ABSTRACT

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Despite recent advancements in automation, human-system interaction failures continue to threaten the safe implementation and usage of automated systems. Given the current automation capabilities of vehicles, it is critical to understand the factors that influence drivers' interactions with the system, particularly driver decision making. Prior research has shown that perceptual load and cognitive load are both influential factors related to information processing as well as the selectivity and allocation of attention, sometimes leading to failures of attention. While research has well documented the role of cognitive load on attention and visual processing, little research has extended such findings to more applied domains. Specifically, little is known about how these decision-making processes are influenced by the cognitive load introduced during driving. The current study examined the role of cognitive load and rapid transitions of cognitive load on decision-making processes when engaging with an automated driving system. Cognitive load was manipulated via a visuo-spatial sandwich task presented prior to the driving scenario and probing drivers after a simulated driving scenario. Drivers decided when and whether to disengage automation and take over manual control in response to an ambiguous roadway hazard (experiment 1) or a system failure of the automated system (experiment 2). Response times and takeover performance were measured to assess decision-making to engage with automation and the influence of load and rapid transitions of load. Rapid transitions of load significantly interacted with load and trial order which influenced operator decision-making processes when engaging with automated driving systems across both studies. Rapid transitions of load influenced decision-making as evident by significant changes in takeover performance and accuracy across all trials as well as trials surrounding rapid transitions of load, highlighting that when and how load changes significantly influences decision-making processes to engage with automated driving systems. Real-world implications and theoretical considerations are discussed.

Keywords: Cognitive load, decision-making, transitions, takeover, driving, automation

The Influence of Cognitive Load on Operator Decision-Making When Using Vehicle Automation

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DEDICATION

To my parents Rick and Judy Wagner, my sister Erin Wagner, as well as my grandparents Gene and Alice Farmer. Thank you for your support and endless encouragement through it all. This is for all of us.

BIOGRAPHY

Blake graduated from North Carolina State University in 2016 with a Bachelor of Arts degree in Psychology. He also received a master's degree in Experimental Psychology from Appalachian State University in 2018 prior to joining the Human Factors and Applied Cognition doctoral program of the Psychology department. During his time at North Carolina State University, Blake worked for multiple research associate and internship positions, including the Laboratory for Analytical Sciences (LAS), the MITRE Corporation, and Reality Labs at Meta which have served as opportunities to continue learning in academic and industry settings while advancing his applied research.

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Introduction

The cognitive and perceptual mechanisms that underlie the selectivity and allocation of attention as well as behavior in a variety of settings remains a large area of investigation in theoretical and applied cognitive psychological research. Individuals' ability to focus their attention and thoughts is necessary for the successful completion of a variety of tasks/behaviors. For many years, research has focused on distraction and attention because an individual's ability to ignore distracting information is a critical and important ability that is relevant to everyday activity. With this, a large body of research has highlighted the importance of understanding the mechanisms of attention and what factors influence one's ability to focus attention as well as factors that distract attention away from a task (Forster and Lavie, 2001). The inability to stay focused on a task can have a range of consequences depending on the criticality of the task. Driving is a highly dangerous activity and one of the most common safety critical activities that we conduct on a regular basis with a leading cause of vehicular accidents being distracted driving where the individual is not fully engaged in the primary task but rather dedicating resources to a secondary task (NHTSA, 2010).

Literature related to distractions while driving has well documented the costly influence of distractors such as the impacts of cell phone usage (Strayer & Johnston, 2001; Strayer, Drews, & Johnston, 2003; Caird et al., 2008), environmental factors (Burdett, Charlton, & Starkey, 2016; Geden & Feng, 2015; Geden, Staicu, & Feng, 2018), and in-vehicle systems (Heck & Carlos, 2008). While a variety of literature has investigated the cognitive and perceptual factors that influence attention during manual driving, a burgeoning area of research is beginning to focus on how these same cognitive and perceptual factors influence autonomous driving as well. Despite the continual technological advances in automation that remove or reduce drivers' responsibilities during interaction with automated vehicle systems, errors and interaction failures continue to occur on the roadways. Given that drivers will interact with automated systems in a variety of scenarios that may result in varied levels of cognitive load or workload, an understanding of how cognitive load influences operator interactions with automated driving systems is critical.

Cognitive Load

While many factors are at work, the added cognitive load from a secondary task is thought to be a major contributor to distraction while driving (Lamble, Kauranen, Laakso, & Summala, 1999), where the driver's cognitive system is additionally loaded by the secondary task as opposed to if the primary driving task of driving was given full attention.

A major factor that can influence an individual's ability to avoid irrelevant distractors and stay attentive to the primary task is the amount of load induced during the task. Load can be induced either from the complexity (or demands) related to the processing of physical features of stimuli or the mental resource demands of the task or stimuli. With this, there are two primary types of load: perceptual load - load induced from the perceptual complexity of stimuli (Lavie, 1995) and cognitive load - the amount of load related to working memory and or the cognitive demands due to the task or stimuli (Lavie, 1995; Sweller, 1988; Sweller, van Merriënboer, & Paas, 1998). While both types of load are influential on task performance, they are also critically related to the types of constraints that are placed on information processing and the allocation of attention. Perceptual load has been shown to be predictive of task-irrelevant information processing in that when high perceptual load is induced by the primary or central task, inhibition of task-irrelevant information is likely to occur compared to when perceptual load is low (Lavie, 1995). This process is theorized to be related to the depletion of attentional resources and capacity limitations prevent the allocation of attentional resources to secondary/irrelevant information and thus information unrelated to the primary or central task is less likely to be processed (Lavie, 2005; Forster and Lavie, 2008). In contrast, cognitive load influences information processing and attention allocation during tasks (Fougnie and Marois, 2007) through mechanisms of executive functions, where late attentional selection processes that inhibit distractors are impacted by top-down processes (i.e., cognitive control, working memory, etc.) that maintain goal-directed behavior (Lavie, 2010). Prior research has shown opposing effects of loading these executive functions compared to perceptual load in that when cognitive load is high, the interference of distractors is more likely. Heightened cognitive load increases interference by distractors where high perceptual load leads to decreased distractor interference (Murphy, Groeger, & Greene, 2016).

Although a plethora of research has investigated the influence of load on a variety of cognitive and behavioral processes, less research has been conducted on periods of load transition (i.e., rapid transitions from high to low load or low to high load). While some research has been conducted on the influence of such transitions of load on performance in a multi-tasking environment (Bowers, et al., 2014), neural correlates of workload transitions during multitasking (Kim et al., 2019), and the effects of rapid changes in workload on manual driving, much less research has been conducted on these effects during automated driving (Merat et al., 2012). Merat and colleagues (2012) investigated the role of changes in workload on driving performance in both automated and manual driving. They point to the need for a greater empirical understanding of how changes of workload such as periods of low load followed by rapid changes to high load and the lack of research literature in the domain of automation and driving. Their study employed a Twenty Question Task (TQT) and a critical roadway incident as manipulations of driver workload during a simulated drive (both manual and automated drives were assessed). Thus, they were able to create scenarios of low, medium, and high load by varying the presence and combinations of these variables. Results of this study showed driving performance differences in anticipatory responses to an upcoming critical roadway incident. When the TQT was present (high load), drivers in the automated condition showed deteriorated speed reduction as compared to the manual driving condition. The authors theorize that these differences may be accounted for by the sudden change in workload creating a situation where previously manageable levels of workload rapidly became elevated when drivers had to navigate a critical scenario in the roadway. This sudden elevation of workload could account for worsened performance, specifically in the automated driving condition, where drivers had to interact with the automated system to retake manual control. These results highlight how rapid changes in workload impact driving performance during states of automated driving. What this work does not show, however, is how similar changes in workload may influence driver decision-making to interact with automated systems during driving. Specifically, this study used critical roadway incidents and secondary task engagement during the drive to manipulate load as well as an eventual critical incident. However, decisions to interact with (engage/disengage) automated driving systems may also be highly influenced by the level of load a driver is under at a given moment, and further so by rapid changes in level of load. This gap in the literature was addressed in the current proposed research.

Manipulation of Cognitive Load

In applied research, multiple methods have been used to manipulate both perceptual and cognitive load. With cognitive load manipulations being common in the driving domain, a variety of methods have been employed to vary the amount of cognitive (and perceptual) load. These manipulation methods include divided attention tasks such as typing random integer strings into a keypad or performing mathematical calculations (Lamble, Kauranen, Laakso, & Summala, 1999), auditory tasks to simulate in vehicle technologies paired with a cueing paradigm using roadside signage (Lee, Lee, & Boyle, 2009), and working memory loading tasks such as the “sandwich task” (de Fockert, Rees, Frith, & Lavie, 2001). While these methods are efficient in manipulating the amount of cognitive load during a given task or scenario, one methodological concern not always taken into consideration is the confounding of increases in perceptual load unintentionally resulting from cognitive load manipulations. For example, an increase in set size to vary cognitive load (as commonly used during a sandwich task or tasks using concurrent visual stimuli) may lead to an unintended consequence of increasing both cognitive and perceptual load. While some methods sufficiently isolate the effects of cognitive load, this concern increases in driving studies where the use of visually displayed information stands to be a methodologically efficient and ecologically valid method of increasing cognitive load. For example, the use of task-relevant billboards or signage information may be considered in a driving study to increase the amount of cognitive load on a driver. However, if the primary manipulation differentiating high and low cognitive load is the amount of visually presented information then this manipulation is also (possibly unintentionally) increasing the amount of perceptual load evoked by the stimuli. Given the differing influences of cognitive and perceptual load on attention, distraction, and other cognitive and behavioral processes, isolating the effects of the intended load type is a critical consideration in research focusing on the effects of cognitive and/or perceptual load. This consideration is particularly critical for applied research in driving as ecologically valid methods of varying load will likely suffer from this confound more so than artificial laboratory-based manipulations. Given that the effects of cognitive load on decision-making processes during driving are the focus of the current proposal, isolating the effects of cognitive load by ensuring that perceptual load is held constant across varying load manipulations was a critical methodological aspect and consideration.

Decision-Making

Given that a primary component of the current research is decision-making, it is important to note prior research on how people make decisions. Traditional research on human decision making highlighted that people made decisions based on optimal judgements as outlined in economic theories by comparing all possible alternative outcomes, making probability estimates for these alternative outcomes, and making decisions based on the most optimal course (Kahneman & Tversky, 1979). However, for the past few decades, decision researchers have elaborated on prior theories from economics and game theory-based accounts and have shown that human beings do not make decisions in this manner. Conversely, work such as the heuristics and biases paradigm (Kahneman, Slovic, & Tversky, 1982), recognition-primed decision model (Klein, 1989; Klein, 2008), and other naturalistic decision-making models (Lipshitz, 1993) have shown that people do not make decisions based on economic and utility-based judgements of all possible alternative outcomes but rather rely on heuristics and prior experience in decision-making processes. Specifically, naturalistic decision-making models have criticized prior laboratory-based settings in which much of traditional decision-making research was conducted and has opted for more field based and real-world scenarios to elucidate how people make decisions under uncertainty, limited resources, or stressful/high stakes scenarios (Klein, 2008).

An important contribution of this wave of decision research was reframing the theoretical view of individual's as suboptimal decision makers but instead focusing on how these factors influence making decisions when decision scenarios are less than optimal. It is clear that individual factors that increase the difficulty of decision scenarios are an important component of decision making.

With this, cognitive load stands to be an important component that influences decision making process but the effects of cognitive load on decision making remains a widely understudied aspect (Murphy, Groeger, & Greene, 2016). Some extent research does exist showing the influence of cognitive load on decision making while extrapolating information from graphic displays (Allen et al., 2015). This research indicated that high cognitive load impaired individuals' ability to make optimal behavioral decisions but did not influence the extrapolation of information from the graphical displays. This shows that when individuals are subjected to situations of limited attentional resources to dedicate to the central task deliberate processing is reduced and decision-making processes are impaired in some instances. Additionally, research has also investigated the influence of underload (i.e., low cognitive load) on cognitive processes, including decision making. Jackson, Kleitman, and Aidman (2014) investigated how low levels of cognitive load influence executive function and decision-making processes during a simulated drive with results of this study indicating a decrement in the practice effect over subsequent trials under low cognitive workload as well as reduced awareness of incorrect decisions across trials. This work highlights how underload can negatively influence performance, metacognitive processes, and decision-making as indicated by decremented benefit of the practice effect across trials and worsened decision-making. This literature, together with aforementioned research and literature on cognition, attention, and performance, highlights the important role that both high and low cognitive load influence driving.

Automated Driving

Research on conditionally automated motor vehicles has become increasingly popular over recent years as technological advancements in automated vehicles continue to be introduced to the roads (Delphi Automotive, 2015; Tesla Motor Company, 2015). For example, various autonomous vehicles can implement such technologies as adaptive cruise control (ACC), lane keeping assistance systems (LKAS) to assist the driver and take over certain driving tasks. While many of these systems offer promising advancements that benefit driving by assisting or removing operators' responsibilities, failures of human operators to appropriately interact with these systems threaten safety. Conditionally automated vehicles can assist in the maintenance of speed, lane keeping, and headway distance but may require the driver to take over manual driving if a scenario arises that exceeds system capabilities (SAE International, 2016). Research on conditionally automated vehicles has highlighted multiple factors that influence how efficiently drivers take over control from an automated system including the complexity or context of a driving environment (Merat et al., 2012; Radlmayr et al., 2014), driver engagement with a secondary task (Merat et al., 2012; Neubauer et al., 2012; Zeeb et al., 2016), and driver vigilance (Greenlee et al., 2018; Molloy & Parasuraman, 1996). While driving is a complex and multi-modal task, the majority of research in this area seems to highlight the influence of behavioral and cognitive factors such as engagement and vigilance on performance in takeover scenarios. Thus, an understanding of the implications of implementing automated systems in vehicles is critical. An important component of implementing effective automated systems in vehicles is assuring that drivers maintain a sufficient level of preparedness should the system require the driver to take over driving functions. While automated systems are engaged, drivers may be less likely and less effective at takeover behaviors due to decremented situation awareness from being “out of the loop” due to automation taking over primary driving tasks and the role of the driver becoming that of a passive system monitor (Endsley & Kris, 1995). With this, the driver must at times make decisions related to interacting with the automated system (e.g., deciding when to activate or deactivate an automated system). These decisions are likely influenced by a variety of scenarios both internal (i.e., cognitive load, mental state, etc.) and external (i.e., perceptual load, environmental/roadway conditions) to the driver. Given that one’s decisions to rely on automated systems during driving can highly influence driving behaviors – and subsequent safety of driving – it stands to be a critical component for research on human automation interaction during driving. Additionally, seeing that automation has been shown to reduce human cognitive and perceptual capabilities as well as increasing load and task errors (Doyle & Cole, 2008), it remains an important domain of interest to study when and how individuals decide to rely on automated systems during driving. Prior research has shown that a number of factors influence reliance in automated systems including the reliability of the system (Dixon & Wickens, 2006), an individual’s trust in the system (Dzindolet et al., 2003; Körber, Baseler, & Bengler, 2018), individual differences in working memory (Rovira, Pak, & McLaughlin, 2017), as well as others. While prior research has shown the influence of cognitive load on a variety of factors with some research on load in decision making in other domains, no research (to the author’s current knowledge) has investigated how cognitive load influences decision making processes related to human-automation interactions during driving.

Gaps in the Literature

There has been a substantial amount of research on load theory since being introduced (Lavie, 1995). While being largely conducted in artificial laboratory settings, a growing amount of research in human factors has expanded traditional findings and predictions of classic load theory into applied domains. The majority of the research has focused on perceptual load and the cognitive load component has been somewhat ignored as well as how cognitive load influences judgment and decision making (similar arguments are proposed in Murphy, 2016, p. 1325-1326). Additionally, current theoretical understandings are limited in their scope due to prior research focusing on artificial laboratory settings. It seems clear that an understanding of both types of load is critical to understanding how these phenomena influence perception, cognition, and behavior in both theory and application. These gaps in the literature, however, leave critical components of load theory - namely cognitive load, its influence on judgment and decision making largely unexplored. Given the complex nature of driving, it stands to be a ripe area in which to study these phenomena in a more applied domain than traditional investigation. With continually increasing advancements to in-vehicle technologies, roadway systems, and automation it becomes ever more important to understand the underlying factors that influence operator interactions with such systems.

The Current Study

The current study investigated how cognitive load influences decision-making during driving. Specifically, the current study examines the decision-making processes related to the use of (and interactions with) automated systems during driving. Under various scenarios, a driver must decide whether to keep using the automated system or to take over vehicle control.

Additionally, this study investigates how cognitive load influences operator interactions with automated driving systems in response to two different scenarios: an ambiguous roadway hazard (experiment 1) and a failure of automation (experiment 2). Results of this series of studies will provide a more robust understanding of the impact of cognitive load (and transitions of load) on driver decision-making related to interactions with automated systems.

This novel contribution seeks to fill the gap in the literature as no research, to the author's current knowledge, has investigated the influence of cognitive load – including transitions of load – on decision making processes related to autonomous driving. Limited research has been conducted on the influence of transitions between high and low loads on decisions to use automation, and the current proposed study will expand this to include three forms of load: low, medium, and high low. Additionally, the current proposed study extends prior research typically conducted in artificial laboratory settings to investigate the influence of cognitive load in the applied domain of driving.

The current study offers two major novel methodological aspects to the literature. First, the current study will manipulate cognitive load via a concurrent non-primary task (i.e., a sandwich task loading task-irrelevant working-memory) as opposed to traditional task-relevant manipulations within the primary task (i.e., task difficulty, etc.). The method of cognitive load manipulation has been widely used in traditional cognitive psychological research in distraction and attention but has not been used (to the author's knowledge) in decision-making research. The use of a cognitive load manipulation not primary to the task holds the benefit of isolating the effects of cognitive load while also separating this effect from the task itself, as opposed to commonly used methods in the driving literature. This novel contribution extends the methodologies into a new domain and isolates the effects of cognitive load by manipulating load in the non-primary task. Second, the current study examines the effect of a transition of workload on driver's decisions to use automation as opposed to using a consistent level of workload. This method allows the assessment both periods of high and low cognitive load on decision-making processes to interact with automation during driving while also allowing the assessment of how rapid transitions in load differentially influence these decisions. To answer these questions, three experiments were conducted:

1. Two pilot experiments were conducted to determine the efficacy of the developed driving videos and to ensure that the online platform is a sufficient method for the current study aims.

2. Experiment 1 investigated the role of cognitive load in decision-making processes to engage/disengage an automated driving system in response to unexpected and ambiguous roadway hazards.

3. Experiment 2 investigated the role of cognitive load in decision-making processes to disengage automation in response to an automated system failure (e.g., system failure of lane keeping, speed control, braking, etc.).

