

Should I give or should I take? Choice issues in automated vehicle control

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Abstract

The advent of automation and communication in vehicles have provided new opportunities to mitigate traffic, increase productivity, and reduce emission. Despite these advantages, connected and autonomous vehicles (CAVs) face deployment and adoption challenges arising from human drivers lack of acceptance and willingness to give control to CAVs. Another roadblock in success of CAVs is drivers' situational awareness and mental workload in safely taking control back from CAVs when required. To gain further insights into behavioral responses of drivers to automation, in this study a stated preference laboratory experiment is designed employing Virtual Reality Immersive Environment (VIRE) driving simulator. Two sets of experiments are conducted: 1) give-away experiments, where participants have full control of the vehicle with an option of giving control to CAV en-route as desired, 2) take-away experiments, where participants are driven by CAV and have to take control back from CAV due to sensor failure. Different traffic, weather and lighting (day, night) conditions are tested. The option to multi-task is available when the participant is being driven by CAV. The aim is to investigate under what conditions drivers are more willing to give control to the automated vehicle and have higher situational awareness to safely take back control from automated vehicles. The NASA-Task Load Index and Detection Response Task Index are used to evaluate participants mental workload. The results obtained show that weather condition and congestion level play a significant role in drivers' willingness to give control to CAV. The results also show that multi-tasking and congestion have the most impact on drivers' situational awareness and mental workload in taking back control safely from CAV.

Keywords: virtual immersive reality environment, laboratory experiments, human machine interaction, connected and autonomous vehicles, mental workload, situational awareness

1. Introduction

In recent years in order to make vehicles safer, reduce human drivers' error, reduce congestion, and reduce GHG emissions, attention has been given to intelligent vehicles that support or overtake driving tasks. Self-driven connected and autonomous vehicles (CAVs) are the disruptive technological innovation that are expected to transform urban traffic, mobility patterns, land use, and economy. It is no longer a question of if CAV technology will be adopted, but when, in what form, at what rate, and through what kind of evolutionary path? Technologies like Tesla's Autopilot are already in the market, and it is expected that by 2045 as much as 45% of the fleet could be CAV-based (Kuhr et al.,

9 2017). The current level of automation is at level 3 where, although steering and accelerating can be
10 performed by the vehicle, the human is still in the loop and has to take control back when necessary
11 or can decide not to give control at all. Therefore, it will be long before 100% level 5 CAVs be on the
12 road. An important factor that has a major effect on the effectiveness of CAVs is drivers' willingness
13 to give control to the system or take it back safely when required. The associated challenge with
14 taking control back safely is driver's mental workload and situational awareness in the operational
15 safety of automated driving. In the case of automation, drivers become passive observers as opposed
16 to information processors resulting in a decrease of drivers' situational awareness and an increase in
17 accident rate (Hirose et al., 2015). In recent years there have been accidents involving CAV where
18 drivers failed to take back control safely from the CAV when there was malfunction in CAV system.

19 Online stated preference surveys (SP) have been widely used in the recent years to explore the
20 factors influencing travelers' acceptance of automated vehicles (Becker & Axhausen, 2017). However,
21 online based SP surveys lack realism, especially when it comes to new and upcoming technologies.
22 Driving simulators and field experiments have also been used to investigate situational awareness
23 and mental workload of drivers when it comes to safely operating automated vehicles (Stapel et al.,
24 2017). However, they also have their own limitations e.g. lack of interaction with environment and
25 controlled environments. Moreover, field studies face the problem of replicability. As a result, virtual
26 reality-based SP surveys have been gaining interest among researchers to study behavioural responses
27 to CAVs, since it allows users to form a visual image of the innovative alternative as opposed to just
28 purely mental image (Djavadian et al., 2019). To gain further insights into behavioral responses of
29 drivers to automation, in this study a stated preference laboratory experiment is designed employing
30 Virtual Reality Immersive Environment (VIRE) driving simulator (Farooq et al., 2018). The aim is
31 to answer following research questions:

32

- 33 1. Under what conditions drivers are more willing to give control to CAV en-route?
- 34 2. Under what conditions drivers have higher situational awareness and ability to safely take back
35 control from CAV?

36

37 The remainder of this paper is organized as follows. In the background section, an overview of
38 existing literature on drivers' adaptation to CAVs is presented. The methodology section presents
39 the design of our SP experiments employing VIRE driving simulator. Then, results and analysis are
40 presented, followed by a summary and future work directions.

41 2. Background

42 Connected and autonomous vehicles have proven in simulation settings that they have the poten-
43 tial of reducing negative impacts of transportation (congestion, emission, accidents). In their recent
44 study, Farooq & Djavadian (2019) developed a dynamic distributed traffic management system using
45 network of intelligent intersections and CAVs that has the potential of reducing travel time by 40
46 % while increasing network throughput and reducing green house gas emission. However, as shown
47 by Alfaseeh et al. (2019) the efficiency of such a system depends on the market penetration rate of
48 CAVs, which is directly related to willingness of drivers to adapt to CAVs and give them control
49 either partially or fully. Therefore, it is necessary to find insight into the adaptation of drivers to
50 CAVs. Online and paper-based SP surveys have been deployed in the majority of experiments to
51 test the factors affecting travelers' acceptance of CAVs. Becker & Axhausen (2017) provide detailed
52 review of recent studies who have used SP.

53 [Djavadian et al. \(2019\)](#) recently investigated willingness of drivers choosing CAV over human
54 driven vehicles (HDV) while going from their origin to their destination. In their study, participants
55 were able to experience being driven by CAV and driving themselves, choosing the one that they
56 preferred the most. The focus of the study conducted by [Djavadian et al. \(2019\)](#) was on Level 5
57 automated vehicles, but as discussed earlier it will be long before we can expect 100% Level 5 vehicles
58 on the road. As such, it is important to look into under what conditions drivers are willing to give
59 control to vehicles, in the presence of partially automated vehicles.

