving metrics we did not analyze. One interesting possibility is to differentiate when drivers were being pushed by wind and when they were correcting their position in hard driving tasks.

Future work might use more sensors to modify our data processing system and to improve the timing of text expansion or contraction. The TaskyApp uses different smartphone sensors such as the gyroscope, accelerometer, battery life, ambient light, and screen status to measure task engagement (Urh and Pejović, 2016). Wesley, Shastri, and Pavlidis (2010) have used thermal readings of a driver's face to detect distraction. Both studies present different ways of understanding driver engagement and could bolster the work presented in this thesis.

Multitasking while driving is a reality we must face. Through this thesis, we have demonstrated a proof-of-concept of a closed-loop driving solution. Rather than shying away from using technology while driving, this solution embraces it. This study lays the groundwork for future work incorporating Brain-Computer Interfaces in driving research to diminish the consequences of multitasking and driving.

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