Hypotheses

Cognitive load

H1: High cognitive load will impair secondary task performance as indicated by increased errors on the cognitive load task in study one and study two.

H2: Higher cognitive load will lead to impaired takeover performance as indicated by longer response times and poorer takeover accuracy in study one and study two.

H3: There will be an order effect of load across trials in that performance will decrease across trials as indicated by an interaction between load and trial order for both response times and takeover accuracy in study one and study two.

Rapid transitions of cognitive load

H4: Rapid transitions of load will lead to impaired takeover performance as indicated by longer response times and poorer takeover accuracy on the trial immediately after the transition compared to the trial prior to the transition in study one and study two.

H5: There will be an order effect of transitions of cognitive load across trials in that performance will decrease across trials as indicated by an interaction between transition type and trial order for both response times and takeover accuracy in study one and study two.

General hypotheses

H6: Participant decision-making processes will be similar between study one and study two, as evidenced by similar patterns in response times and takeover performance across both studies.

H7: Response times will show less variance within study two compared to study 1, indicating a more salient response to failures of automation when compared to ambiguous roadway hazards.

Study Aim

The aim of the current studies is to assess the influence of cognitive load on decision-making processes related to human-system interactions with an automated system during driving. Further, the current study will extend traditional theories into the applied domain of driving while also validating the use of online driving scenarios for the assessment of human-system interactions during driving.

Pilot Study

Method

The primary purpose of the pilot experiment was to develop and validate online driving scenarios to assess driver decision making in automated driving. Driver behavior in automated driving has been typically studied via in-person laboratory settings using driving simulators or on-road driving. This pilot study will aim to identify several working simulated driving scenarios and fine tune task settings and procedures based on participants' responses collected online. These video types were chosen because the takeover task itself is of reasonable difficulty, which allows for meaningful variation of takeover accuracy and response times under different load conditions. Scenarios that are designed with concrete hazards that indicate an impending vehicular crash or scenarios where there are never roadway incidents do not allow for variance in the types of behavioral measures being collected for these studies. Further, the nature of these videos will inherently reduce the likelihood of ceiling or floor effects that may come from overly easy/hard or direct task stimuli. These identified driving scenarios and task settings were used in experiment 1 and 2.

Participants

Twenty-three participants were recruited for pilot experiment a (to develop scenarios for Experiment 1) and 21 participants were recruited for pilot experiment b (to develop scenarios for Experiment 2). All participants were recruited for participation via Amazon's Mechanical Turk (MTurk) and the SONA recruitment pool at North Carolina State University. Given this is a pilot study, the sample size is arbitrarily determined with the primary goal to evaluate the working of the tasks and procedure. Participants from MTurk or the SONA pool were paid 2 dollars (USD) or one course credit, respectively, for their participation in the study. Participants were required to have normal or corrected-to-normal vision as well as a valid driver's license to participate in the study. All participants were also required to have more than two years of licensure (thus no novice driver) and have been driving at least three times a week for one year prior to the Covid Era or the participation in this study.

Online Automated Driving Task

For both pilot experiments, driving videos were created and recorded using STISIM Drive 3, and videos were presented online using Qualtrics. The experimental session consisted of a number of roadway driving scenarios where participants view simulated driving videos with the instruction of imagining taking a driver’s role in a Level 2 automated vehicle (i.e., partial automation such as a combination of lane keeping and adaptive cruise control). At a certain point during the driving scenario, a potentially hazardous event was presented, and drivers were instructed to indicate when (if at all) they would disengage the automated driving system and take over vehicle control. All hazardous events were left ambiguous as to whether or not they would necessitate a response and/or whether these events would directly lead to a crash (see Table 1 for a list of planned hazardous scenarios).

This ambiguity allows the participant to decide whether or not they would like to keep engaging automated driving or whether they would prefer to manually drive and navigate the scenario. These scenarios are ambiguous and do not necessitate takeover from automated driving, leaving participants to decide whether or not to engage automation during ambiguous scenarios allows the current study to assess this. Therefore, this study did not examine participants’ responses to takeover requests, rather, it focuses on understanding participants’ decision on whether to keep using automation. No crashes occurred throughout the course of the drives and a video ended immediately after a participant indicates an attempt to take over. All responses were collected by pressing a button presented on the screen alongside each driving video. For the “sandwich” task that induced cognitive load, responses were also collected via button press. All instructions were presented visually on the screen as well as a video giving instructions about the sandwich task and the procedure of the experimental trials. The primary manipulations within the simulated driving videos were related to cognitive load and automated driving (automated driving navigating ambiguous scenarios in experiment 1 and failures of an automated driving system in experiment 2). A total of 18 task trials were developed for pilot testing with the 6 best (per study) being selected for testing to ensure the efficacy of the cognitive load manipulation and a reasonable separation of the manipulation of load. These 6 videos were selected based on performance on the cognitive load task to ensure reasonable separation of high and low load as well as responses to automation to ensure that the scenarios provide sufficient reason for participants to engage automation. Two methods of driver response were developed for pilot testing: driver probed response and driver self-initiated response. For driver probed response, participants were probed multiple times during the drive to solicit their choice of whether to continue or discontinue the use of automation. For driver self-initiated responses, drivers will not be probed but were instructed to respond as soon as they decide they would like to discontinue vehicle automation. This variation in task design was exploratory in nature to assess which method is more appropriate for subsequent studies.

Cognitive load

Cognitive load was manipulated using a traditional memory task where drivers were presented with a number string and asked to remember the string for later recall. This method of manipulation was chosen to isolate the effects of cognitive load by having the loading task be non-driving related. Additionally, this method will ensure that perceptual load is kept consistent across load conditions by not increasing visually presented set size. Load was manipulated by the amount of strain placed on working memory (Baddeley & Hitch, 1974; Engle, 2002) or how cognitively effortful the given task is. Cognitive load was manipulated using a “sandwich” task which presents a cognitively loading stimuli set prior to the experimental stimuli and participants are then probed about the initial set. The current study employed a visuo-spatial task consisting of a grid (see Appendix D) that contained two houses - one in the bottom left corner and one in the top right corner of the grid. The grid contained arrows indicating a path from house A (the house in the bottom left corner) to house B (the house in the top right corner). House A and house B were always in the same locations and the grid was always the same size. Participants were instructed to remember the order, orientation, and location of the arrows presented and were told that they would be asked questions related to their memory of the previously presented grid (see Appendix C).

The pilot experiment employed two levels of cognitive load (low and high cognitive load) by using rule-based manipulations of cognitive load as indicated above (see Appendix C for full instructions). The rationale for this rule-based manipulation as opposed to set-size manipulations was to keep the perceptual load of the sets consistent across trials so as not to confound the influential impacts of cognitive and perceptual load.

Procedure

Prior to the experiment, participants first completed the informed consent followed by a brief demographics questionnaire including age, gender, driving experience, as well as their opinions on automated vehicle technology (Schoettle & Sivak, 2014). After this, participants were given instructions for the task, practice trials and then experimental trials. During the practice trials, participants were familiarized with the task and were instructed that they would view simulated driving scenes from the driver's point of view in which an automated driving system with Level 2 automation (SAE, 2021) was active. Participants were told that this level of automation could control both lane position and speed of the vehicle, but the driver had to remain vigilant of the situation and take over control if/when the driver felt the need to. After the completion of the experimental driving scenarios, participants completed the NASA TLX (Hart & Staveland, 1988) to assess perceived workload and were debriefed. To further allow quality control in online data collection, participants were asked to make an honest report of whether they were solely focused on the task during the study and the responses will not impact their compensation. All instructions and tasks were presented on screen.

Results

The goal of the pilot studies (a and b) was to down-select the experimental stimuli that would be used in study 1 (ambiguous roadway hazards) and study 2 (failures of automation). For each set of potential stimuli, participants rated the video on a scale of 1 (strongly disagree) to 7 (strongly agree) where 4 is neutral or ambiguous, how they would rate the prior scenario as a hazardous scenario. The rating measure was kept consistent across both pilot studies.

Videos selected were those that were rated as ambiguously hazardous, meaning rated as neutral or ambiguous (a rating of 4) or whose distribution of responses was non-consistent (taken to indicate ambiguity). Table 3 (Appendix F) contains mean and standard deviations for each video for both pilot studies. Table 1 (pilot study a) and Table 2 (pilot study b) contain descriptions of all videos used during pilot testing.

Table 1. Description of the stimuli onset, event, and environment used in pilot study a.

Video	**Study**	**Onset**	**Event**	**Environment**
1	P1	57	(Lane Change) Car swerves around vehicle	Urban
2	P1	43	(Lane change) Car swerves in front of vehicle	Urban
3	P1	63	(Pedestrian) Children cross the street	Suburban
4	P1	60	(Vehicle blocks road) Car backs up in front of driver	Suburban Highway
5	P1	35	(Pedestrian) Dogs cross the street in front of car	Busy Freeway
6	P1	50	(Lane Change) Swerve around vehicle	Urban
7	P1	42	(Lane Keeping) Lane construction with cones	Rural
8	P1	54	(Lane change and Speed) Vehicle heading towards car	Rural
9	P1	26	(Lane Change) Move around vehicle with fast speed	Rural Highway
10	P1	1	(Lane Change) Car passes vehicle on road	Rural
11	P1	31	(Vehicle Moves) Vehicle cuts in front of car	Rural Highway
12	P1	49	(Lane Keeping) Construction causes lane change	Urban Freeway
13	P1	46	(Pedestrian) Person crosses the street	Urban
14	P1	28	(Pass vehicle) Pass two trucks over yellow lines	Urban
15	P1	21	(Lane Deviation) Lane change without signal	Rural Roadway
16	P1	20	(Lane Deviation) Vehicle changes lanes	Suburban Area
17	P1	63	(Lane keeping) Lane deviation	Urban
18	P1	19	(Lane Deviation) Vehicle changes lanes	Urban Highway
19	P1	64	(Pedestrian) Crosses street during a turn	Urban

Table 2. Description of the stimuli onset, event, and environment used in pilot study b.

Video	**Study**	**Onset**	**Event**	**Environment**
1	P2	86	(Speed change) Come to close to the car in front of vehicle	Rural Freeway
2	P2	20	(Lane Change) Pass vehicle over double yellow line	Rural Freeway (trees)
3	P2	88	(Speed change) Speed increase, too close to the car in front	Rural Freeway
4	P2	19	(Lane Change) Pass Vehicle with oncoming traffic	Rural Freeway
5	P2	03	(Lane Change) Pass Vehicle with oncoming traffic	Rural Freeway
6	P2	55	(Speed Change) Rapid speed increase	Rural Highway
7	P2	33	(Speed change) Car passes in front of you	Rural
8	P2	73	(Lane keeping) Lane deviation	Rural
9	P2	73	(Lane change) Lane deviation into car	Busy Freeway
10	P2	74	(Speed change) Car moves in front of you abruptly	Busy Freeway
11	P2	13	(Speed Change) Rapid speed change to rear end vehicle	Rural Freeway
12	P2	10	(Lane Keeping) Swerving on road	Rural Freeway

Study 1

The primary aim of study one was to assess the influence of cognitive load, including rapid transitions of cognitive load, on participant decision-making processes when engaging with automated driving systems in response to ambiguous roadway hazards. With this, study one hypothesizes that higher cognitive load will lead to impaired takeover performance (H1) as well as impaired secondary task performance (H2). Additionally, significant interactions are hypothesized for cognitive load with order (H3) and rapid transitions of cognitive load (H4).

Participants

A total of 72 individuals completed the study. All participants must have had a valid driver’s license to participate in the current study. Recruitment was conducted at a rolling bases while a researcher actively checked for the validity of online responses. Any responses that demonstrated careless responding or were missing sections of data (incomplete responding) were replaced with another participant. This recruitment method was stopped once the necessary sample size was reached. This sample size was estimated using a power analysis assuming a medium effect size (Cohen’s d = .5) and a Type I error probability of .05. This followed the same participant inclusion criteria on vision, driving licensure and exposure, as in the pilot study. Participants were compensated at the same rate as in the pilot study.

Online Driving Task

Driving videos were those selected from the pilot study. The experimental session consisted of a roadway driving scenario where participants viewed simulated driving videos and made decisions of whether and when to discontinue automated driving. At a certain point during the driving scenario, a potentially hazardous event was presented and drivers were instructed to indicate when (if at all) they would disengage the automated driving system and take over vehicle control. All hazardous events were left ambiguous as to whether or not they would necessitate a response and/or whether these events would directly lead to a crash. This ambiguity allows the participant to decide whether or not they would like to keep automated driving or whether they would prefer to take over and manually navigate the scenario. While it may be the case that a takeover request (TOR) issued by the vehicle prompts the driver to take over, the driver may decide to take over even if/when they feel necessary, but it was technically not necessary or when automation was failing without an indication/warning of an impending failure. It is worth noting that no crashes occurred throughout the course of the drive, thus no responses were required to prevent an oncoming collision. All responses were collected via button presses as one button was presented on screen alongside each driving video to indicate a takeover. For the cognitive load “sandwich” task, participants’ responses were collected by their input to the memory question. Figure 1 illustrates the general procedure of the task. Each trial began with the memory load display shown for 1000ms; participants were instructed to remember the visuo-spatial information provided on the grid. Then a driving video was shown during which an ambiguous situation (study 1) or failure of automation (study 2) occurred, and a participant pressed a button to indicate takeover. The duration of the driving videos lasted 45s to 75s with an average of 60 seconds. Once a participant indicated takeover or the video ended, the response display for the load task would appear. After the participant made a response to the load task, a between-trial interval would occur for about 15 seconds before the start of the second trial. A total of six trials were presented to each participant.

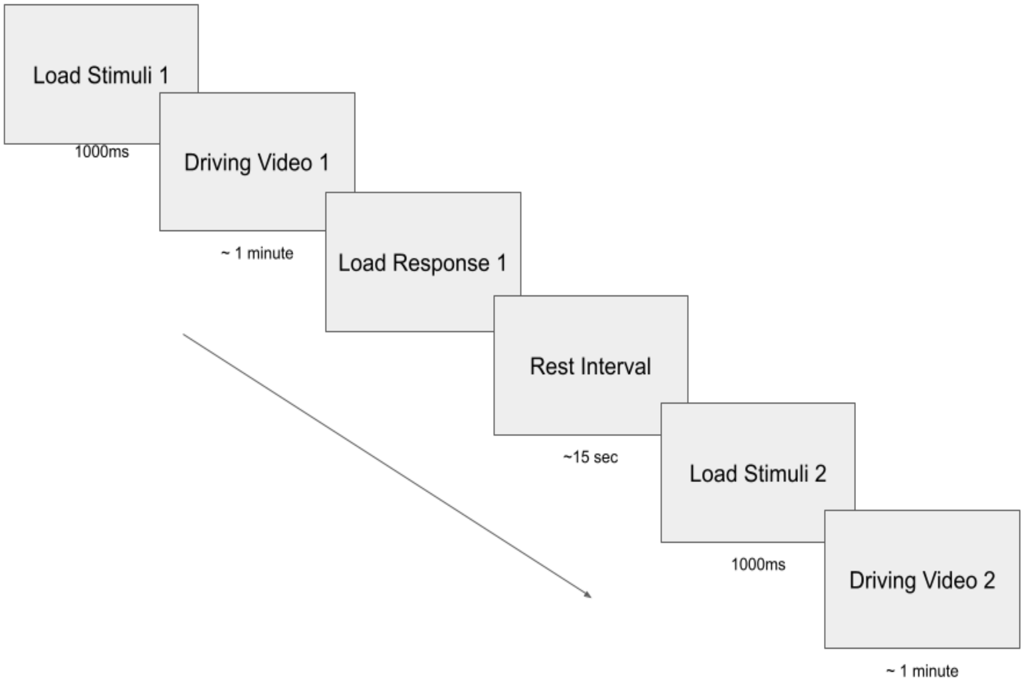

Figure 1. An example procedure of two trials.

Cognitive load

The load task followed the same method as used in the pilot studies. A key aspect of the cognitive load manipulation in this experiment was the rapid change from low to high or high to low load during the drive (Figure 2). During phases of the drive, the cognitive load task rapidly changed from high load to low load or vice versa from trial 3 to trial 4. With this, the current study was able to assess periods of high and low load specifically (the isolated periods before and after the transition) as well as the transition during which a load increase or decrease took place (Figures 1 & 2).

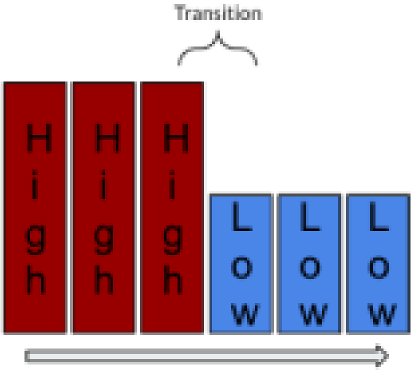

Figure 2. An example experiment session with six trials under various trial-level load conditions and a transition from high to low load. In this example, trials 1 - 3 would be high cognitive load trials while trials 4 - 6 would be low load trials.

Experimental Design

This study follows a 2 x 3 x 2 mixed design. The factors include trial-level load (high vs. low; within-subject), trial order within the same load set (one to three; within-subject), and transition type (high to low vs. low to high; between-subject). Every participant completed six trials in total, either first three under high load followed by three trials under low load, or first three trials under low load followed by three under high load. The dependent variables were takeover correctness (whether button press occurred within specified time window of a critical event), takeover response time (from onset of event to response), and accuracy on the cognitive load task.

Procedure

Prior to the experimental drive, participants completed a brief demographics questionnaire including age, gender, driving experience, as well as their opinions on automated vehicle technology (Schoettle & Sivak, 2014). After this, participants completed the informed consent and then proceeded to the experimental procedure. During a practice trial, participants were familiarized with the task instructions and were instructed that they would view simulated driving scenes from the driver's point of view in which a manual drive was taking place. At certain points of the drive, they were instructed that they may switch to automated driving at any point if they felt comfortable and/or would prefer to. After the completion of a total of six experimental trials, participants completed a survey identical to the one completed prior to the study and were debriefed (Appendix E). All instructions and tasks were presented on screen.

Study 1 Results

Cognitive Load Task

To assess the impact of cognitive load on secondary task performance (H1), percentage of correct responses were plotted across trials for each transition of load. Figure 3 highlights the impact of cognitive load on secondary task accuracy. Participants were more accurate on low load trials (84.26%) than on high load trials (58.33%). Further, Figures 4 and 5 highlight the accuracy on the secondary loading task across trials when load rapidly transitioned from low to high (Figure 4) and from high to low (Figure 5).