60 Aside from drivers' willingness to adapt to CAVs and give them control, another major factor
61 affecting the success of CAVs is the drivers' ability to operate the intelligent vehicles and be able to
62 take back control safely when necessary. This is of particular interest to automobile manufacturers
63 in order to provide clear and on-time instructions to drivers when it is necessary for them to take
64 back control from the vehicle.

65 Many studies have investigated driver attentiveness and workload in the context of the transition
66 from automated driving to manual. [Stapel et al. \(2019\)](#) evaluated workload using both automation-
67 inexperienced and automation-experienced participants driving in a in a Tesla Model S on public
68 highways in various traffic complexities. In the experiments, when using automation, automation-
69 experienced drivers perceived a lower workload, while automation-inexperienced drivers perceived
70 their workload to be similar to manual driving. It was found that drivers under-estimate the actual
71 task load of attentive monitoring due to the detection-response task indicated an increase in cognitive
72 load with automation.

73 [Hirose et al. \(2015\)](#) investigated the driving characteristics of low-alert drivers after a change
74 from automated driving to manual driving. The participant is driven by an AV at high speed along a
75 highway and the driving mode changes from automated to manual, after which the participant must
76 react to a vehicle turning in front of them. A significant difference was observed in both reaction
77 time and brake pedal operation when the driver is in a low-alert state relative to a normal-alert state,
78 resulting in unsuccessful collision avoidance in some instances and giving credence to the need for a
79 prior and explicit warning of transition of control.

80 [Merat et al. \(2014\)](#) designed a driving simulator to investigate drivers' ability to resume manual
81 control of an AV. The two situations considered were a transition of control at a regular, system-
82 based interval and a transition of control based on the length of time drivers were looking away
83 from the road. Driver attentiveness was monitored and estimated based on drivers' eye movements.
84 Results of the study indicate that drivers' performance in stabilizing their vehicle was worse when
85 the transition occurred as a result of the driver's lack of attention to the road. In these cases, drivers'
86 visual attention continued to be erratic for up to 40 seconds after the transition of control.

87 [Willemsen et al. \(2015\)](#) explored the transition of control between vehicle and driver, imple-
88 menting different strategies for the automated function to switch itself off in case of attentive or
89 inattentive drivers and using a driving simulator to do so. Drivers' were presented with strategies
90 that display warnings of transition and confirmation prompts at varying distances from the manual
91 driving task requested of the participant. In some situations, participants were distracted by a sec-
92 ondary task. Differences between the tested conditions were small in both subjective and objective
93 results, prompting repetition of the experiment with a larger population and a larger variance in
94 experiment conditions.

95 In contrast to the mentioned literature, this study utilizes virtual immersive reality driving simula-
96 tor to investigate factors (i.e. traffic , weather, lighting, multi-tasking) that affect drivers' willingness
97 to give control to CAVs. In addition, this study looks at factors playing significant role on drivers'
98 situational awareness when it comes to taking back control safely from CAVs when necessary . The
99 main advantage of adapting virtual reality in our research is the ability to present and immerse the

100 participant in a wider variety of scenarios such as rainy conditions. As mentioned earlier, virtual
101 reality environment experiments have been conducted successfully in the past (Djavadian et al.,
102 2019; Farooq et al., 2018; Kalatian et al., 2019) and studies have shown that participants are able
103 to develop realistic spatial knowledge in the virtual reality environment that is comparable to actual
104 physical environments (O’Neill, 1992; Ruddle et al., 1997; Tlauka & Wilson, 1996).

105 3. Methodology

106 To analyze the drivers’ behaviour in giving and taking control, laboratory experiments are de-
107 signed in virtual reality. This section presents methodology used to design the experiments and
108 model travelers’ behaviours.

109 3.1. Objectives

110 In this study, VIRE driving simulator Farooq et al. (2018), pre-experiment questionnaire, weighted
111 NASA Task Load (NASA-TLX) index (Hart, 2006) and Detection Response Task (DRT) index (NEN-
112 ISO 17488, 2016) are used to investigate under what conditions drivers are willing to give full control
113 to CAVs and under what conditions are they able to safely take back control from CAVs. The aim
114 of the VIRE driving simulation is to help answer the following questions:

- 115 1. What are the effects of traffic congestion (low, high), weather condition (clear, rainy), time of
116 the day (day, night), and multi-tasking on willingness to give control to CAV and safely taking
117 back control when necessary?
- 118 2. What is the effect of the order of the experiments in the choice of participants to give control
119 to AV or not?
- 120 3. What is the effect of the order of the experiments on how well participants perform once they
121 take back control from AVs?
122

123 Whereas the pre-experiment questionnaire is used to answer the following questions:

- 124 1. What are the effects of gender, age, driving experience, risk index, locus of control index and
125 prior knowledge/experience of AV on drivers’ willingness to give control to CAVs?
- 126 2. Will participants with different socio-demographic and personal behaviour have different ac-
127 ceptance of AVs under different traffic conditions/scenarios?
- 128 3. Will drivers who are familiar with AVs have more trust in AVs and as such, be less attentive
129 when they are passenger and fail to take back control safely?
130

131 Lastly, the NASA-TLX index and DTR index are used to measure mental workload and situational
132 awareness of drivers and the impact on safely taking back control from CAVs.

133 *3.2. Dependent & Independent Variables*

134 *3.2.1. Dependent variables*

135 As discussed earlier, the aim of this study is twofold: 1) to investigate factors that affect willing-
136 ness of drivers to give control to CAVs and 2) to investigate factors that affect the ability of drivers
137 to safely take back control from CAVs. As such, there are two independent variables that are set to
138 binary:

- 139 1. Y_1 : Yes for giving control to CAV and no otherwise,
- 140 2. Y_2 : Yes for safely taking back control from CAV, and no otherwise.