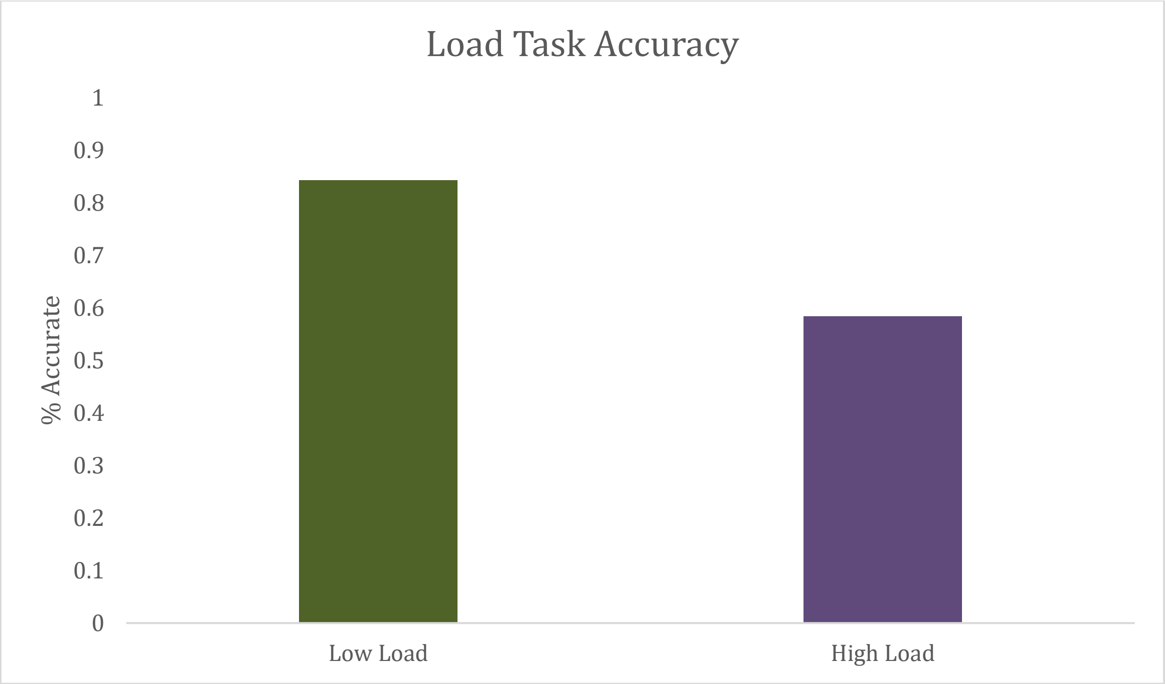

Figure 3. Percent of accurate responses on the secondary load task for low and high cognitive load.

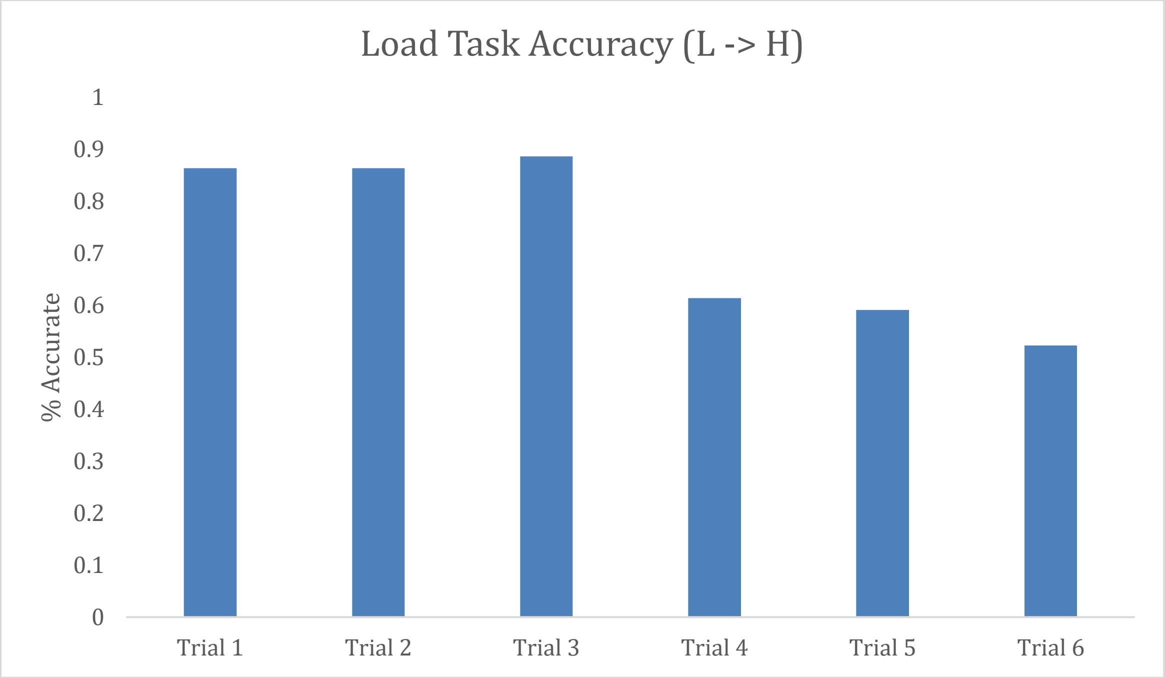

Figure 4. Percent of accurate responses on the secondary load task across trials when load transitioned from low to high.

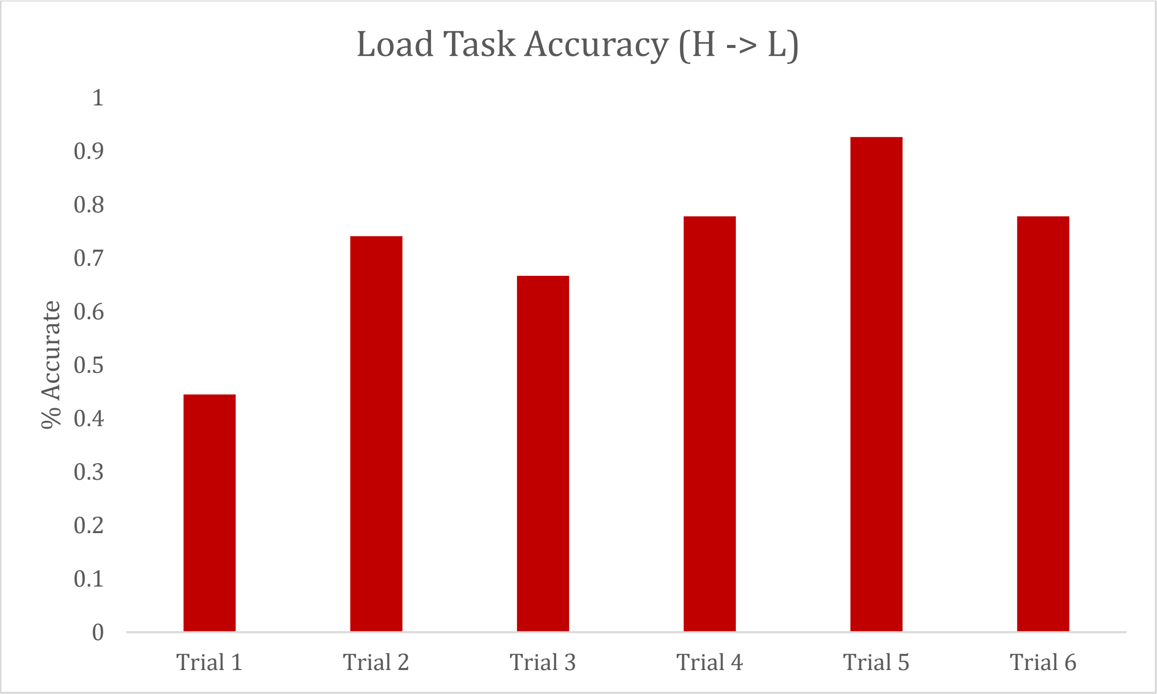

Figure 5. Percent of accurate responses on the secondary load task across trials when load transitioned from high to low.

Together, these highlight secondary task performance as well as how rapid transitions of cognitive load influence participant performance across trials. This data shows that not only cognitive load but also rapid transitions of load influence participant performance, and that when and how load changes across tasks is crucial to assess in tandem with cognitive load.

Takeover Performance

For each video, a specific time window was identified as the effective response time window (window for each scenario listed in Table 1). In the current study, takeovers that occurred two seconds after the onset of the critical event would be considered “correct” or “accurate” takeovers as this allows for variance after the onset of the critical roadway event (ambiguous hazards in study 1) and adjusts for potential lag times given that all stimuli were presented online (see description of each video and its time window in Table 1). This two-second window was arbitrarily decided upon in order to provide for potential latency that could be experienced in online driving while also collecting meaningful responses that occurred after the onset of the stimuli but not so far after the stimuli was no longer present that a takeover could not be associated with the stimuli onset. Given that these hazards were intentionally ambiguous, participants could choose to take over immediately at the start of the scenario, during the scenario, or never take over control given that no crash was visible in any scenarios. Thus, “correct” or “accurate” takeovers will be discussed as takeovers that occur within this window.

To assess the effects of cognitive load on takeover performance (H2 & H3), an analysis using Generalized Estimating Equations (GEEs) was conducted for takeover accuracy. GEEs are a similar statistical modeling method to Generalized Linear Models (GLM), but GEEs account for the covariance structure of the repeated measures (Liang & Zeger, 1986) and allow for non-normal distributions in order to handle discrete binary data. Additionally, this method has been used to analyze discrete binary data in previous driving studies to model binary response data (Abdel-Aty & Abdalla, 2004). These models provide Wald Chi-Square significance tests as well as parameter estimates (i.e., model coefficients) for each term in the model. Given that takeover accuracy is a binary variable (i.e., 1 means correct takeover thus button press within the specified time window, 0 means incorrect or no takeover thus button press outside the time window or button press), this modeling method was chosen.

Takeover Correctness

Results of these analyses on takeover correctness indicate non-significant main effects of load [X^2 (1, N = 432) = .05, p = .825], transition type [X^2 (1, N = 432) = .47, p = .491], and order [X^2 (2, N = 432) = 5.05, p = .080]. While main effects were non-significant, significant interactions were noted between transition type and order [X^2 (2, N = 432) = 7.67, p = .022] as well as cognitive load and order [X^2 (2, N = 432) = 7.64, p = .022]. These results highlight that participants were significantly more likely to take over (Figure 6) within the appropriate takeover window of the appearance of the roadway stimulus on early trials (trial order = 1) when load rapidly transitioned from low to high (M = .64, SE = .055), compared to high to low (M = .39, SE = .075). Additionally, the lowest accuracy level was on middle trials (trial order = 2) when load was low (M = .40, SE = .060), compared to high to low M = .55, SE = .062).

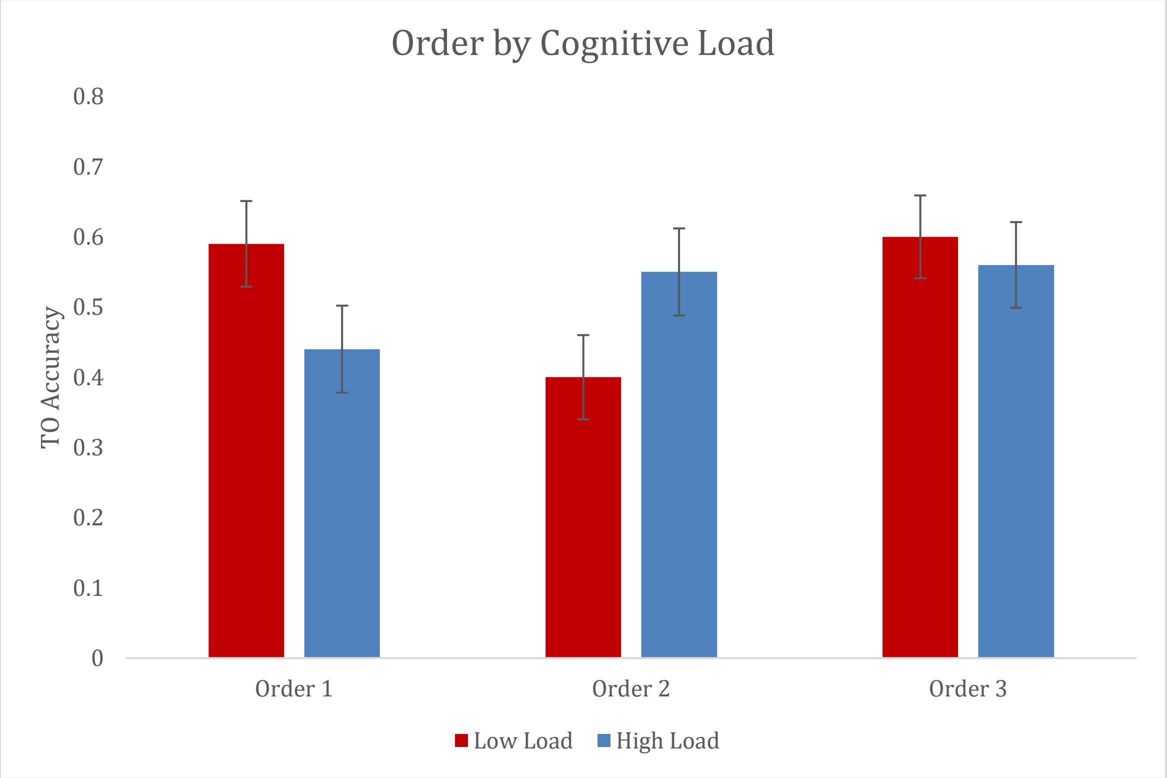

Figure 6. Estimated marginal means of take over accuracy for the interaction of trial order by load. Error bars represent standard errors of the mean (SEM).

Response Times

To analyze the influence of cognitive load (H2) and order (H3) on response times to take over control during an automated driving scenario, a Repeated-Measures ANOVA was conducted with trial-level load (low or high) and order (1, 2, or 3 within the same load set) as within-subjects factors and transition type (low to high or high to low) as the between-subjects factor. Response times were calculated as the time difference between the onset of the critical roadway event and the time of button press. A negative response time indicates a response that occurred prior to the onset of the critical roadway event.

Mauchly's test indicated that the assumption of sphericity was violated for the main effects of Order, χ^2 (2) = 14.58, $p < .001$, therefore the corrected degree of freedom ($\varepsilon = .87$) using Huynh-Feldt estimates of sphericity will be reported (Field, 2013).

Results of the repeated-measures ANOVA indicate non-significant main effects of cognitive load (high or low load) [$F(1, 67) = .76$, $p = .388$, $\eta_p^2 = .011$] and order [$F(2, 66) = .28$, $p = .756$, $\eta_p^2 = .008$]. However, significant interactions were noted for cognitive load by transition type [$F(1, 67) = 4.39$, $p = .040$, $\eta_p^2 = .061$), order by transition type [$F(2, 66) = 6.92$, $p = .002$, $\eta_p^2 = .173$), as well as cognitive load by order [$F(2, 66) = 10.84$, $p < .001$, $\eta_p^2 = .247$)]. A three-way interaction between cognitive load, order, and transition type was non-significant [$F(2, 66) = .64$, $p = .533$, $\eta_p^2 = .019$)]. Of note is the large standard errors for response times which make interpreting statistical significance difficult. This will be discussed further in the discussion and limitations sections.

Taken together, these results indicate that participants in this study performed moderately in terms of takeover accuracy. Figure 6 highlights the influence of load condition and trial order where participants showed much higher takeover performance on initial trials when under low load conditions and this takeover performance degrades to trial two (H2 & H3). However, this flips for high load trials where participants showed below average takeover performance on trial one (M = .44, SE = .062) but this increases on the subsequent trial (Trial 2; M = .55, SE = .062). This switch between trial order one and two between load conditions helps to parse apart and understand the non-significant main effects of load and order but the significant interaction between load and order. Here highlights the interaction between load conditions that has a notedly different pattern across trials. Across low load trials, there seems to be a U-shaped curve for performance where middle trials (trial order two) show a degradation compared to one and three. This pattern is not fully opposite on all high load trials, but the interaction effect can be clearly seen in this opposing pattern of takeover performance across trial order between low and high load trials. This may be the case because participants under initial higher cognitive load have less resources to dedicate to accurately assessing the ambiguity of the scenario and deciding to take over control. Under initial lower load conditions, participants have additional resources to dedicate to both the secondary load task and the primary driving task. However, on subsequent trials this interaction occurs across cognitive load conditions where lower cognitive load shows increased performance from trial one to trial two and higher cognitive load shows decreased performance from trial one to two. One explanation for this may be that under higher cognitive load, participants must focus and increase effort given to the task in order to accurately take over control during potentially dangerous scenarios. In other words, participants may be reallocating resources from the secondary cognitive load task to the primary driving task in order to manage their cognitive resources and maintain performance across trials.

Rapid Transitions of Load

To assess the influence of rapid transitions of cognitive load on takeover performance (hypothesis four), the following analyses were conducted. Figure 7 highlights the influence of transition type on takeover where takeover accuracy changes across order based on the type of transition (low to high or high to low) that participants experienced. Additionally, the interaction between order and transition type can be seen in that more accurate takeovers were seen in order one when load transitioned from high to low but when load rapidly transitioned from high to low, more accurate takeovers were seen in order three. Takeover rates on trial two are nearly identical between transition types. Given the decreased performance on the secondary load task under high load when load rapidly transitions from low to high (Figure 7), it may be that participants dedicate more resources to the primary driving task which is evident in an increase in performance from trial one to trial two and a decrease in subsequent performance on the cognitive load task.