141 *3.2.2. Independent variables*

142 Table 1 presents the independent variables used in this study. One of the key independent
143 variables used is the Locus of Control index (Rotter, 1966) which as shown by Djavadian et al.
144 (2019) has significant impact on the willingness of drivers to give control to CAVs or not. According
145 to Rotter (1966), people are divided into two categories: a) those who believe there are external
146 forces out of their control affecting their lives and b) those who believe they have control over events
147 in their lives. The first group has external locus of control whereas the second group has internal
148 locus of control. The higher the locus of control index means that the person has higher external
149 locus of control. Djavadian et al. (2019) showed in their study that drivers with higher index of
150 control are less willing to give control to CAVs. In this study the order in which experiments are
151 presented to participants is also taken into account. For example, a participant may first experience
152 taking back control from the CAV and may not perform safely, and in the next experiment where
153 the participant has the option of giving control to the CAV may not do so due to the previous bad
154 experience. Likewise, it is possible that a participant first experience being a passenger in a CAV
155 and then in the next experiment, has to take back control from the CAV. Since the participant
156 already has experience being driven by CAV, they may perform differently than a participant who
157 goes through that same experiment without having experienced riding in a CAV.

Table 1: Independent Variables

User attributes	Travel attributes
Age	Congestion level
Gender	Weather condition
Education	Time of day (e.g. day, night)
Vision	Multi-tasking
Employment	
Driving experience	
Risk index	
Locus of control index	
Prior knowledge/experience of CAVs	
Order of experiments & previous choice	
Mental work load	

158 3.3. Choice Model

159 In this study, Binary Logit model is used to model willingness of drivers to give control to CAVs.
160 Equation 1 presents the utility function for each condition.

161

$$U_{k,n} = \beta_{0,k}^T + \beta_{x,k}^T X_{k,n} + \beta_{z,k}^T Z_{k,n} + \epsilon_{x,k} \quad (1)$$

162 where:

163 $U_{k,n}$: expected utility of option $k \in K$ for participant $n \in N$. In the case of willingness to give
164 control to CAVs the options are choosing to continue to drive manually or switch to CAV;

165 $X_{k,n}$: set of attributes related to option k;

166 $Z_{k,n}$: set of participant n attributes, e.g. socio-economic variables;

167 $\beta_{x,k}^T, \beta_{z,k}^T$: set of parameters corresponding to the attributes;

168 $\epsilon_{k,n}$: unobserved utility modeled as a Gumbel distribution.

169

170 The probability of each participant n giving control to CAV depending on β is shown by Equation
171 2. $k = 1$ represents giving control to CAV.

$$P_{1,n}(\beta) = \frac{1}{1 + e^{-(\beta_{0,1}^T + \beta_{x,1}^T X_{1,n} + \beta_{z,1}^T Z_{1,n})}} \quad (2)$$

172 3.4. Experiment Setup

173 The laboratory experiment is divided into four sessions as shown below:

174 3.4.1. Information session

175 In the information session, the participants are provided with information about the experiment
176 and are asked to fill out the pre-experiment questionnaire which consists of 4 sections as described
177 below.

178 A **Socio-economic/Demographic Attributes and Driving Experiences**: Collects partic-
179 ipants' age, gender, occupation, education level and income level. In addition, it collects
180 information regarding real-life driving experiences in terms of years of experience.

181 B **Personality Attributes**: Collects participants' attitudes toward adventure and discovery
182 through risk index (Khattak et al., 1995). A risk index is estimated for each subject, based
183 on a scoring system. Alternative answers for each question are given a score from 0 to 4 in an
184 ascending order; starting with 0 for option (i). The risk index, for each subject, is estimated to
185 be the sum of scores of all questions. High risk index indicates a risk-seeking type of personality.
186 Similar test was also used by Talaat (2008).

187 C **Locus of Control**: Collects subjects' internal versus external control reinforcement and
188 provides information on personal perception of self-efficacy and control of a situation. The test
189 is developed by Rotter (1966). Scores range from 0 to 13. A low score indicates an internal
190 control while a high score indicates external control.

191 D **Technology based Indicators:** Collects information regarding participants familiarity with
192 the concept of self-driving cars and factors affecting their choice of buying one in the future.
193 In addition, it collects information regarding participants prior experience driving self-driving
194 cars or being driven by one.

195 3.4.2. Learning session

196 The second session is the learning session where participants are familiarized with driving in the
197 virtual reality environment. In addition the aim of this session was to reduce effect of virtual reality
198 novelty on the choices of the participants.

199 3.4.3. Actual experiment

200 The actual experiment is conducted in the VIRE driving simulator. Every participant is asked
201 to try 4 experiments, each lasting roughly 5 minutes. The experiments fall into two main categories:
202 giving control to a CAV and taking back control from a CAV. For each category, different traffic
203 conditions, weather conditions, lighting conditions (e.g. day, night) and multi-tasking options are
204 tested. For both categories, users either drive or are driven along a 2km stretch of a multi-lane
205 highway as shown in Figure 1.