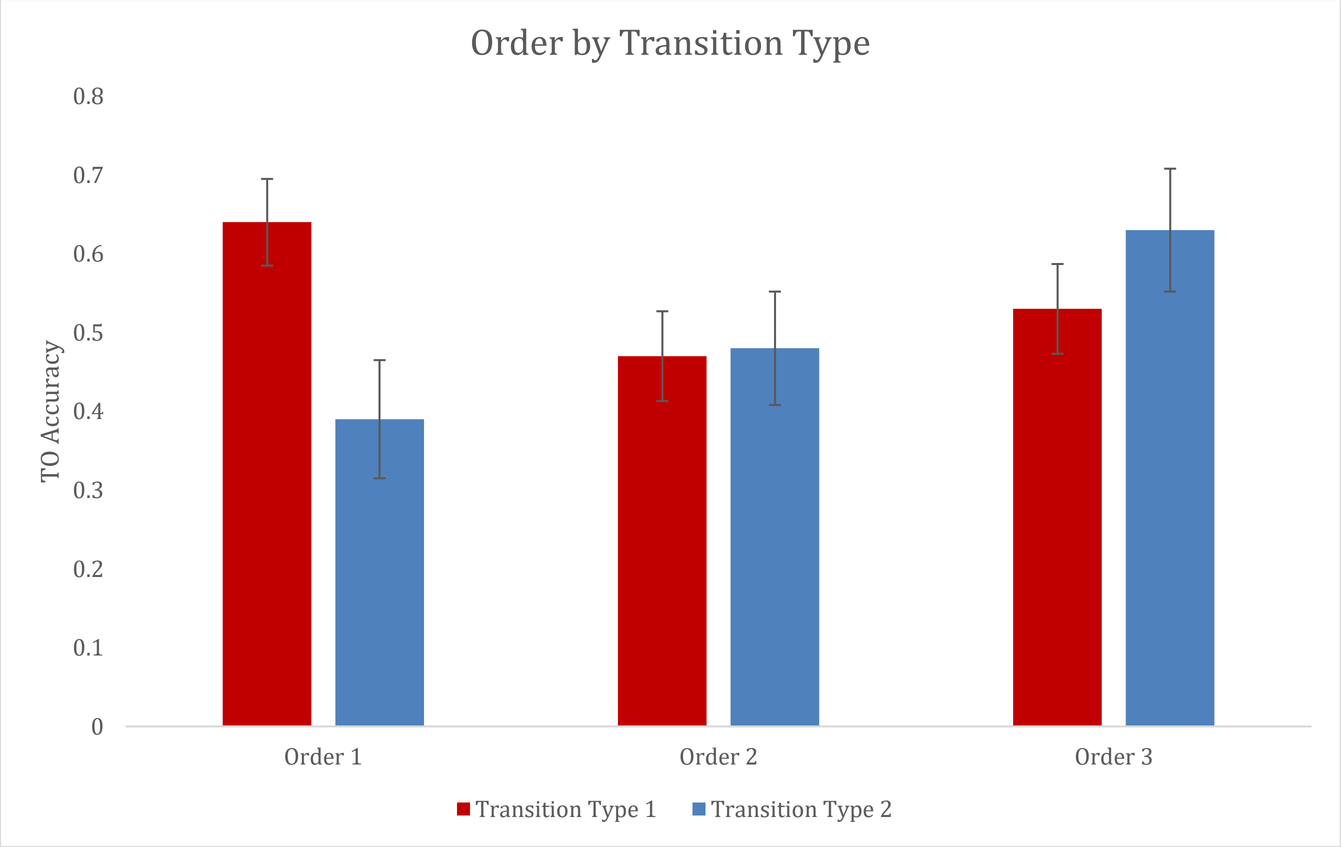

Figure 7. Estimated marginal means of take over accuracy for the interaction of trial order by transition type. Error bars represent standard errors of the mean (SEM).

Additionally, Figure eight contains the percentage of correct takeovers grouped by transition type. This figure highlights the influence of load and transitions of load on participant takeover across all six trials before and after the transition occurs. Participants showed the highest percentage of correct takeovers under low load when load rapidly transitioned from low to high load, and their takeover performance decreased after load transitioned. On the other hand, when load rapidly transitioned from high to low, takeover performance also decreased but at a lesser rate. Together, it is clear that a rapid transition of load decreases participants' takeover performance and the type of transition is also critically important. Interestingly, the highest rate of correct takeover performance was on trials prior to the transition of load for transitions of load from low to high. These would have been on low load trials prior to participants experiencing high load trials, which highlights the influence of both when and how participants experience load as well as the transition event itself.

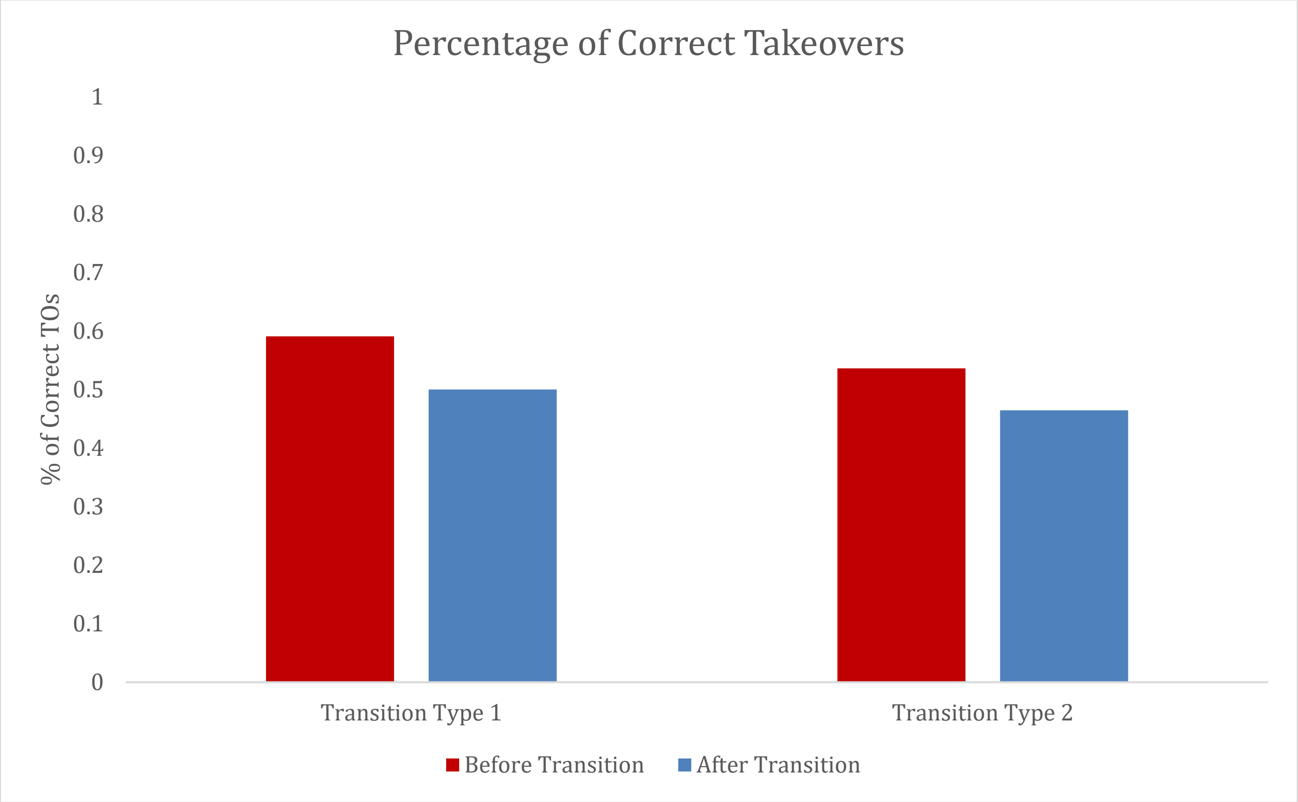

Figure 8. Percentage of correct takeovers across transition types.

Taken together, these data highlight the influential role of cognitive load and rapid transitions of load across trials on participants' takeover performance. Takeover performance was higher on low load trials, between transition types. Given that transition type changes when participants experience high or low load (e.g., order one and transition type one would be a low load trial but order one and transition type two would be a high load trial), the order in which participants are exposed to load as well as when/how a rapid transition of load occurs seemingly influences participants’ ability to accurately respond to ambiguous roadway hazards.

To test differences between trials surrounding the rapid transition of load and isolate the effect of the transition, pairwise comparisons were conducted for each transition type (low to high and high to low) on the trials surrounding the rapid transition. Results of these pairwise comparisons indicated a significant difference in mean RTs between trial three (M = 4.99, SE =

4.42) and trial five (M = -15.05, SE = 4.80) when load rapidly transitioned from low to high [t(27) = 4.66, *p* < .001]. Additionally, results indicated a significant difference between trial four (M = -.12, SE = 3.00) and trial five (M = -15.05, SE = 4.80) [(t(27) = 3.45, *p* < .001)] as well as trial five (M = -15.05, SE = 4.80) and trial six (M = -.12, SE = 4.05) [(t(27) = -3.04, *p* = .003)] when load rapidly transitioned from high to low. Figures nine and ten show mean RTs for transition from low to high cognitive low and transitions from high to low, respectively.

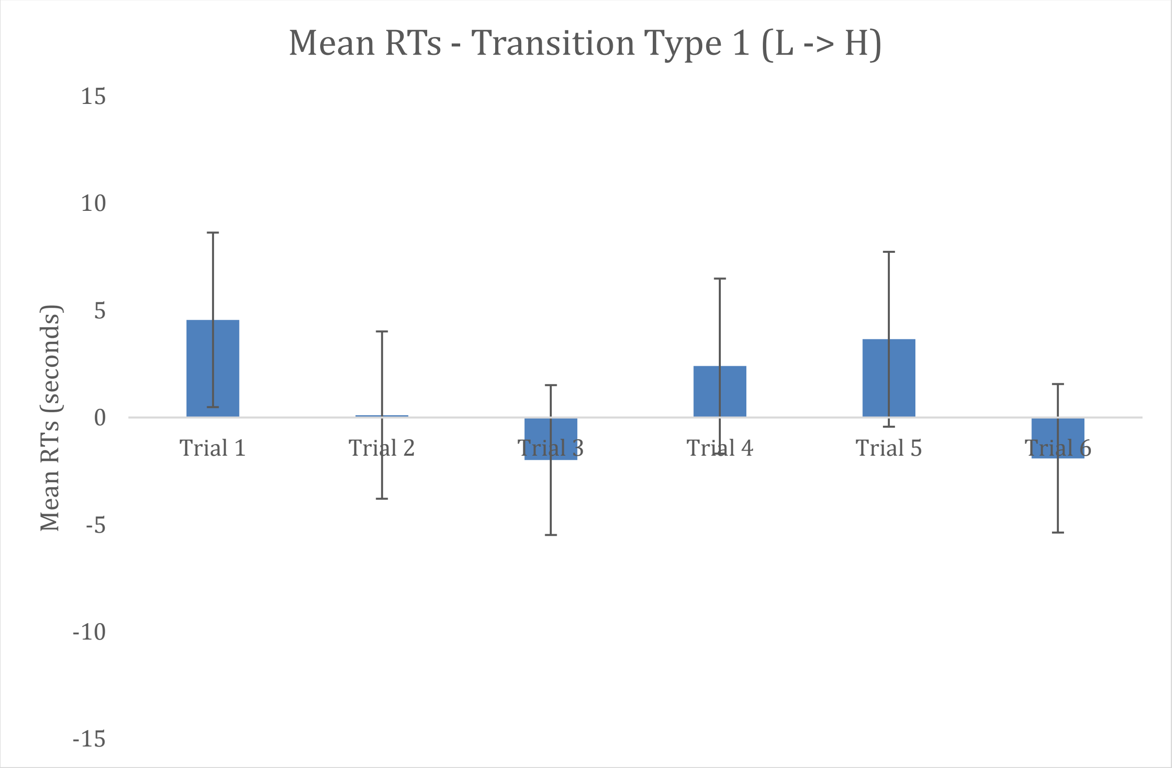

Figure 9. Mean response times (RTs) for all trials where load rapidly transitioned from low to high (transition type 1). Error bars represent standard errors of the mean (SEM).

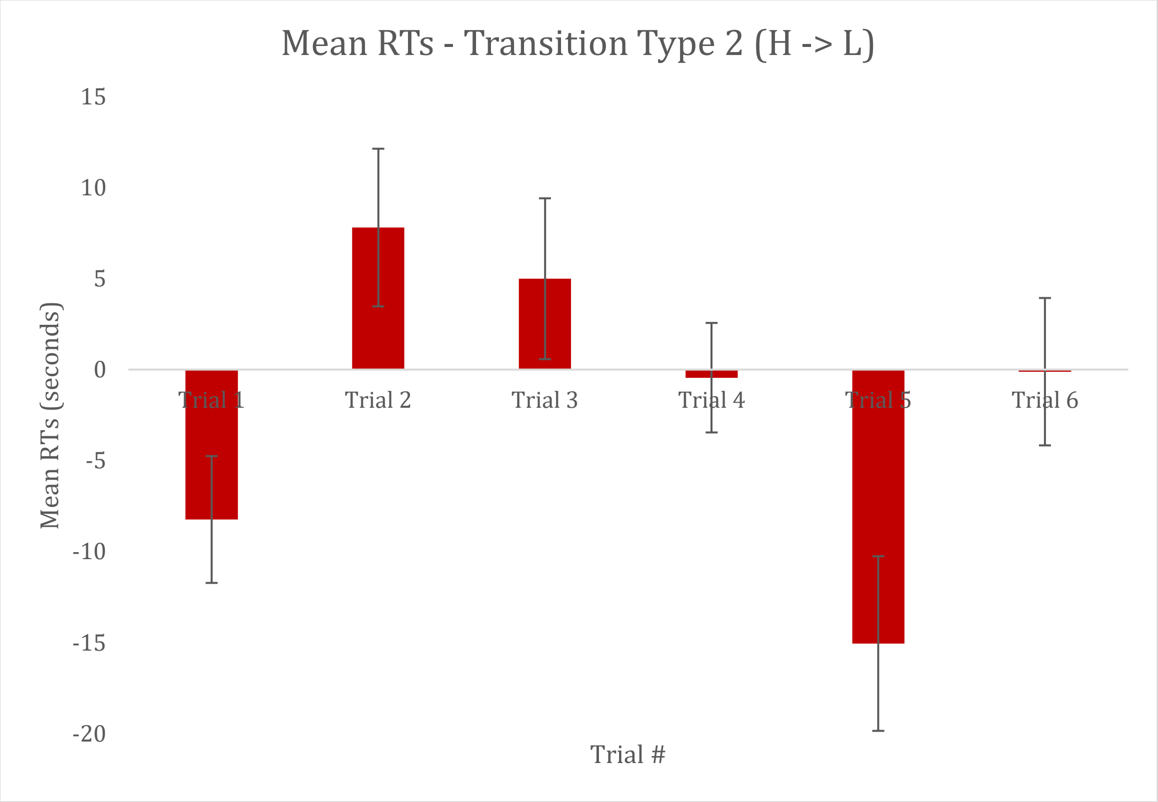

Figure 10. Mean response times (RTs) for all trials where load rapidly transitioned from high to low (transition type 2). Error bars represent standard errors of the mean (SEM).

Results of these analyses further highlight the influence of a rapid transition of load on participants' decision-making processes and willingness to engage with an automated driving system. When load rapidly transitioned from high to low, participants were much more likely to take over manual control significantly before the onset of the critical event and this difference was most evident on trials immediately preceding (trial 3) and the trial following the rapid transition of load (trial 5). While the differences were not statistically non-significant, there seems to be a trend (Figure 9) where participants tend to take over before the onset of the critical event (i.e., roughly two seconds prior to any changes in the environment) before a rapid transition of load from low to high cognitive load but then take over after the onset of the event after the transition has occurred (i.e. roughly two and a half seconds and three and a half seconds after the critical event has been introduced in the environment). Figures 9 and 10 highlight how rapid transitions of load opposingly influence decision-making processes to engage with the automated driving system and take over manual control of the vehicle in response to (or prior to) a roadway stimulus. Given that negative RT values indicate participants taking over manual control prior to any changes in the roadway environment, rapid transitions of load are seemingly influencing participants' sensitivity to the onset of these roadway events and manipulating their willingness to engage with and rely on automation to continue to "handle" a scenario. This may be due to the fact that when under conditions of high cognitive load, participants do not have the additional mental resources to dedicate to the change in conditions invoked by the introduction of a critical roadway event (e.g., the ambiguous hazards presented in this study). Further, it is evident by the opposing influence of rapid transitions of load from low to high and high to low. Given that the trending directionality of RTs changes directions based on the type of transition (Figures 9 & 10), this may be further evidence of how rapid transitions of load and the type of load interact to influence participants' decision-making processes when assessing and subsequently responding to roadway hazards. Most outstandingly, under high cognitive load participants show degradation in decision-making around if and when to engage with automation in response to roadway hazards as evidenced by RTs significantly after the onset of the roadway hazard and RTs significantly prior to the onset of the roadway hazard. These results may also indicate a brief "carry over" effect of load in that the impacts of a rapid transition of load are minimally evident on the trial immediately following the transition (trial 4) but are significantly evident on the subsequent trial (trial five), as evident in Figure 10. While the difference between trials 3 and 4 is not statistically significant, large standard errors in RTs should be noted that influence the interpretation of statistically significant results. This will be discussed in limitations and general discussion sections.

Discussion

Taken together, results of experiment one indicates the impact of cognitive load as well as rapid transitions of load on operator decision-making and performance when interacting with an automated driving scenario in response to ambiguous roadway hazards. Hypothesis one was supported in that higher cognitive load impaired takeover performance as seen by increased response times, but only when rapid transitions of load were considered (H4). Interestingly, main effects of load were non-significant but interactions with rapid transitions were significant for the metrics collected in this study. This indicates that load and rapid transitions of load across trials (H3) are equally important when understanding the impact of cognitive load in this study. This is taken to indicate that rapid transitions of load are cognitively load events in and of themselves that participants dedicate cognitive resources to deal with, specifically in the tradeoff between performance on the primary driving task and the secondary cognitive load task.

The influence of cognitive load and the interactive effect with rapid transitions of load can be seen in response time and takeover accuracy data. On low load trials, reaction times were significantly lower during rapid transitions from high load to low load while these transition effects do not impact high load trials. Further, the influence of rapid transitions of load across trials differs between the type of transition (low to high compared with high to low). Given that RTs decreased across trials when cognitive load transitioned from low to high (Figure 9) but increased across trials when cognitive load transitioned from high to low (Figure 10), along with the lower RTs on low load trials, it appears that conditions of high cognitive load increases response times in that participants slower (higher RTs = slower responses after the appearance of the stimulus) to respond to a roadway hazard compared to conditions of low cognitive load.

Further, the type of rapid transition of load influences these effects in that rapid transitions from low to high load decrease mean reaction times compared to rapid transitions from high to low load. Figures 9 and 10 highlight the influence of rapid transitions of load on participant response times while Figures 7 and 8 highlight the influence on takeover accuracy or “correctness”, where there appears to be opposing trends in participants responses to ambiguous hazards under differing levels of load as well as when and how load rapidly transitions.

These findings indicate the influence of cognitive load as well as the role that rapid transitions of load play in participants’ responses to ambiguous roadway hazards. Given the non-significant main effect of load but significant interaction effects noted above, it is clear that rapid transitions of load play a largely influential role in impacting decision-making processes to engage with automation in response to ambiguous hazards.

Study 2

The primary aim of study two was to assess the influence of cognitive load, including rapid transitions of cognitive load, on participant decision-making processes when engaging with automated driving systems in response to failures of automation driving system. With this, study two hypothesizes that higher cognitive load will lead to impaired takeover performance (H1) as well as impaired secondary task performance (H2). Additionally, significant interactions are hypothesized for cognitive load with order (H3) and rapid transitions of cognitive load (H4).

Participants. A total of 85 individuals were recruited for participation. The recruitment methods, inclusion criteria and compensation were the same as in Experiment 1. Recruitment was conducted at a rolling basis in the same manner as Experiment 1.

Online Driving Task. Driving videos (see Table 1) were created and recorded using STISIM Drive 3 and videos were presented online using Qualtrics. The experimental session consisted of a roadway driving scenario where participants viewed simulated driving videos and made decisions of whether and when to discontinue automated driving and take over manual driving in response to a failure of automation. Beginning at a certain point during the driving scenario, the automated system failed and began to deviate from previously established system capabilities (i.e., proper lane keeping, headway distance before automated braking would occur, etc.) at a progressive rate that eventually led to a crash after running off the roadway. With this, participants were instructed that a system failure may occur and to indicate when they would decide to disengage automation and take over manual driving in response to these system failures.

Design and Procedure. Study 2 followed an identical experimental design and procedure to study one, including the cognitive load manipulation, except for the content of the driving videos as described above. Every participant completed a total of six experimental trials. All instructions and tasks were presented on screen.

Study 2 Results

Cognitive Load Task

To assess the impact of cognitive load on secondary task performance (H1), percentage of correct responses were plotted across trials for each transition of load. Figure 11 highlights the impact of cognitive load on secondary task accuracy. Participants were marginally more accurate on low load trials (79.46%) than on high load trials (77.13%). Further, Figures 12 and 13 highlight the accuracy on the secondary loading task across trials when load rapidly transitioned from low to high (Figure 12) and from high to low (Figure 13). Interestingly, the influence of rapid transitions is evident in both Figures where a difference in accuracy is seen on trials following the rapid transition of load (after trial three). When load rapidly transitioned from low to high cognitive load, accuracy increased from trial three (M = 84.09) to trial four (M = 93.18) but then decreased from trial four to trial five (M = 52.27). This may indicate a performance tradeoff where participants are unable to continue dedicating resources to the primary driving task and the secondary cognitive load task once the cognitive load task has become a higher load.

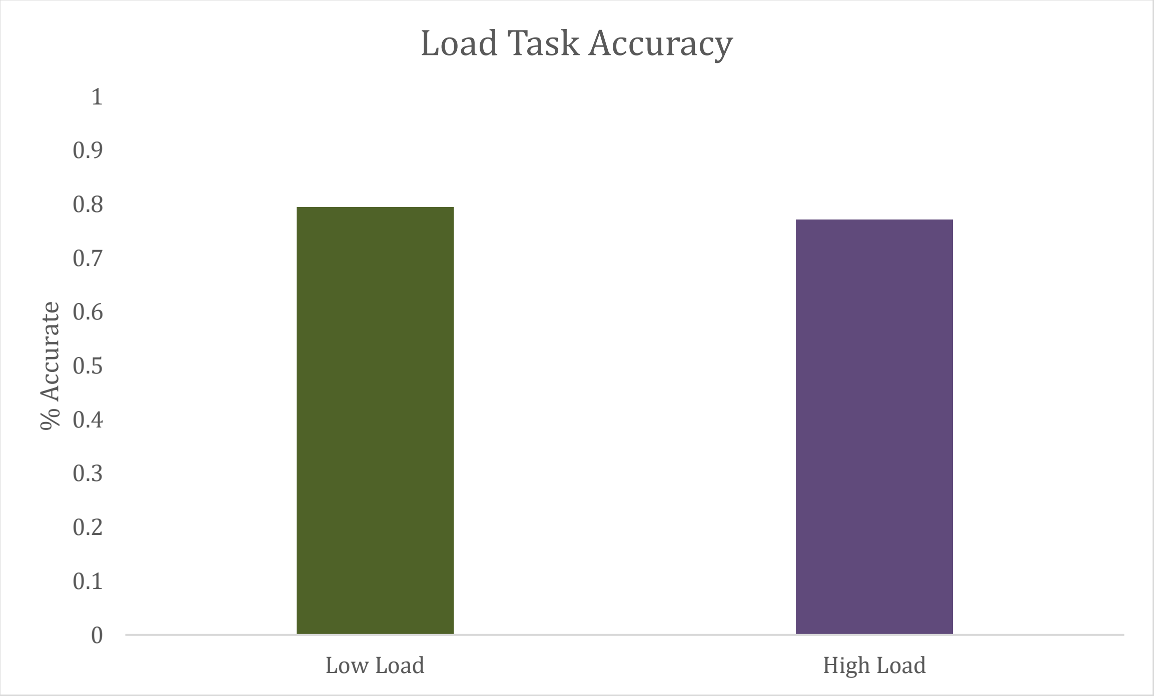

Figure 11. Percent of accurate responses on the secondary load task for low and high cognitive load.

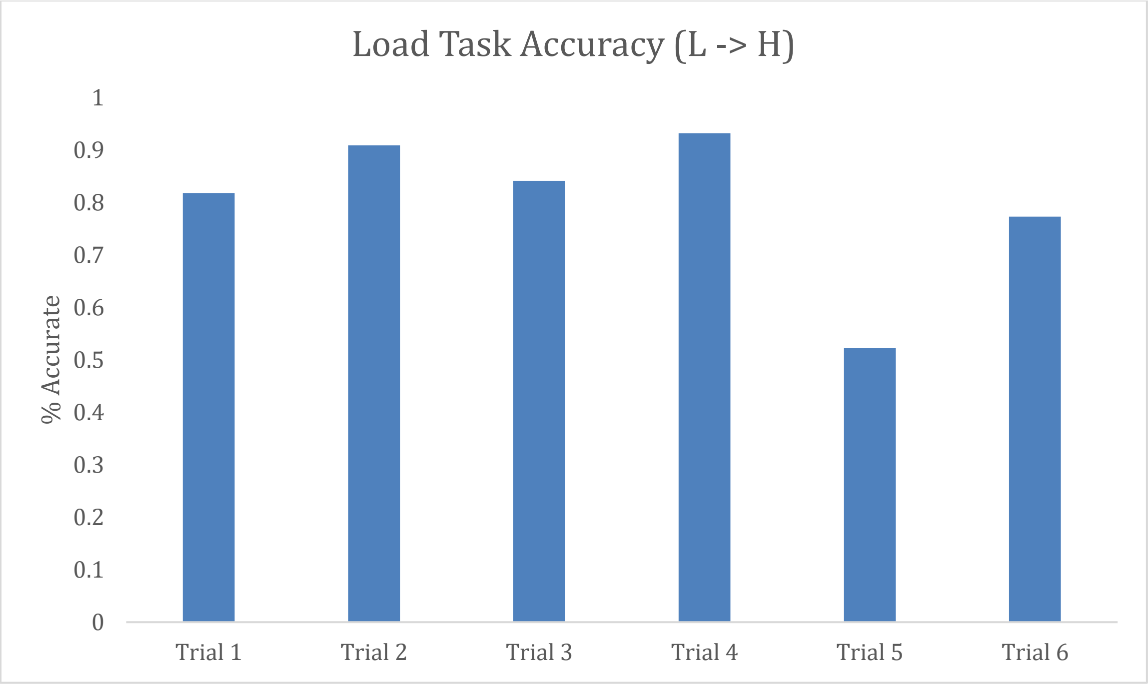

Figure 12. Percent of accurate responses on the secondary load task across trials when load transitioned from low to high.

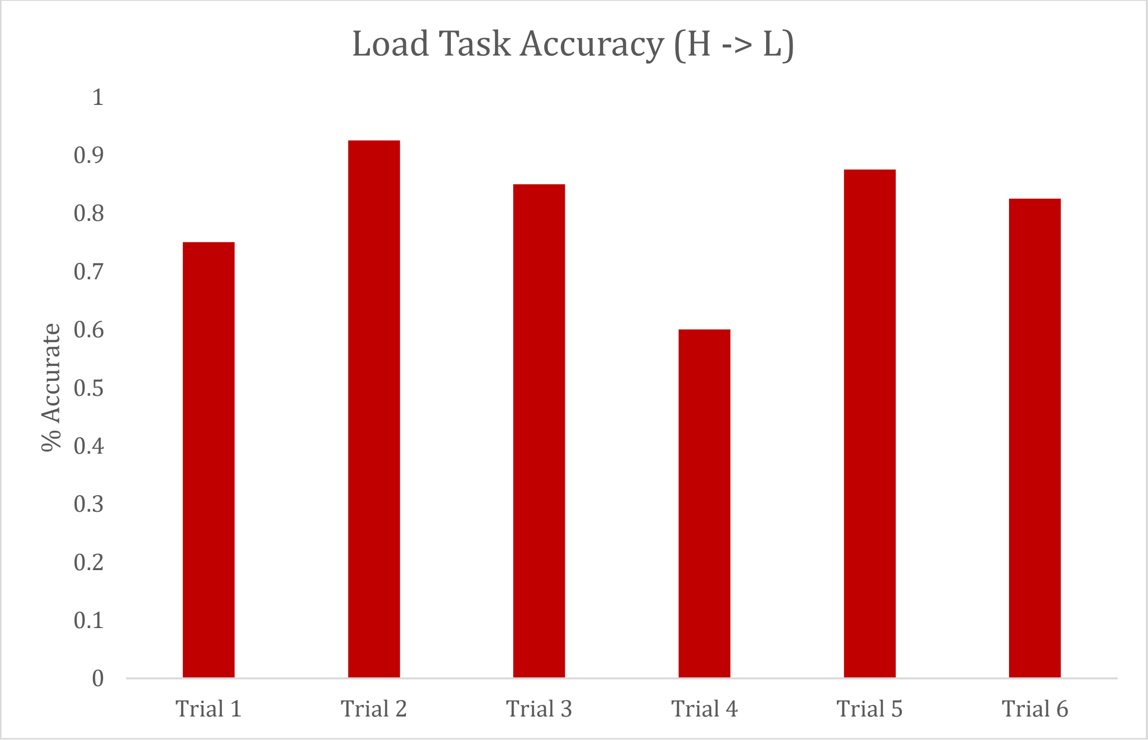

Figure 13. Percent of accurate responses on the secondary load task across trials when load transitioned from high to low.

One the other hand, when cognitive load rapidly transitioned from high to low (Figure

13), performance dropped from trial three (M = 85.00) to trial four (M = 77.27) but then increased from trial four to trial five (M = 87.50). This opposing impact of a transition of cognitive load may indicate that the rapid transition is a cognitively loading event in and of itself. In both cognitive load transition types, performance changed after the rapid transition. However, when load changed from low to high, performance on trial five was the poorest of any trials. This may indicate, as mentioned, the tradeoff of resources to maintain performance on the secondary cognitive load task and primary driving task. When load rapidly transitioned from high to low, performance decreased after the transition but then increased on trials five and six. This may indicate that once participants had time to adapt to the new scenario of cognitive load, they were able to perform at a similar level as prior to the transition.

Together, these data are taken to show the influence of cognitive load and rapid transitions of load on secondary cognitive load task accuracy. With this, the rapid transition of load seems to be a cognitive loading event which influences performance on subsequent trials after the transition and participants needed time to adapt to new trial demands.

Takeover Performance

These analyses were conducted to assess the influence of cognitive load on takeover performance (hypothesis one). In line with the analysis methods used in study 1, Generalized Estimating Equations (GEEs) were conducted to assess the effects of cognitive load on takeover accuracy.

Takeover Correctness

Results of these analyses indicate non-significant main effects of transition type [X^2 (1, *N*

= 147) = .38, p = .537], load [X^2 (1, N = 147) = .029, p = .866], and order [X^2 (2, N = 147) = .484, p = .785]. Significant interactions were noted between transition type and load [X^2 (1, N = 147) = 3.94, p = .047], transition type and order [X^2 (2, N = 147) = 12.61, p = .002], and trial-level load and order [X^2 (2, N = 147) = 8.36, p = .015]. Additionally, a three-way interaction between transition type, load, and order was significant [X^2 (2, N = 147) = 6.28, p = .043].

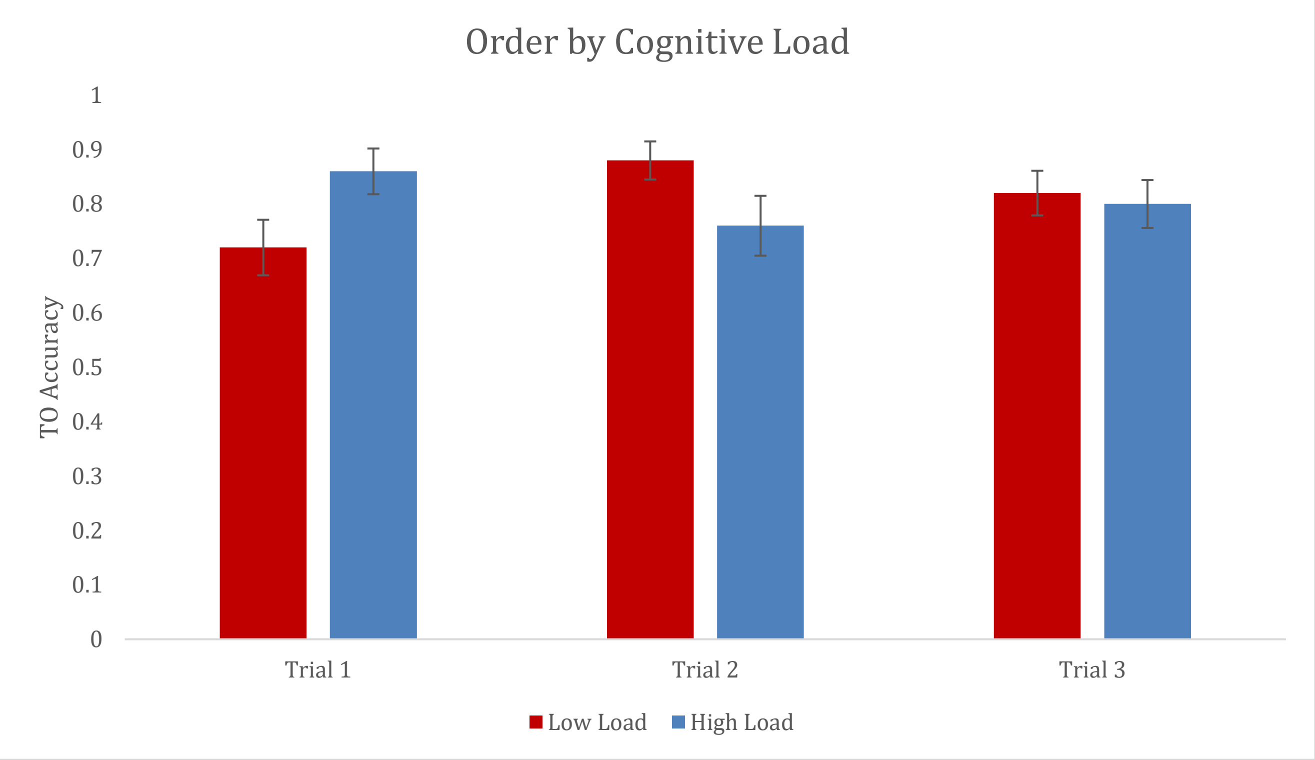

Figure 14. Means plot for takeover accuracy on low and high load conditions across trials. Error bars represent standard errors of the mean (SEM).

In general, participants in this study had relatively high accuracy at taking over control during the time window specified. These results indicate that participants were more accurate in taking over manual control on middle trials (trial 2) when load was low and earlier trials (trial 1) when load was high (Figure 14) with later trial performance (trial 3) being similar. This highlights the influence of load on takeover performance across trials. When trials were low load, participants showed improved performance from trial one (M = .72, SE = .051) to trial two (M = .88, SE = .035) while showing the opposite for high load where takeover performance degrades from trial one (M = .86, SE = .042) to trial two (M = .76, SE = .055). This flip in takeover correctness across trials helps to understand the significance interaction between load and trial order on takeover performance. Taken on its own, this shows the influence of cognitive load on takeover performance across trials but does not highlight the significant role of transitions of load on takeover performance. Given the significant interactions between transition type and load as well as transition type and order, takeover performance is further broken down by transition type to further investigate the role of rapid transitions of load on takeover performance.

Response Times

To analyze the influence of cognitive load on response times (H1) a Repeated-Measures ANOVA was conducted with trial-level load (Low/High) and trial order (henceforth called "Order") as within-subjects factors and transition type (low to high or high to low) as the between-subjects factor. Mauchly's test indicated that the assumption of sphericity was not violated for the main effects of Order, χ^2 (2) = .997, p = .872 nor the interaction between Load and Order, χ^2 (2) = .999, p = .979, therefore the non-corrected degree of freedom will be reported.

Results of the repeated-measures ANOVA indicate a non-significant main effect of cognitive load [$F(1, 83) = .002$, $p = .967$, $\eta_p^2 = .000$] and a significant main effect of order [$F(2, 82) = 25.83$, $p < .001$, $\eta_p^2 = .386$]. Significant interactions were noted for order by transition type [$F(2, 82) = 21.00$, $p < .001$, $\eta_p^2 = .339$), as well as cognitive load by order [$F(2, 82) = 4.40$, p =

.015, $\eta_p^2 = .097$)]. A three-way interaction between cognitive load, order, and transition type was non-significant [$F(2, 82) = .92$, $p = .403$, $\eta_p^2 = .022$)]. Of note is the large standard errors for response times which make interpreting statistical significance difficult.

Rapid Transitions of Load

Figure 15 further highlights the influence of rapid transitions of load on takeover performance by representing the percentage of correct takeovers on trials before and after the rapid transition of load occurred. In this, takeover performance decrements after a rapid transition of load across both transition types. The highest rate of takeover performance is seen on low load trials when load rapidly transitioned from low to high load and takeover performance decreased after load transitioned. Again, when load rapidly transitioned from high to low, takeover performance decreased after the rapid transition of load had occurred, but at a lesser rate. Taken together, rapid transitions of load seem to decrease participants' takeover performance as evidenced by degraded takeover performance after the transition of load has occurred. Additionally, it is also important to note that the type of transition seemingly influences takeover performance as well; the pattern of takeover performance is similar across transition types but there is notedly decreased takeover performance prior to the transition of load when trials begin with high load trials and then transition to low load trials (Figure16). Together, this data demonstrates the influence of cognitive load and rapid transitions of load on takeover performance by highlighting the influence of how load influences takeover performance and indicating (given that main effects were non-significant, but interactions were significant) that the interaction between load and rapid transitions of load across trials are more important in influencing takeover performance than these factors in isolation.