- 206 1 **Giving control to CAV:** For this part of the experiment, the participants are asked to drive
207 for approximately 5 minutes along a virtual highway. At any point, they are able to switch
208 from manual driving to automated driving. To be able to switch to automated driving, the
209 participants are asked to change lane to a dedicated CAV lane. The experiments vary in terms of
210 traffic conditions, weather condition, lighting (day, night) and multi-tasking option. A pilot
211 study was first conducted with participants not having the option of taking back control after
212 they switched to autopilot, however after analysing participants' feedback it became apparent
213 that option of taking back control played an important role in their decision to switch to
214 autopilot. Hence, for the actual experiment participants are given the chance of switching back
215 to manual after they switched to autopilot.
- 216 2 **Taking control back from CAV:** CAV systems contain a multitude of sensors that process
217 collected data in order to make operational decisions and many of these sensors have limita-
218 tions. For example, data collected by LIDAR can be distorted by falling rain and snow, while
219 night time and limited visibility conditions can affect cameras (Kuhr et al., 2017). With this in
220 mind, it is realistic to expect scenarios in which an CAV requests that the driver take control
221 due to sensor disruption in safe functionality of the CAV. How situationally aware they are
222 will affect their performance. For this part of the experiment, participants are driven by the
223 CAV along a stretch of highway. At 1km from the start, the participant is prompted to take
224 over control due to sensor failure or bad weather conditions. An auditory and visual warning
225 is presented to the participant to bring back their focus on the road. Simultaneously, they
226 approach an accident blocking their lane located approximately 200m after the initial warning
227 is triggered. The warning is presented to allow participants enough time to either safely stop
228 behind the accident or change lane and pass the accident. In order for the participant to take
229 back the control from the CAV, they must pull a trigger found behind the steering wheel.
230 Figure 1 presents the layout of this scenario. These experiments also vary in terms of traffic
231 conditions, weather condition, lighting (day, night) and multi-tasking option.
232

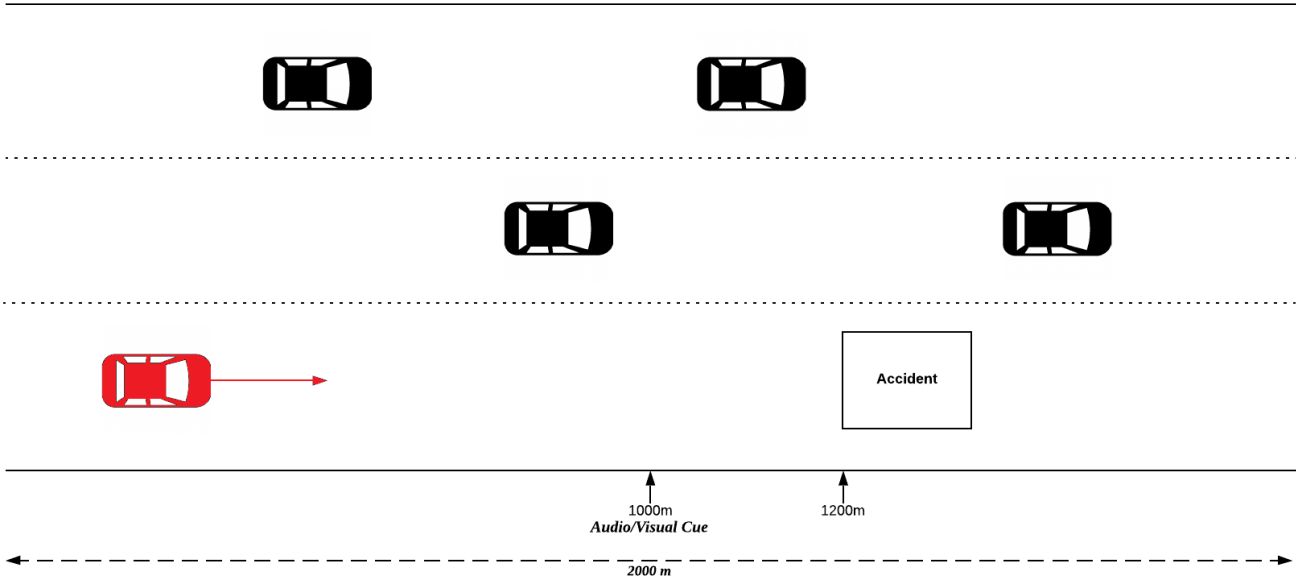


Figure 1: Taking control experiment setup

233 As shown in Figure 2 in total there are **32 scenarios (8 scenario per control type)** and out
 234 of these 32, we randomly assign 4 scenarios to each participant in such a way that all scenarios are
 repeated an equal number of times.

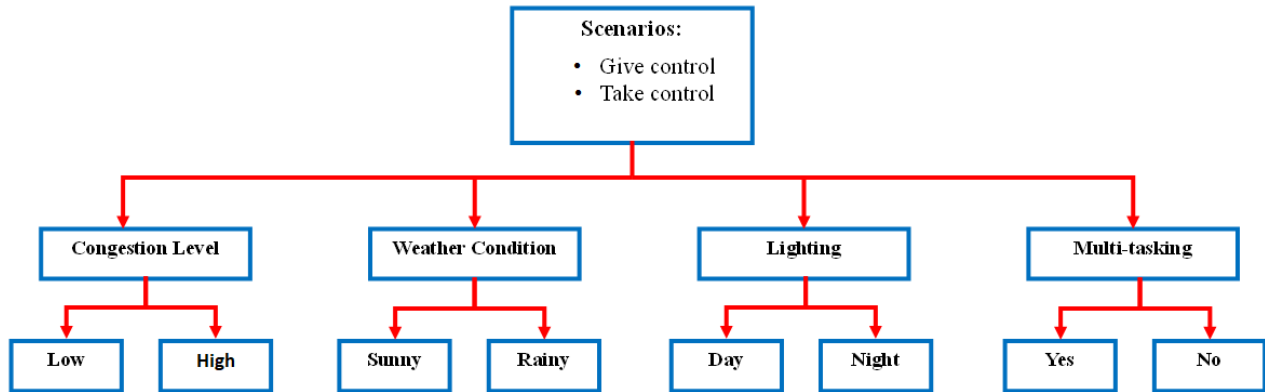


Figure 2: Scenarios.

235 Table 2 presents a description of each scenario, giving control to CAV (1-16), taking control
 236 back from CAV (17-32). In the label column: C (clear), R (rainy), D (day), N (night), H (high
 237 congestion), L (low congestion) and M (multi-tasking). If M is not present in the label then it means
 238 that multi-tasking is not available.
 239

240 3.4.4. De-briefing

241 At the end of each experiment, participants are asked to fill out the NASA-TLX questionnaire
 242 rating their mental work load for the experiment they just performed. The NASA-TLX index (Hart,

Table 2: Scenarios

Scenarios	Label	Weather		Time		Multi-Tasking		Congestion	
		Clear	Rainy	Day	Night	Yes	No	High	Low
1,17	CDMH	x		x		x		x	
2,18	CDH	x		x			x	x	
3,19	CNMH	x			x	x		x	
4,20	CNH	x			x		x	x	
5,21	CDML	x		x		x			x
6,22	CDL	x		x			x		x
7,23	CNML	x			x	x			x
8,24	CNL	x			x		x		x
9,25	RDMH		x	x		x		x	
10,26	RDH		x	x			x	x	
11,27	RNMH		x		x	x		x	
12,28	RNH		x		x		x	x	
13,29	RDML		x	x		x			x
14,30	RDL		x	x			x		x
15,31	RNML		x		x	x			x
16,32	RNL		x		x		x		x

243 2006) is commonly used in aviation and automotive research to subjectively measure individual’s
244 mental workload on six dimensions: mental demand, temporal demand, physical demand, perfor-
245 mance, effort and frustration. Stapel et al. (2019) also used the NASA-TLX index to measure mental
246 workload of participants in interaction with AV. The NASA-TLX allows participants to score the
247 relevance of each of these items, reducing variability between participants and task contexts. As
248 stated by Miller (2001), the NASA-TLX is more reliable than physiological measures. Aside from
249 using NASA-TLX to measure mental workload of participants subjectively, the DRT index is also
250 used to measure cognitive load (NEN-ISO 17488, 2016) objectively. DRT measures the delay between
251 stimulus and response. In this case the stimulus is the auditory and visual warning and response is
252 pulling the trigger behind the steering wheel. We call this delay reaction time from this point on.

253 In the case of giving control to CAVs, participants are asked to explain what affected their choice.
254 At the end of laboratory session, a short interview is conducted with the participants to receive their
255 feedback regarding the experiment itself.

256 3.5. Virtual Immersive Reality Environment

257 The multi-lane stretch of highway was created in the open-source gaming engine Unity which
258 VIRE (Farooq et al., 2018) is based on. To allow participants to drive in the virtual environment,
259 VIRE is modified to include driving hardware such as a motion simulator, steering wheel and ac-
260 celeration and braking pedals. VIRE is also modified such that it provides participants the option
261 of fully giving control to AV en-route to their destination, allowing us to explore under what condi-
262 tions (e.g. traffic condition, weather, time of day) users are more willing to give up control to AV.
263 In addition, VIRE is further modified such a way that while being driven to their destinations by
264 CAV participants are able to take over control from CAV in order to investigate their situational
265 awareness. To investigate the effect of multi-tasking on the choices of drivers and their situational
266 awareness, the option to multi-task is also introduced such that the participant riding CAV can read
267 a virtual newspaper or play a maze game on a virtual mobile phone. Moreover, different traffic

268 conditions (low, high), different weather conditions (clear, rainy) and different lighting (day, night)
269 are added to VIRE to measure their impact on the choices of drivers in giving control to CAVs and
270 taking control back safely. During experiments, the following hardware was used:

- 271 . Oculus Rift with motion and touch sensors
- 272 . Thrustmaster T150 Force Feedback Racing Wheel and pedals,
- 273 . Intel Core i7-8700 CPU,
- 274 . DOFReality Consumer H3 Platform,
- 275 . NVIDIA GeForce RTX 2080

276

277 Figure 3 presents the snapshots of the virtual reality setup for the two travel options. Figure 3a is
278 the snapshot of taking control away from CAV scenario where as Figure 3b is the snapshot of giving
279 control to CAV and multi-tasking scenario. Figure 3a presents sunny weather conditions where as
280 Figure 3d presents rainy day scenario.

281 *3.6. Results & Discussion*

282 This section provides results and analysis of the pilot study tested with graduated students and
283 employees from Ryerson University and University of Toronto. The following information is collected
284 from the laboratory experiment:

285

286 *Data that collected from the pre-experiment questionnaire*

- 287 ● socio-demographic characteristics (e.g. age, gender, education, etc.)
- 288 ● driving experience
- 289 ● risk index
- 290 ● locus of control index
- 291 ● knowledge/experience of CAV/AVs

292 *Data collected from the VR simulator for each scenario*

- 293 ● participant's choice (switching to CAV or not)
- 294 ● time of switching to CAV from manual driving
- 295 ● reaction time to visual or auditory trigger
- 296 ● force on the brake pedal after they take back control
- 297 ● speed before and after taking cover
- 298 ● performance after taking back control (safe stop/lane change or not?)
- 299 ● distance to the object at stop position



(a)



(b)

Figure 3: Participant in VIRE driving simulator.

- 300 • time to full stop/ lane change
- 301 • head position before the occurrence of the incident

302 ***Data collected from the post-experiment questionnaire***

- 303 • workload from NASA-TLX
- 304 • reason behind participants choices

305 ***3.7. Pre-experiment Questionnaire***

306 ***3.7.1. Socio-demographic characteristics of participants***

307 A brief description of our participants is presented in Table 3. As can be seen from Table 3 there
 308 is a heterogeneity among participants.