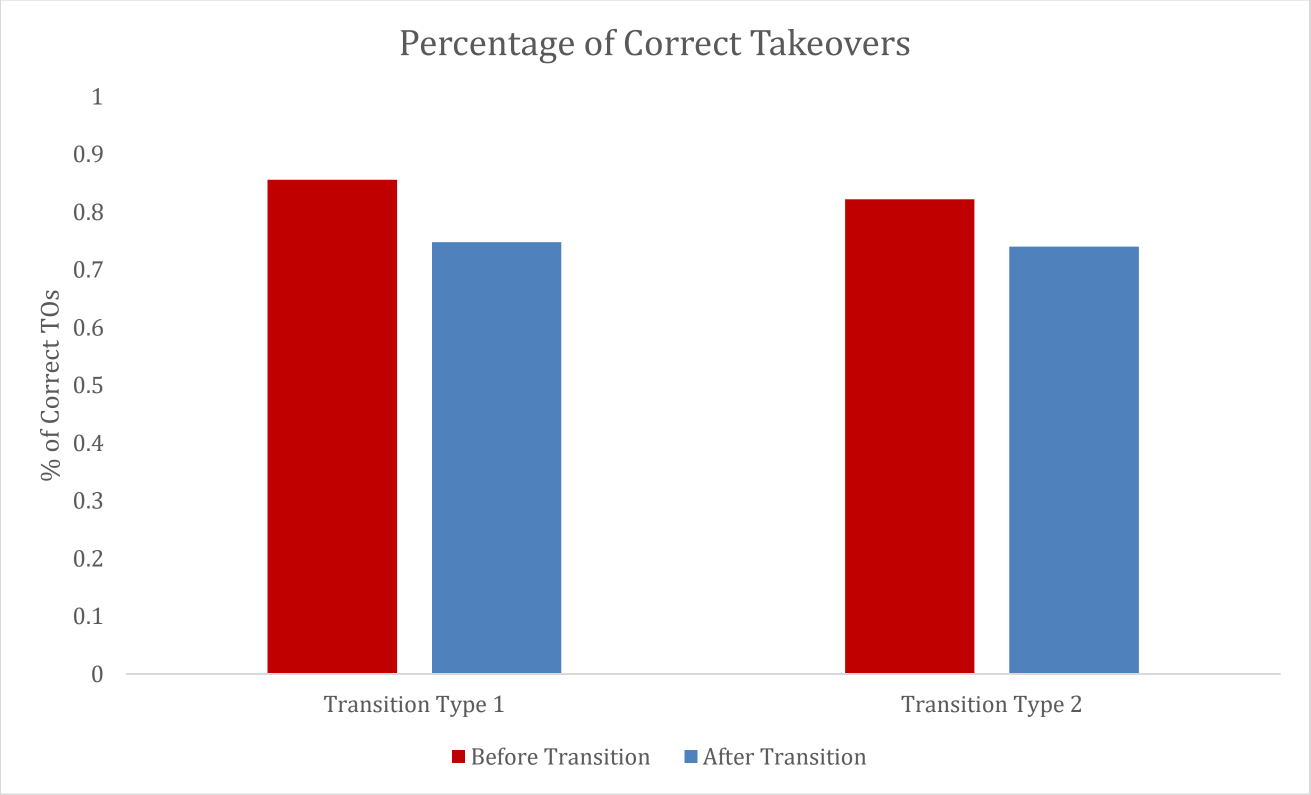

Figure 15. Percentage of correct takeovers across transition types.

Figure 16 highlights the influence of the interaction between cognitive load and transition type on takeover accuracy. Participants showed higher takeover accuracy on high load trials when cognitive load rapidly transitioned from high to low cognitive load, but the opposite was seen when load transitioned from low to high. When cognitive load transitioned from low to high, participants were more accurate in taking over manual control on low load trials compared to high load trials. These opposing effects for takeover accuracy highlight the noted influence of rapid transitions of load on participants' ability to take over control during an accurate window after the onset of the stimuli. Additionally, trial order influenced takeover accuracy across trials for both transition types. Figure 17 highlights this in that participants were much more accurate on trial one when load rapidly transitioned from low to high (compared to transitions from high to low). However, on trial two, this flips and participants showed higher accuracy when load transitioned from high to low (compared to transitions from low to high). Similarly to the influence of load across trials, trial three showed nearly identical outcomes. Breaking down the data by transition type helps to highlight the influence of rapid transitions of load and highlights the interactively influential role that load and rapid transitions of load influence participant takeover performance across trials.

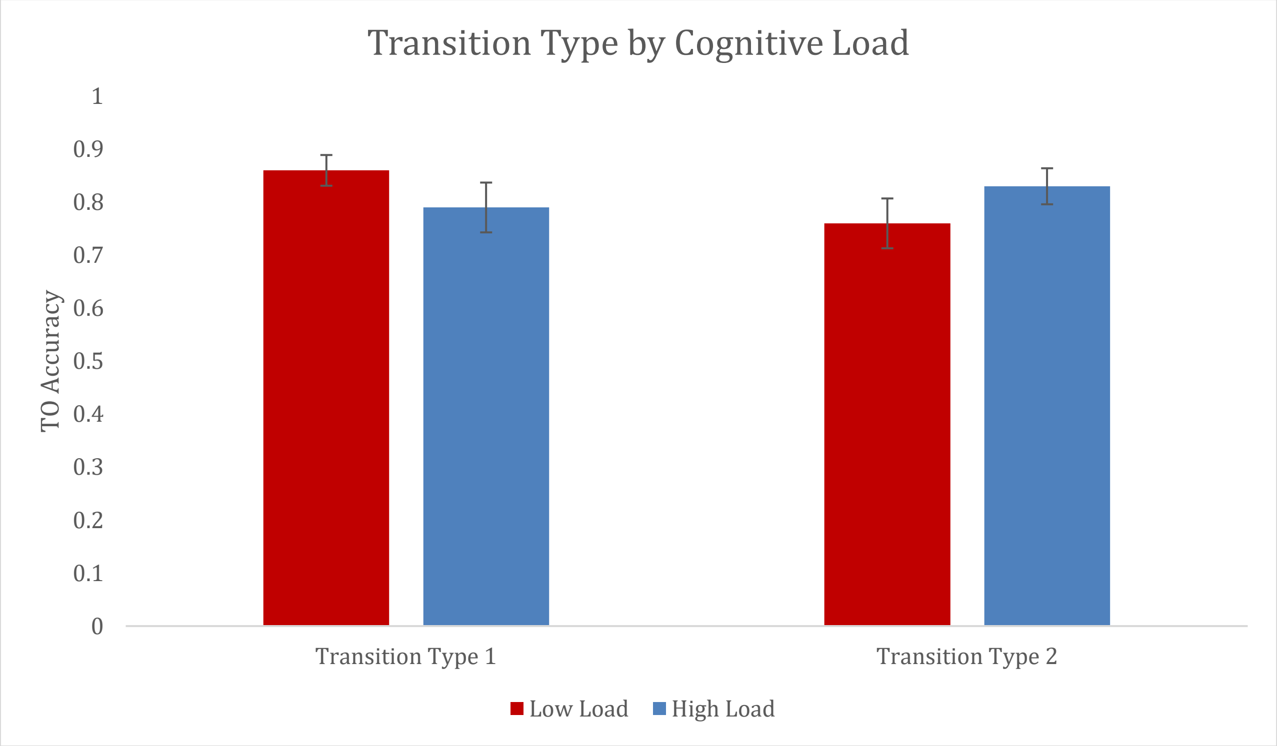

Figure 16. Means plot for takeover accuracy on low and high load conditions between transition types. Error bars represent standard errors of the mean (SEM).

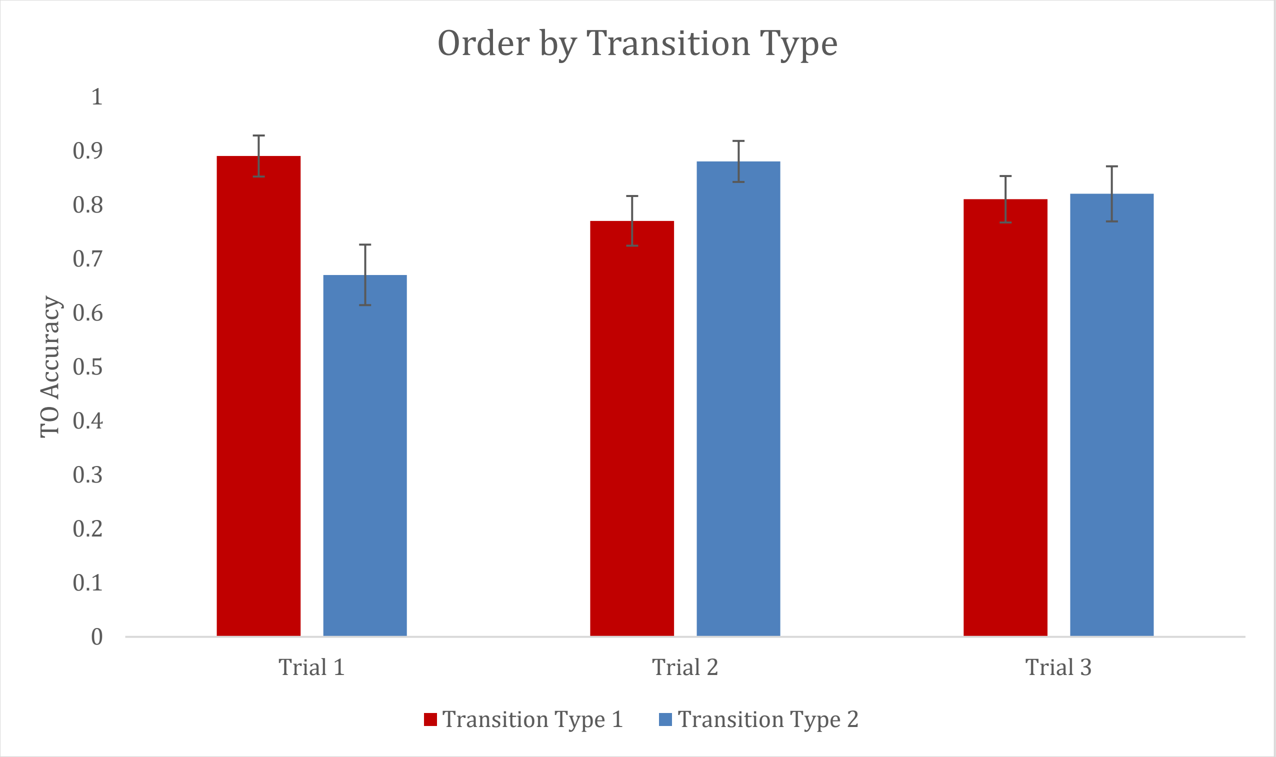

Figure 17. Means plot for takeover accuracy on transition types across trials. Error bars represent standard errors of the mean (SEM).

Figures 18 and 19 show participant RTs broken apart by transition type, highlighting the influence of rapid transitions of load on participants decisions to engage with the automated system in response to the failure of automation (H4 & H5). To test differences between trials surrounding the rapid transition of load, pairwise comparisons were conducted on the trials surrounding the rapid transition. Given the significant influence of transition type, RTs were split by transition type for the following analyses.

Results of these pairwise comparisons indicated significant difference in mean RTs between trial three (M = -25.63, SE = 4.36) and trial four (M = 11.27, SE = 4.84) [t(43) = -5.62, *p* < .001] as well as trial four (M = 11.27, SE = 4.84) and trial five (M = -25.11, SE = 5.96) [t(43) = 6.29, *p* < .001] when load rapidly transitioned from low to high. Additionally, when load rapidly transitioned from high to low, significant differences were noted between trials three (M = 1.19, SE = 5.53) and trial four (M = -11.68, SE = 5.29) [t(40) = 2.09, *p* = .021] as well as trial three (M = 1.19, SE = 5.53) and trial five (M = -14.41, SE = 5.61) [t(40) = 2.10, *p* = .021]. These differences further highlights the role of rapid transitions of load on takeover performance and decision-making processes when engaging with automation. These show the influence of rapid transitions of cognitive load and cognitive load (together) on takeover performance by impacting how and when participants choose to take over. Additionally, these may be evidence that rapid transitions of load are cognitively loading events in and of themselves.

Figure 18 shows mean RTs across trials that transitioned from low to high cognitive load. For these, trials one through three are low load trials while trials four through six are high load trials. Given this, participants tended to take over relatively after the onset of the critical event on trial one, but this trends downward to trials two and three where participants took over manual control prior to the onset of the critical stimuli on trial three (immediately prior to the transition of load). After the rapid transition of cognitive load from low to high, participant behaviors switch from taking over prior to the onset (RT of 0 would indicate a takeover exactly at the onset) of the failure of automation to after automation had begun to fail. On the other hand, when load rapidly transitioned from high to low (Figure 19), participants tended to take over after the onset of the failure of automation and this changed on the following trial where they took over prior to the onset of the automation failure once the load transition had occurred.

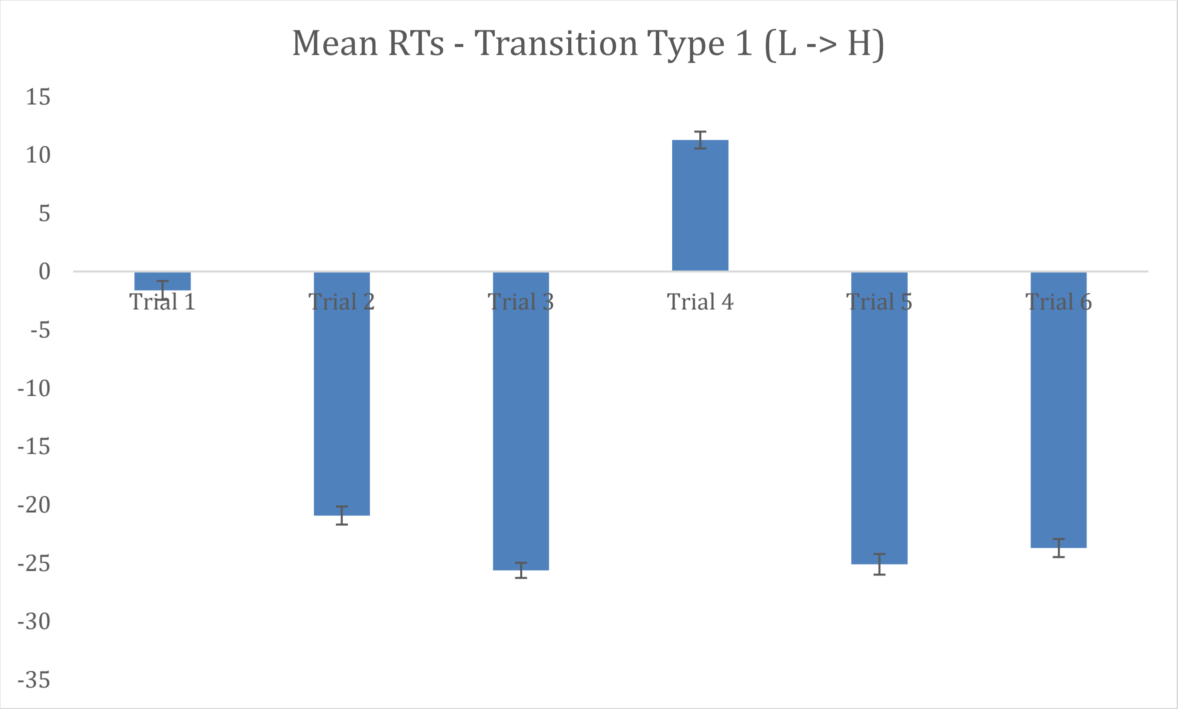

Figure 18. Mean response times (RTs) for all trials where load rapidly transitioned from low to high (transition type 1). Error bars represent standard errors of the mean (SEM).

This flip in response times highlights the influence of rapid transitions of load on participants decision-making processes when engaging with a failure in automation. Additionally, the type of transition seems to play a critical role in participants ability to accurately engage with the system in response to the automated system failing during the course of the drive. When participants experience a sudden increase in load (Figure 18), their response times drastically changed from before to after the automated system began to fail. Interestingly, across all six trials for transitions from low to high load, participants tended to take over prior to the onset of the failure. When participants experience a sudden decrease in load (Figure 19), the shift occurs in the opposite direction where participants tended to take over after the onset of the failure of automation on trial three (prior to the rapid transition of load) and then before the failure of automation begins on trial four (immediately after the rapid transition of load). Together, these results highlight how influential not only cognitive load, but rapid transitions of load are in influencing participants' decision-making processes when engaging with an automated system.

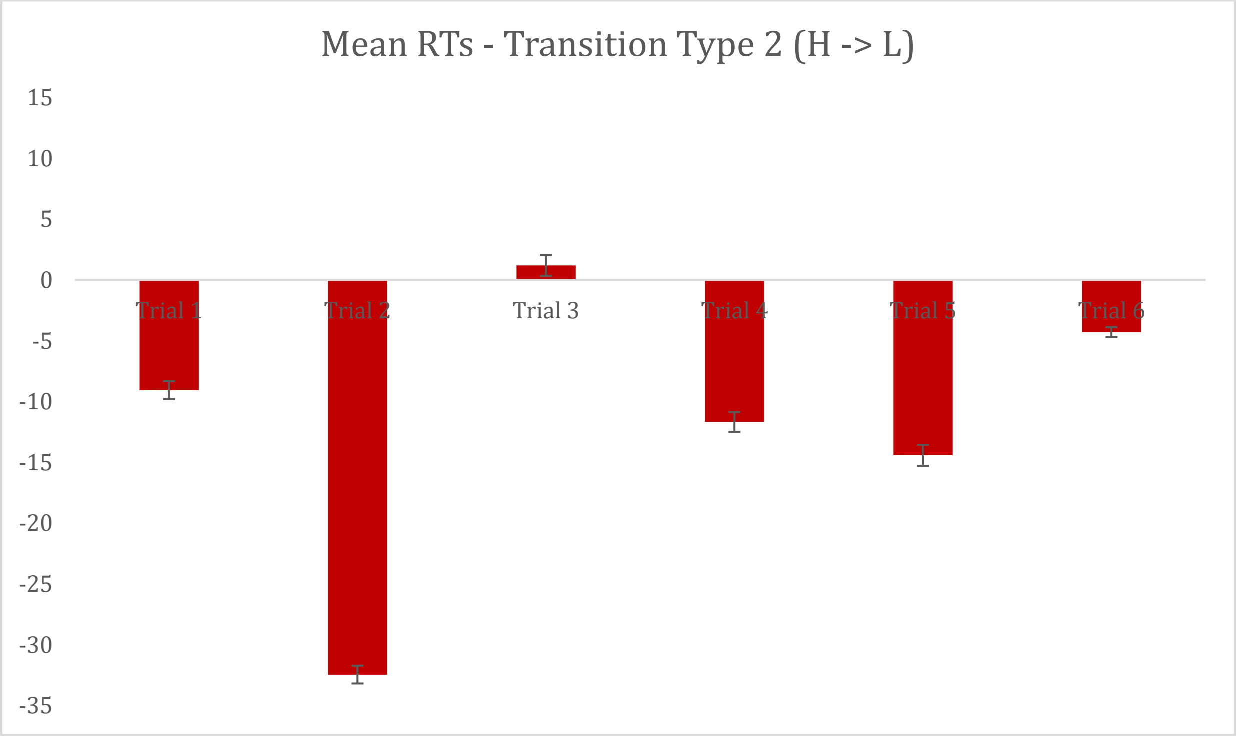

Figure 19. Mean response times (RTs) for all trials where load rapidly transitioned from high to low (transition type 2). Error bars represent standard errors of the mean (SEM).