Table 3: Socio-demographic characteristics of the participants

Characteristics	Number of Participants, by Age (years)						Total
	18-24	25-29	30-39	40-49	50-59	60+	
All Participants	27	15	15	4	2	2	65
Gender							
Female	7	5	8	2	1	2	25(38%)
Male	20	10	7	2	1	0	40(62%)
Occupation							
Student	25	13	6	0	0	0	44(68%)
Employee	2	2	9	4	2	2	21(32%)
Education							
Bachelor	3	2	2	1	0	2	10(15%)
Masters	2	9	3	0	1	0	15(23%)
Doctorate	0	3	6	3	1	0	13(20%)
Uni/College	21	1	4	0	0	0	26(40%)
Highschool	1	0	0	0	0	0	1(2%)
Driving experience (years)							
Not at all	3	0	0	0	0	0	3(5%)
< 2	8	1	1	0	0	0	10(15%)
2-5	11	2	1	0	0	0	14(22%)
5-10	5	7	4	1	0	0	17(26%)
> 10	0	5	9	3	2	2	21(32%)

3.7.2. Perception towards AV/CAV

As part of pre-experiment questionnaire, participants were asked questions regarding their prior knowledge of and experience with AV/CAVs, and as shown in Table 4, 90 % of the participants were familiar with the concept of AV while 4 % of them had experience riding a AV/CAV shuttle at a technology fair. Aside from their knowledge of AV/CAVs, participants were asked which factors affect their choice of buying AV/CAV positively and negatively. Figure 4 presents factors play an important role in their willingness to purchase/ride an AV/CAV. As can be seen from Figure 4a, the three main factors negatively affecting participants willingness to buy an AV/CAV in descending order are concerns about safety & equipment failure, hacking, and giving full control to AV/CAV. From Figure 4b, it can be seen that participants would purchase AV/CAV because of higher safety, less congestion, and less time spent on finding a parking space. As shown by Figure 4c, participants are more willing to give ride (give control to) AV/CAV mostly in heavy congestion, on highways, and on unfamiliar networks.

Table 4: Participants' prior knowledge/ experience of AV/CAV

Technology based indicators	Results	
	% Yes	% No
Prior familiarity with the concept of AV	90.00	10.00
Prior familiarity with concept of CAV	60.00	40.00
Experienced being driven by an AV	4.00	96.00

3.8. VIRE Driving Simulator Results

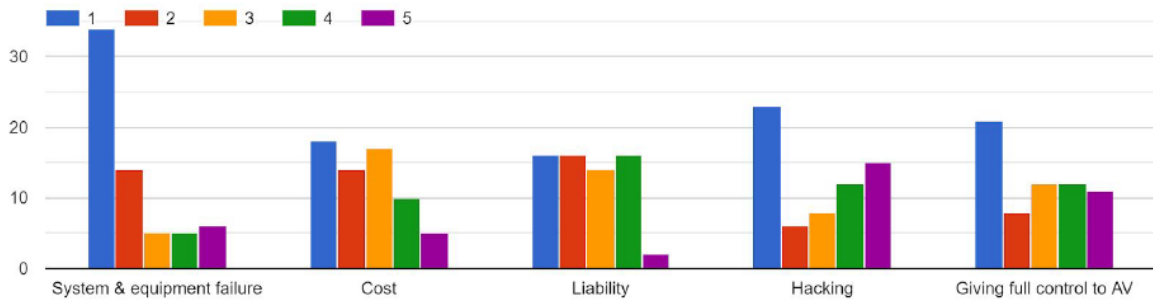
Figure 5a shows the percentage of times participants were willing to give control to CAV and Figure 5b presents the percentage of times participants were able to safely take back control from CAV. Table 5 provides summary of Figure 5. Looking at Figure 5a and Table 5 it can be seen that participants 12.77 % of times were more willing to give control to CAV en-route when multi-tasking option was available as opposed to when the option wasn't available. This results is inline with the results of questionnaire and the results of VIRE experiment conducted by Djavadian et al. (2019). On the other hand it can be observed from both Figure 5b and Table 5 that multi-tasking had significant negative impact on participants' ability to safely take control back from CAV when it was necessary to do so. On average participants failed to safely take back control from CAV 35.94% of times more more when multi-tasking was available as opposed to when it wasn't available. The reason for this substantial drop in participants ability to take back control when multi-tasking was able was due to the fact that they were distracted hence it took them longer time to react and take back control, this will be discussed in more details in the next section. In fact, recently there was an accident involving Tesla autopilot where the driver was distracted playing a game on his phone and failed to safely take back control of the car when he was prompted (News, 2020).

Looking at Figure 5a and Table 5 it can be seen that participants 11.57% of the times were more willing to give control to CAV when the sky was clear as opposed to when it was rainy. Based on the results of the de-briefing questionnaire, poor visibility in the rain was the main contributor to this phenomenon. In addition, on the de-briefing questionnaire participants mentioned that they enjoyed giving control to CAV when sky was clear because they could enjoy the scenery. When it came to taking back control safely from CAV, surprisingly participants were 8.40 % less successful under clear sky. This might be due to the fact that when sky was clear they were less vigilant. As reported by participants in de-briefing questionnaire even when multi-tasking was available when it was rainy and it was night time, they preferred to keep their eyes on the road.