These findings indicate the influence of cognitive load as well as the role that rapid transitions of load play in participants' responses to failures of automation. Given the non-significant main effect of load but significant interaction effects noted above, it is clear that rapid transitions of load play a largely influential role in impacting decision-making processes to engage with automation, namely failures of automation.

Discussion

Taken together, results of experiment two indicate the impact of cognitive load as well as rapid transitions of load on operator decision-making and performance when interacting with an automated driving scenario in response to failures of automated driving systems. Similarly to experiment one, rapid transitions of load were a highly influential component in understanding how cognitive load influences decision-making to engage with the automated system. Hypothesis one was supported in that higher cognitive load impaired takeover performance as seen by increased response times when considering the interaction of cognitive load and rapid transitions of load (hypothesis four). Cognitive load (i.e., main effects of cognitive load) was non-significant in isolation but when considered across trials and how and when load transitioned across trials (rapid transitions of load), the influence on participant decisions to engage with the system was evident.

Results of these analyses further highlight the influence of a rapid transition of load on participants' decision-making processes and willingness to engage with an automated driving system. In this study, when load rapidly transitioned from low to high, participants were more likely to take over manual control significantly after the onset of the critical event and this difference was most evident on trials immediately preceding (trial 3) and the trials after the rapid transition of load (trials 4 & 5). This may indicate that participants need time to adjust and adapt to the sudden change in trial level conditions and the rapid change in attentional demands influence individuals' willingness to engage with automation. In other words, during a rapid transition of cognitively loaded individuals require a period of transition to adapt to the new demands imposed by the sudden change of conditions. This change is evident in reduced response times and could be taken to imply that decision-making processes are slowed in order to allocate cognitive resources to the demands of the task. These findings may also shed light on individuals' willingness to allow an automated system to navigate a driving scenario. Following a rapid transition of cognitive load, individuals may not have the resources to allocate to meet the new demands of the task while also monitoring the roadway and thus allow the automated driving system to continue to operate even through risky circumstances (more so than when under low cognitive load). Thus, cognitive load and rapid transitions of load seem to influence operators' ability to engage with automation in response to hazardous situations such as a failure of automation.

In contrast, when load rapidly transitioned from high to low, response times were well before the failure of automation occurred on trials prior to the transition (positive RTs) but notably decreased after the transition occurred. Similar to the "carry over" effect discussed earlier, this effect of rapid transitions was most evident on trial 5 after the rapid transition from high to low cognitive load (Figure 19). This drastic change in decisions to engage with the automated system may be due to the fact that participants have additional cognitive resources available that were not available prior to the drop in cognitive load. With this, given the change in task-level demands, participants may feel they are able to better handle both the primary driving task and the secondary cognitive load task. In other words, participants may feel more suited to handle the driving task on their own without the automated system while maintaining accurate performance on the cognitive load task (Figure 13). Interestingly, this may be indicative of participants being more willing to allow the system to navigate risky (or potentially risky) scenarios when under higher cognitive load. Once cognitive load has been reduced (low cognitive load trials), participants may be less willing to off-load this risk to the automated system and take over manual control much earlier in the drive. This drastic change in sensitivity and decision-making to take over manual driving control could be an attitudinal shift in that participants are more willing to handle the driving demands and deal with potential hazardous events (such as failures of automation) once the cognitive load demands had decreased. Once cognitive load had decreased, participants were left with additional resources to dedicate to the primary driving task and this drastic change in takeover behavior may be indicative of this once the situational cognitive load had been removed.

These findings further indicate the influence of cognitive load and rapid transitions of load in that participants were significantly more sensitive to the onset of the critical event under high cognitive load but after a rapid transition to low load, participants took over manual control significantly before any changes in the environment occurred. Further, these highlight the interactive nature of cognitive load and rapid transitions of load on takeover performance and decision-making processes when engaging with automation (i.e., when and how load changes critically impact takeover performance, not just cognitive load itself). Additionally, it highlights that rapid transitions of cognitive load may be cognitively loading events in and of themselves.

General Discussion

While prior lines of research have shown how perceptual load and cognitive load differentially influence attention and visual processing, to the author's current knowledge, no study investigated the effects of load on judgment and decision-making during driving. Prior reviews (Lavie, 2010; Murphy, Groeger, & Greene, 2016) have called for such research, highlighting the need for the systematic assessment of different methods used to manipulate and measure load as well as extending manipulations of cognitive load to include judgment and decision making (JDM) as it is the least studied aspect of cognitive load at the current moment. Additionally, few studies (spare Greene and Murphy, 2016) have studied how the predictions of cognitive and perceptual load hold up in applied or real-world scenarios. The majority of studies on both cognitive (and perceptual) load take place in laboratory settings using artificial tasks to measure the levels of load and how this influences task performance, attention, etc. but few have attempted to extend these findings to applied settings such as driving. Even fewer studies have used online driving scenarios to investigate different factors related to interacting with automated driving systems. With this, the primary aim of this research was to investigate the influence of cognitive load on operator decision-making processes when interacting with automated driving systems in response to ambiguous roadway hazards (study 1) as well as failures of automation (study 2).

Findings from this study highlight the critical influence of cognitive load, as well as rapid transitions of load on decision-making processes when engaging with automation. Results across both studies highlight the influence of cognitive load on response times and takeover accuracy/correctness in response to ambiguous roadway hazards (study 1) and an automated driving system failure (study 2). Further, results of these studies highlight the influence of rapid transitions of load on takeover performance. The significantly interactive nature of rapid transitions of load are seemingly influencing participants' sensitivity to the onset of roadway events and manipulating their willingness to engage with and rely on automation to continue to "handle" a scenario. Across both studies, these findings indicate that cognitive load and rapid transitions of load across trials influences participants' decision-making processes in that their sensitivity and responsiveness to critical events shifts under differing levels of load.

Interestingly, the impact of cognitive load in and of itself does not tell the fully story as the data from these studies shows that how and when load changes (i.e., trials starting under low load and switching to high load or starting high and switching to low) is a critical factor that influences decision-making processes to engage with the system in response to these events as well as takeover performance. Specifically, rapid transitions of cognitive load seem to cognitively loading events in and of themselves. The most drastic changes in performance were seen surrounding rapid transitions of load and the type of rapid transitions is also a crucial component.

When load rapidly transitions from low to high, participants tend to go from taking over prior to the onset of the critical event (trial 3) to after the event had occurred (trials 4 and 5). Practically, this implies that during rapid transitions from low to high load, participants' sensitivity to ambiguous roadway hazards changes. Prior to the transition of load, participants tended to take over manual control prior to the onset of any event. After the rapid transition of load, participants tended to take over manual control after the onset of the critical event. These patterns, paired with the statistically significant interaction effects and significant pairwise comparisons on subsequent trials, may imply a "carry over" effect in that differences in participant response times may only become evident across trials. Given this rapid transition of load and the changes in RTs on trials surrounding the rapid change, participants may be adjusting their behavior to allow more time to accurately make decisions in response to environmental stimuli in order to keep up with the secondary load task. Rapid transitions of load seem to decrease participants' takeover performance as evidenced by degraded takeover performance (e.g., degradations in takeover performance and significant differences in response times) after the transition of load has occurred. This drastic change in decisions to engage with the automated system may indicate an attitudinal and behavioral shift where participants feel they are able to better handle both the demands of both the primary driving task and the secondary cognitive load task.

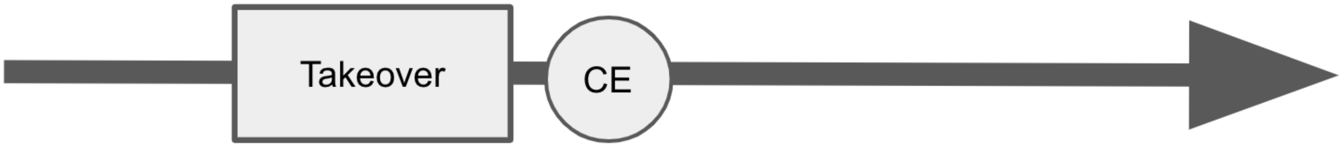

Figure 20. Visual representation of the influence of cognitive load and rapid transitions of load. Where participants took over manual control before the introduction of the critical event (CE).

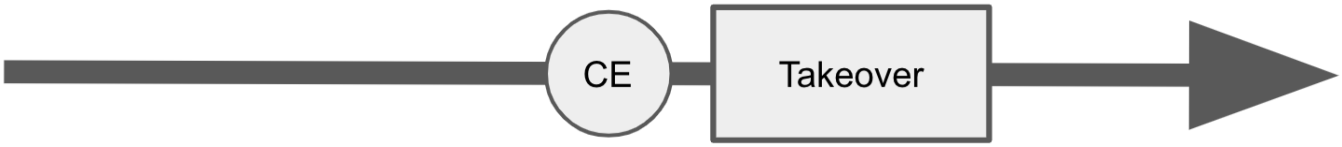

Figure 21. Visual representation of the influence of cognitive load and rapid transitions of load. Where participants took over manual control after the introduction of the critical event (CE).

While participants were more likely to take over manual control during this appropriate window around the onset of the roadway stimulus during low cognitive load, similar results were seen for trials of rapid transitions of low load to high load. While this may seem contrary to the prior results of higher takeover accuracy during low cognitive load trials, it may be the case that participants' cognitive resources had not yet been depleted by earlier high load trials. Additionally, this rapid transition of load from low to high may have caused participants to decide to allow the automated system to carry on driving control (higher RTs indicating responses after the onset of the critical event) given that the participant may have not had the additional cognitive resources to dedicate to the task (Figures 20 & 21). While large variations in standard deviations may reduce the likelihood of seeing significant mean differences, there seems to be a trend highlighting a tradeoff in speed and accuracy for trials surrounding the rapid transition of load. Specifically, it seems that participants were more likely to slow their reaction times to take over vehicle control on the trial immediately following the transition of load. Paired with data highlighting increased RTs for high load trials, a rapid transition of load may be loading in and of itself and thus slows participant decision-making processes and subsequent responses to the potentially hazardous event. Together, it may be the case that participants are more likely to accurately respond and take over manual control when load rapidly transitions from low to high load; however, once the load transition occurs and “stabilizes” on trials following the rapid transition, the load effects of the trials following the transition become evident. For example, on the trial immediately following a rapid transition of load from low to high (trial 4), participants may be more likely to accurately process a hazardous scenario and decide to take over manual control within a window of time closely following the onset of the hazard. However, on trials after this transition of load (trials 5 & 6), participants may be more likely to show effects of high load given that the subsequent trials would all be high load trials.

One possible explanation for this is a hysteresis effect which is described as prior task-level demands impacting subsequent demands (Kim et al., 2019). Prior research has shown that subsequent trials are impacted after a transition of workload or task-level demand but a majority of this research in the area of workload transitions investigates transitions from high to low and showing that performance increases after workload transitions from high to low but not from low to high (Morgan & Hancock, 2011). One notable difference in the current research is the specific emphasis of comparison of rapid transitions of load between subjects (transition type) and within subjects (trial-by-trial transitions of load) that allowed us to examine the influence of transitions of cognitive load in a different manner than traditional research on transitions of workload. Additionally, these studies look at dual-task performance while the current research examined the impacts of a secondary task on primary task performance in a non-concurrent task. Further research is needed to isolate and more deeply test the varying factors that influence this and compare and contrast with these differential lines of research.

Overall, results from this line of research highlight the influence of cognitive load, as well as rapid transitions of load, on takeover performance. When trial-level cognitive load was low and when load rapidly transitioned from low to high, participants were more likely to take over manual control within the window of time after the onset of the roadway stimulus. These results indicate that when participants are under low cognitive load, they are more able to process and rapidly respond to roadway hazards and are more likely to decide to take over manual control from an automated system. This may be due to the fact that they have additional resources available that are not being depleted by the secondary load task, compared to high load trials where the cognitive load task is depleting cognitive resources. In these scenarios of low load, it may be reasoned that operators are more likely to take over manual control because they have these resources available to dedicate to the task and are more likely to safely navigate the scenario. On the other hand, during high load conditions, it could be reasoned that operators were less likely to take over manual control during this appropriate window around the onset of the roadway stimulus because they do not have the additional resources available to dedicate to the task as these resources are being depleted by the higher load task (compared to the low load conditions). Thus, on high load trials, operators are more likely to allow the automated system to navigate the hazardous scenario because they do not have the additional resources to dedicate to the task. Given the results of these studies, it is clear that cognitive load in and of itself may not be the only critical factor in influencing drivers' ability to assess potential scenarios in the roadway - including automated systems they are interacting with - and respond correctly and safely. As automation becomes an ever more salient feature of driving, it is continually necessary to understand what factors influence the safe implementation of autonomous systems in vehicles as well as driver decision making in relation to these systems.

Implications and Future Directions

Practical implications of this study in the driving domain may relate to the design of in-vehicle technologies and interfaces as some tasks will impose higher levels of perceptual load while others will impose higher levels of cognitive load. Further, a key takeaway from this study is the influence of rapid transitions of load on decision-making processes when engaging with an automated system. In both studies, significant interactions were noted involving rapid transitions of load which indicated the critical influence of transitions of load on operator performance when engaging with automation in response to the scenarios used in each study. Real-world scenarios such in-vehicle technology should consider these results in the context of designing for safe systems. For example, a notification system to alert drivers to changes in the roadway (such as in experiment 1) may invoke a rapid transition of load which could impede the driver’s ability to respond to the roadway hazard sufficiently and safely. Additionally, a similar scenario would be in-vehicle notification systems to alert drivers that an automated system is failing, and the driver should take over manual control of the vehicle (such as in experiment 2). Future research should be conducted to further understand these processes and how they interact with each other to influence operator decision-making processes when engaging with automation. A plethora of scenarios could be designed to further investigate how these processes play a role in non-driving related scenarios such as human-robot interactions, automated systems in industrial settings, the role of smart glasses or other smart devices, and many more.

Further, two aspects of future research to explore in terms of decision-making in using vehicle automation are signal detection theory and reliance on automation. In line with the first study on ambiguous roadway hazards, future research could assess correct/incorrect responses in the framework of signal detection theory to assess detection of hazards and takeover responses given the ambiguity of the situations presented. In line with the second study, future research could assess participants' willingness to take risks in line with individual differences in trust and reliance on automation. While these topics were beyond the scope of the current studies, these are relevant areas of exploration for future research.

As automation and relevant devices/systems continue to evolve and become more present in everyday life, these areas of study become increasingly critical to our understanding of human-systems interactions so as to understand the complex roles of human cognition when interacting and engaging with automation systems. This line of research will continue to be crucial for the design of safe and helpful systems across the variety of scenarios where automation plays a role in human life.

Limitations

A major limitation of the current studies was the online nature of data collection. Presenting simulated driving videos and collecting response time data using online platforms may introduce variance and bias into the data that is difficult to control compared to more controlled environments such as in-person driving simulators. While manipulation checks and thorough data cleaning methods were used, it is impossible to ensure that all participants fully dedicated their attention to the study materials and tasks. Additionally, given the scope of the current studies, measures of working memory capacity (WMC) were not collected. With this, future research could examine the role of working memory (WM) and working memory capacity to rule out potential confounds of individual differences in WM and/or WMC that could exist in this line of research.

One significant limitation of the current studies are large variations as evidenced by rather large standard errors of the mean in response times (RTs). Given the large standard errors, it is difficult to detect statistically significant differences even when trends in the data seem to indicate that differences existed. Further research and analyses can address these statistical limitations by controlling the driving scenarios using in-person testing methods such as driving simulator studies. However, it is unknown whether or not this would fully control for this issue given the varied nature of collecting response times as a behavioral measure. Given that study one was intentionally designed to collect data around judgment and decision-making processes in response to ambiguous situations, it makes sense that data would vary greatly. Further, study two collected similar response time data in response to failures of automation that occurred slowly and without warning. Given that there was no clear and distinct beginning to the automation failure (e.g., a warning alert or notification or a sudden jerk in the steering wheel) but rather a slow degradation of the automated systems' functionality, it also makes sense that large variations in response times to these would be seen. Given the large amount of variability in data from study one, future research could also investigate methods to manage this to more deeply understand sources of variance. One method of correcting this could be Z-score transformations to attempt to statistically rule out individual variances that could arise from differential responding across stimuli types (i.e., participants may respond significantly differently to different video stimuli). Another potential explanation could be that ambiguous roadway hazards naturally create more variance in behavioral responses (RTs) but additional research would be needed to validate such claims.

To the author's current knowledge, this study is the first to directly investigate the role of cognitive load on operator decision-making when engaging with an automated driving system. Given the complexity of the influencing effects as well as their interactive effects highlighted in these studies, further research will be needed to isolate these complex phenomena in order to further our understanding of how cognitive load and rapid transitions of load influence decision-making processes when engaging with automated driving systems.

Conclusions

Together, this research highlighted the influence of cognitive load and rapid transitions of cognitive load on decision-making processes to engage with automated driving systems. These data highlight that when and how cognitive load changes/transitions influences driver decisions to engage with automated driving systems. Additionally, rapid transitions of load may be cognitive loading events in and of themselves. Given that the impetus of this research was focused on the domain of driving, data and implications of this research can be applied to understanding how cognitively loading scenarios influence decision-making processes and takeover performance when engaging with automated driving systems. Further, this research highlighted the crucial role of rapid transitions of cognitive load in understanding these processes across different scenarios. Given that real-world scenarios involving automation and driving are most likely dynamic and changing (both the driving system itself and the environment in which the automated system is acting within), understanding the impact of cognitive load in these dynamic scenarios will provide a more holistic understanding of the underlying theoretical models as well as predictions of these models in applied settings. Findings from this line of research can provide insight for the development of in-vehicle technologies as well as automated driving systems to ensure the safe implementation of these technologies across a wide array of scenarios and systems as well as for the individuals who engage with these systems.