Aside from multi-tasking option and weather condition, traffic condition as shown in Figure 5a and Table 5 also played an important role on the choices of participant in giving control to CAV en-route. It can be seen that under low traffic congestion participants gave control to CAV 10.83 % of times more in contrast to when the congestion level was high. As discussed on the de-briefing questionnaire participants were more willing to switch to CAV when traffic was low because they liked being driven on an open road and enjoying the scenery. It can be seen that observed results from VIRE pre-experiment questionnaire (Figure 4c where participants mentioned that they are more willing to give control to CAV when it is congested, this shows the difference between having visual image (VIRE) as opposed to just mental image (online SP). There were still some participants who gave control to CAV when there was high congestion because it reduced the hassle of stop-and-go for them. It should be noted that in this study the CAV was only traveling on single lane with no lane changing and taking over capability, as such when there was congestion the CAV would get stuck behind the leading vehicle, and this was one reason that participants didn't enjoy being driven by CAV for too long. It was observed that participants would put the car on auto-pilot and when there was congestion they would take control back switch lane, overtake the leading car and then would switch back to auto-pilot. It could be possible that in the future when CAVs have the capability of switching lane and taking over other vehicles, drivers would be willing to give control to CAV even when there is high congestion level.

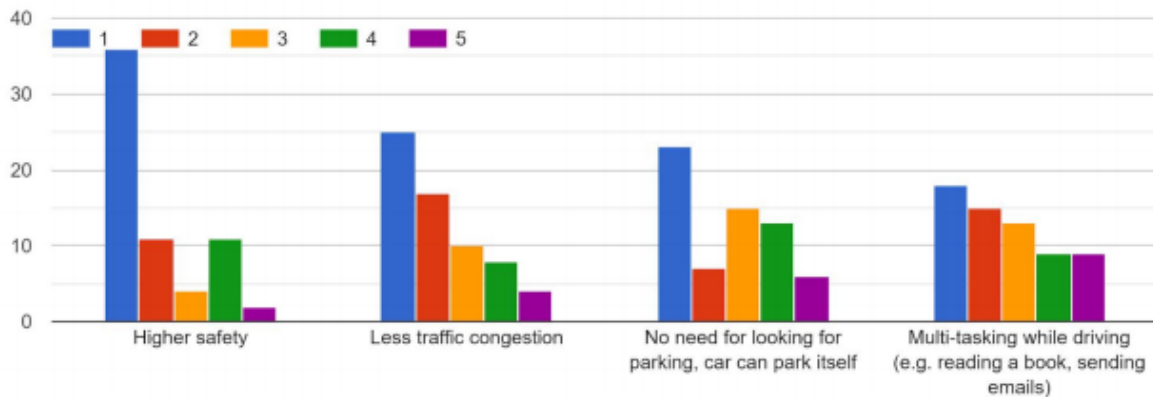
It is worth mentioning that traffic condition as shown in Figure 5b and Table 5 had a very minuscule effect on the performance of participants when it came to safely taking control back from CAV. The reason for the aforementioned phenomenon is that ability of drivers to safely take back control depends highly on factors affecting their reaction time and their visibility such as multi-

Please rank factors that may NEGATIVELY affect your choice of buying AV/CAV, with 1 being most important and 5 being least important.



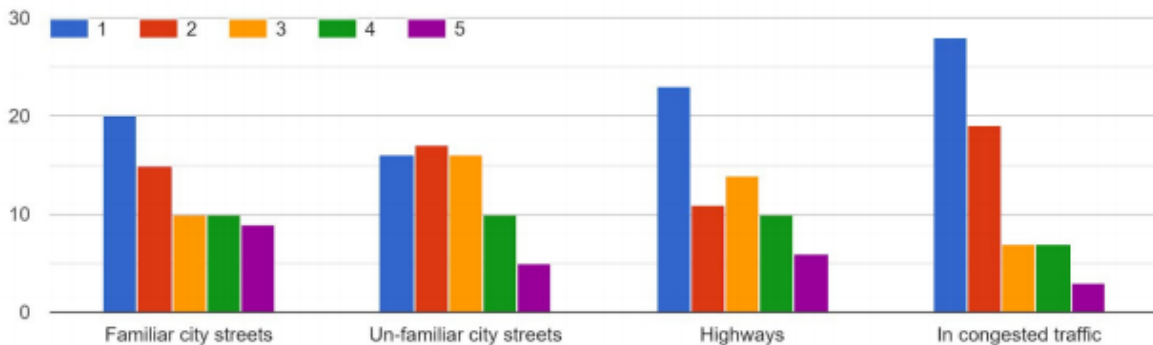
(a)

Please rank factors that may POSITIVELY affect your choice of buying AV/CAV, with 1 being most important and 5 being least important.



(b)

Under which scenario will you be more willing to ride AV/CAV? Please rank with 1 being most interested and 5 being least interested.



(c)

Figure 4: Factors affecting willingness to buy and ride AV/CAV

369 tasking, weather condition and time of the day. When it was night time, as observable from Figure 5
 370 and Table 5, participants were 5.50% of the times more eager to switch to auto-pilot and give control
 371 to CAV but they were 8.51 % times less successful to take control back successful at night due to
 372 visibility.

373 Before the start of this experiment a pilot study was conducted with 20 participants where they
 374 mentioned that they would have given control to CAV more often if the trip was longer and if they
 375 had the option of taking back the control after switching to CAV. The experiments were adjusted
 376 accordingly and the results showed that aside from weather condition, congestion level, time of the
 377 day and option of multi-tasking , factors such as trip length and ability to take back control when
 378 desired played important role on choices of participants.