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APPENDICES

Appendix A

Consent Form

<u>What are some general things you should know about research studies?</u> You are invited to take part in a research study. Your participation in this study is voluntary. You have the right to be a part of this study, to choose not to participate, and to stop participating at any time without penalty. The purpose of this research study is to gain a better understanding of how drivers' attention is influenced during driving. We will do this by having drivers watch videos and respond by pressing buttons at certain times, and then answering question about the driving environments.   You are not guaranteed any personal benefits from being in this study. Research studies also may pose risks to those who participate. You may want to participate in this research it will contribute to a better understanding of driving performance, and lead to fewer driving-related injuries or deaths. You may not want to participate in this research because it will require effortful concentration while you perform the task.   Specific details about the research in which you are invited to participate are contained below. If you do not understand something in this form, please ask the researcher for clarification or more information. A copy of this consent form will be provided to you. If, at any time, you have questions about your participation in this research, do not hesitate to contact the researcher(s) named above or the NC State IRB office. The IRB office's contact information is listed in the *<u>What if you have questions about your rights as a research participant?</u>* section of this form.

<u>What is the purpose of this study?</u> The purpose of the study is to gain an understanding of attention and driving performance. **<u>Am I eligible to be a participant in this study?</u>** There will be approximately 200 participants recruited to participate in this study. In order to be a participant in this study, you must agree to be in the study and have had a valid driver's license, normal or corrected vision, healthy neurological status, and reside in the United States. You cannot participate in this study if you do not want to be in the study or are under the age of 18, do not have a driver’s license, do not have normal or corrected vision, suffer from a neurological condition, have already participated, or are not a U.S. resident.

What will happen if you take part in the study? If you agree to participate in this study, you will be asked to do all of the following: 1.Provide informed consent 2.Complete a survey 3.Watch static images or animated driving videos, recorded from the driver’s point of view, and pretend you are driving the vehicle. 4.While watching the videos, you will be asked to periodically provide responses. 5.At the end of each video, you will be asked to answer a few questions about the experiment. The total amount of time that you will be participating in this study will be between 30-60 minutes.

Risks and benefits There are minimal risks associated with participation in this research. The risks to you as a result of this research include feelings of discomfort when focusing on computer screens and possible motion sickness while viewing videos. If you feel any discomfort you can quit and there will be no penalty. Additionally, some of the survey questions may involve divulging information that could put you at risk for civil or criminal litigation. In order to protect you from this, all responses will made completely anonymous (i.e., no identifying information will be recorded to connect you to the survey responses). The information and participation log will not be shared with anyone outside of the research group, and all data will require a password to access. There are no direct benefits to your participation in the research. The indirect benefits are an appreciation for the nature of research on driving, and the opportunity to contribute to research that could improve traffic safety. Right to withdraw your participation You can stop participating in this study at any time for any reason. In order to stop your participation, please contact Richard B. Wagner, rbwagner@ncsu.edu or Jing Feng, 2310 Stinson Dr, Raleigh, NC, 27695, jing_feng@ncsu.edu, 919-515-3411. If you choose to withdraw your consent and to stop participating in this research, you can expect that the researcher(s) will redact your responses from their data set, securely destroy your data, and prevent future uses of your responses for research purposes wherever possible. This is possible in some, but not all, cases. Confidentiality, personal privacy, and data management. Trust is the foundation of the participant/researcher relationship. Much of that principle of trust is tied to keeping your information private and in the manner that we have described to you in this form. The information that you share with us will be held in confidence to the fullest extent allowed by law.

Protecting your privacy as related to this research is of utmost importance to us. However, there are very rare circumstances related to confidentiality where we may have to share information about you. These are limited to instances in which imminent harm could come to you or others. How we manage, protect, and share your data are the principal ways that we protect your personal privacy. Data generated about you in this study will be anonymous. Data that will be shared with others about you will be anonymous. **Anonymous**. Anonymous data means that at no time can we or anyone else link your real identity to the information collected during this research. This means that we cannot identify you at all, even when the data is combined with other information. We will also not seek to identify you using any techniques or technology. To help maximize the benefits of your participation in this project, by further contributing to science and our community, your anonymous information will be stored for future research and may be shared with other people without additional consent from you. **Compensation** for your participation in this study, you will receive $1 dollar (USD) *or* 2 course credits (up to 60 minutes). If you withdraw from the study prior to its completion, you will only receive compensation if your reason for withdrawing is related to one of the foreseeable risks mentioned in this document (above). Due to this study being online, there are areas of this study that are closely watched. If your answers do not relate to this study, or if you click through without trying, you will not receive payment. This is to detect r..o.b.o..t.s. What if you have questions about this study? If you have questions at any time about the study itself or the procedures implemented in this study, you may contact the researcher, Richard B. Wagner, rbwagner@ncsu.edu or Jing Feng, 2310 Stinson Dr, Raleigh, NC, 27695, jing_feng@ncsu.edu, 919-515-3411 **What if you have questions about your rights as a research participant?** If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact the NC State IRB (Institutional Review Board) Office. An IRB office helps participants if they have any issues regarding research activities. You can contact the NC State IRB Office via email at irb-director@ncsu.edu or via phone at (919) 515-8754. Consent To Participate By clicking “I agree to participate” on this consent form, I am affirming that I have read and understand the above information. All of the questions that I had about this research have been answered. I have chosen to participate in this study with the understanding that I may stop participating at any time without penalty or loss of benefits to which I am otherwise entitled. I am aware that I may revoke my consent at any time.

Consent To Participate By signing this consent form, I am affirming that I have read and understand the above information. All of the questions that I had about this research have been answered. I have chosen to participate in this study with the understanding that I may stop participating at any time without penalty or loss of benefits to which I am otherwise entitled. I am aware that I may revoke my consent at any time.

Appendix B

Pre-Study Survey

Welcome to this study!

Please answer the following questions as part of the Driving Survey. The following questions ask about yourself and your driving behaviors.

What year were you born?

Gender What is your gender?

○ Male (1)

○ Female (2)

○ Other (3)

○ Prefer not to say (4)

Employees of North Carolina State University are not eligible to participate in this study. Please indicate whether you are an NCSU employee (students, faculty, full-time, part-time):

○ Yes (21)

○ No (22)

Do you currently have a valid government issued driver's license?

○ Yes (1)

○ No (2)

What is the level of your driver's license?

○ Full license (1)

○ Learner's license (2)

When did you obtain your full driver's license? (You may skip this question if you only have a learner's license.)

○ Enter Year (yyyy) (1) ____

○ Enter Month (mm) (2) ____

How often do you drive a car or other motor vehicle? (In pre-pandemic times)

○ Almost every day (1)

○ A few days a week (2)

○ A few days a month (3)

○ A few times a year (4)

○ Never (5)

Over the last year, how many miles did you drive?

○ None (1)

○ Under 1, 000 (2)

○ Between 1,000 and 5,000 (3)

○ Between 5,000 and 10,000 (4)

○ Between 10,000 and 15,000 (5)

○ Between 15,000 and 20,000 (6)

○ Over 20,000 (7)

○ I do not know (8)

Everyone likes to watch television programs. Recently, sports television programs have seen a major increase in ratings. Many sports start with the letter 'B.' However, we ask that from the list below you select a sport that does not start with the letter 'B'. Thank you for doing this task.

○ Basketball (4)

○ Soccer (5)

○ Bowling (6)

○ Baseball (7)

○ Hockey (8)

On a scale of 1 to 10, with 1 being very unsafe and 10 being very safe, how safe of a driver do you think you are?

○ 1 (1)

○ 2 (2)

○ 3 (3)

○ 4 (4)

○ 5 (5)

○ 6 (6)

○ 7 (7)

○ 8 (8)

○ 9 (9)

○ 10 (10)

In the past five years, how many times have you been stopped by a police officer and received a WARNING (but no citation or ticket) for a moving violation (i.e. speeding, running a red light, running a stop sign, failing to yield, reckless driving, etc.)?

In the past five years, how many times have you been stopped by a police officer and received a CITATION OR TICKET for a moving violation?

In the past five years, how many times have you been in a VEHICLE CRASH where you are the driver of one of the vehicles involved?

How confident do you feel in the following activities?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	8 (8)	9 (9)	10 (10)
Driving in your local area (1)	○	○	○	○	○	○	○	○	○	○
Driving in heavy traffic (2)	○	○	○	○	○	○	○	○	○	○
Driving in unfamiliar areas (3)	○	○	○	○	○	○	○	○	○	○
Driving at night (4)	○	○	○	○	○	○	○	○	○	○
Driving with people in the car (5)	○	○	○	○	○	○	○	○	○	○
Responding to road signs/traffic signals (6)	○	○	○	○	○	○	○	○	○	○

Merging with traffic (7)	○	○	○	○	○	○	○	○	○	○
Turning left across oncoming traffic (8)	○	○	○	○	○	○	○	○	○	○

Below is a list of statements for evaluating trust between people and vehicle automation. There are several scales for you to rate the intensity of your feelings of trust, or your impression of the system in general.

Please indicate which best describes your feeling or impression of automated vehicles in general.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
Automated vehicles are deceptive (1)	○	○	○	○	○	○	○
Automated vehicles behave in an underhanded manner	○	○	○	○	○	○	○

(2)							
I am suspicious of automated vehicles' intent, action, or outputs (3)	○	○	○	○	○	○	○
I am wary of automated vehicles (4)	○	○	○	○	○	○	○
Automated vehicles' actions will have a harmful or injurious outcome (5)	○	○	○	○	○	○	○
I am confident in automated vehicles (6)	○	○	○	○	○	○	○
Automated vehicles provide security (7)	○	○	○	○	○	○	○

Automated vehicles have integrity (8)	○	○	○	○	○	○	○
Automated vehicles are dependable (9)	○	○	○	○	○	○	○
Automated vehicles are reliable (10)	○	○	○	○	○	○	○
I can trust automated vehicles (11)	○	○	○	○	○	○	○
I am familiar with automated vehicles (12)	○	○	○	○	○	○	○

Based on the text below, what would you say your favorite drink is?

This is a simple question. You don't need to be a wine connoisseur or an avid beer drinker in order to answer. When asked for your favorite drink, you need to select carrot juice.

○ Wine (4)

○ Beer (5)

○ Vodka (6)

○ Whiskey (7)

○ Carrot Juice (8)

○ Other (9)

Does your car provide assistive driving technologies such as adaptive cruise control, lane departure warning, blind spot warning, or obstacle detection?

○ Yes (1)

○ No (2)

If yes, how often do you use any of these functions?

○ All the time (1)

○ Sometimes (2)

○ Never (3)

○ N/A (4)

Does your car provide partial automation functions that can manage both your vehicle steering and speed under certain conditions?

○ Yes (1)

○ No (2)

If yes, how often do you use any of these functions?

○ All the time (1)

○ Sometimes (2)

○ Rarely or never (3)

○ N/A (4)

Does your car provide conditional automation functions that your car can handle all driving tasks under certain conditions, and you only need to be on standby in case something doesn't go as intended?

○ Yes (1)

○ No (2)

If yes, how often do you use any of these functions?

○ All the time (1)

○ Sometimes (2)

○ Rarely or never (3)

○ N/A (4)

How would you rate your level of knowledge of vehicle automation (e.g., driver assistance functions, semi-autonomous, or fully-automated vehicle technologies)?

○ Very knowledgeable (1)

○ Some knowledge (2)

○ Very little knowledge (3)

○ No knowledge at all (4)

Appendix C

Instructions

Instructions In this experiment, you will be viewing simulated driving videos from a first-person perspective. Imagine you are behind the wheel of the automated vehicle from the point of view of the driver's seat while the automated driving system is activated, meaning that the car is driving itself through the scenarios. This automated vehicle will be handling the driving task, but you are required to monitor the environment and its performance just in case a takeover is needed.

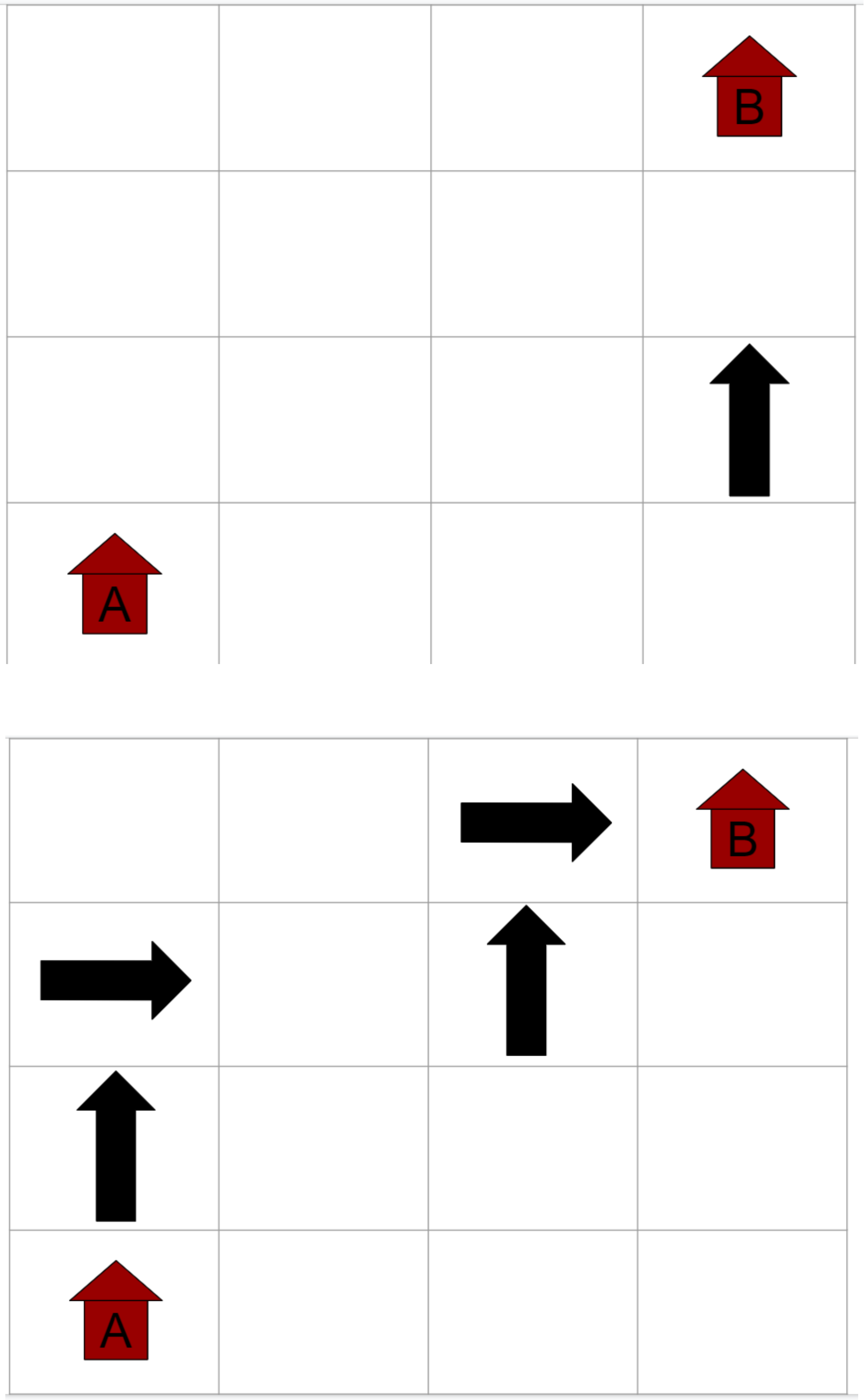
In each drive, there may or may not be some hazardous situations. **Your task** is to view each video clip and use your mouse to click the red button labelled "Takeover" at the bottom right of the screen to indicate if at any point you would take over vehicle control. You may take over because you do not believe the automated system is/will handle a situation appropriately, or when you feel uncomfortable with the automated system's capabilities to safely drive.

Before each driving video, you will be viewing grids that contain two houses - one in the bottom left corner and one in the top right corner. Along with these, you will see arrows indicating a path from house A (the house in the bottom left corner) to house B (the house in the top right corner). House A and house B will always be in the same locations and the grid will always be the same size. **Your task** is to remember the **order, orientation, and location of the arrows** presented. Some grids will contain a small number of directional arrows while others may contain more. After viewing the grid image, you will be asked questions related to your memory of the previously presented grid.

NOTE: This is intended to be a memory based task so we ask that you **not** use any memory aids (such as jotting down responses, etc.) to aid your completion in this. You will now be presented with a brief instructional video to help familiarize you with the task and help you to understand the overall order of the study.

Appendix D

Example of visuo-spatial cognitive load stimuli



Appendix E

Post Study Survey

The following are standard questions that allow researchers to determine how representative the group of participants in a study is of the general population.

Please describe the highest level of formal education you have completed.

○ Some high school of less (1

○ High school graduate (2)

○ Some college (3)

○ College graduate (4)

○ Some graduate education (5)

○ Completed graduate or professional degree (e.g., Masters, JD, PH.D., MD, etc) (6) (6)

Please describe your general health condition

○ Excellent (1)

○ Very Good (2)

○ Good (3)

○ Fair (4)

Are you currently taking any medication on regular bases? (e.g., Anti-depression or anti-anxiety medications)

○ Yes (1)

○ No (2)

Do you wear glasses or contact lenses?

○ Yes (1)

○ No (2)

Are you color blind?

○ Yes (1)

○ No (2)

Do you have any other vision problems? Indicate below.

☐ Glaucoma (1)

☐ Cataract (2)

☐ Lazy eyes (3)

☐ Others (4)

Do you have any difficulty with your hearing?

○ Yes (1)

○ No (2)

Do you think your memory is worse than others of the same age groups as yourself?

○ Yes (1)

○ No (2)

Have friends/family expressed concerns about your memory?

○ Yes (1)

○ No (2)

Please explain any strategies that you used to complete the tasks (both mental and/or physical). For example, did you jot down any notes, did you use any specific memory tricks to complete the task, etc.?

None of your answers will impact your completion and/or compensation for this study. We just want to know your truthful responses in how you completed these tasks.

Was there anything unclear or confusing to you about this study?? If so, please elaborate below. If not, please type "N/A"

Please consider how carefully you have responded to items in this study. In your honest opinion, should we use your data? You will be compensated regardless of your answer, but your honesty helps to improve our work.

○ Yes (1)

○ No (2)

Appendix F

Pilot Study Ratings

Pilot Study	Video	Mean	SD
1	1	2.65	1.67
1	2	4.30	1.46
1	3	4.35	1.87
1	4	4.26	1.98
1	5	4.39	1.85
1	6	3.04	1.92
1	7	3.65	2.06
1	8	4.52	2.39
1	9	5.13	2.16
1	10	4.09	1.88
1	11	3.43	2.29
1	12	2.91	1.98
1	13	3.74	2.14
1	14	4.26	1.86
1	15	3.43	2.29
1	16	3.48	2.41
1	17	4.00	2.09
1	18	3.70	2.30
1	19	3.61	2.35
2	1	4.77	1.58
2	2	5.41	1.90
2	3	5.14	1.37
2	4	5.14	2.06
2	5	5.60	2.03
2	6	5.20	1.91
2	7	4.50	2.37
2	8	4.53	2.09
2	9	4.53	2.09
2	10	5.58	1.49
2	11	5.58	2.35
2	12	3.67	1.91