379 In this study as discussed in the methodology section, 4 experiments were randomly assigned
 380 to each participants and the effect of previous scenarios were also investigated on the choices of
 381 the participants. The results showed that order of experiments to some extent had affected the
 382 choices of participants, for example if a participant in their first scenario was unsuccessful to take
 383 back control safely from CAV, in their second scenario they he/she prevented themselves from giving
 384 control to CAV. On the other hand a positive take away experience resulted in higher willingness
 385 to switch to auto-pilot next time that they had the chance. This shows the effect of experience on
 386 the choices of drivers and this is something that I can hardly be measured using traditional online
 387 or paper based SP. Similarly, results showed that experiment orders in the case of take-away control
 388 from CAV also played a significant role on the performance of the participants. Those participants
 389 who went through two or more take-away scenarios their attentiveness and performance improved
 390 in subsequent experiments. For example, those who forgot to pull the trigger behind the steering
 391 wheel remembered to pull it in subsequent experiments. This shows once again the importance of
 392 using virtual reality not only to test the behaviour of drivers with respect to AV/CAV but also as
 393 a learning tool since in reality it is not possible to replicate accidents repeatedly in a safe manner.
 394 Also, repetition improved vigilance of the participant, once they were aware that auto-pilot can fail
 395 at times, they paid closer attention to the road, increasing their situational awareness and reducing
 396 their reaction time.

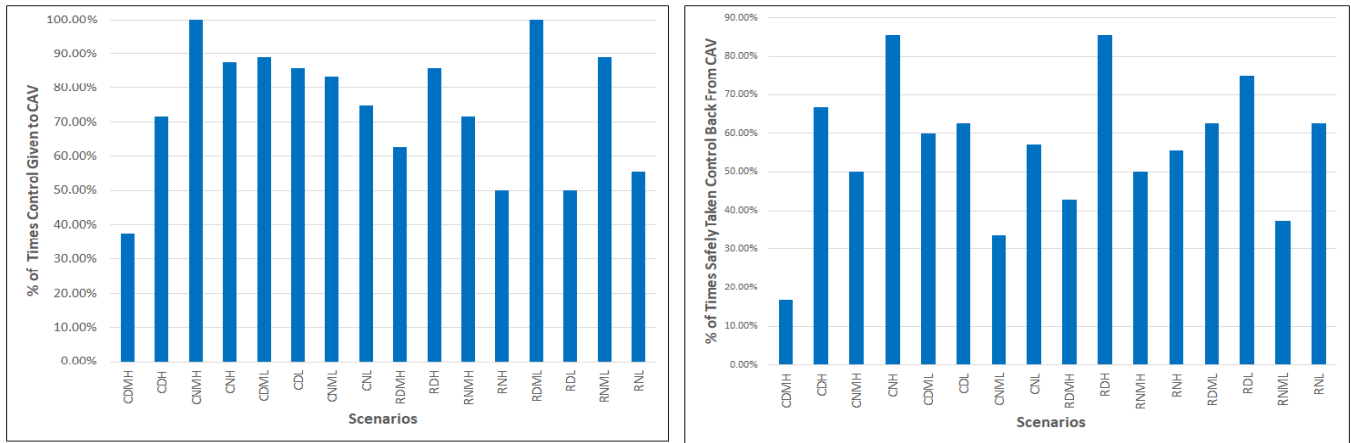
397 An interesting observation from Figure 5 is that scenarios that participants were more willing to
 398 give control to CAV where the same scenarios that they were less successful to take back control
 399 safely when necessary. This should be taken into consideration when developing policy and designing
 400 CAVs.

Table 5: Factors affecting drivers’ willingness to give control to and take away control from CAVs

Variables	% differences	
	Giving Control	Safely taking control back
Multi-tasking vs. No multi-tasking	12.77	-35.94
Clear Sky vs. Rainy	11.57	-8.40
Low vs. High congestion	10.83	-0.60
Night vs. Day	5.15	-8.51

401 3.9. Mental Workload

402 Figure 6 presents the breakdown of the composition of weighted mental workload score. It
 403 should be noted that participants were asked to rank the mental workload from the moment they



(a) Giving control to CAV

(b) Taking control back from CAV

Figure 5: % of times a) Giving control to CAV , b) Safely taking control back from CAV

404 received the sensor failure warning and prompted to take back control till the moment they safely
 405 passed the accident and finished traveling the highway. The overall mental workload calculated
 406 using NASA-TLX questionnaire was 50.60 (scale 0-100). As can be seen from Figure 6, temporal
 407 demand, frustration and mental demand contributed the most to the overall workload and as a
 408 result to the performance of the participants in taking back the control from CAV and safely passing
 409 the accident. Temporal demand is associated with time pressure for performing a task, and mental
 410 demand is associated with amount of thinking required to perform a task successfully and frustration
 411 is the amount of stress participant felt in doing the task.

412 Figure 7 presents average mental workload and reaction time for each individual scenario whereas
 413 Table 6 shows statistical summary for mental workload and reaction time. The average reaction-
 414 time was 4.04 seconds (the delay between when warning was presented to the participant and when
 415 the participant pulled the trigger to switch to manual control). The lowest reaction-time was 1.83
 416 seconds associated with scenario CDL (Figure 7b due to the fact that option of multi-tasking was
 417 not available therefore participants were paying closer attention to the road. In addition it was
 418 day time and clear sky as such participants were more vigilant. Not only scenario CDL had lowest
 419 reaction time but it also had the least overall mental workload (Figure 7a associated with it for the
 420 aforementioned reasons. Second and third lowest reaction times (Figure 7b) were associated with
 421 scenarios RNL and RNH for the same reason that multi-tasking was not available and participants
 422 were focusing on the road. However, from Figure 7a it can be noticed that although these two
 423 scenarios had low reaction time, they had high overall mental workload this is due the fact that
 424 it was rainy and night time so participants had lower visibility and found the task stressful even
 425 though they were paying more attention to the road. The discrepancy between reaction time and
 426 overall mental workload level shows the difference between how subjectively participants rated their
 427 mental workload and how it was objectively measured using DRT (reaction time). There is clearly
 428 disassociation between them. This seems to be the general trend for other scenarios as well, the ones
 429 with multi-tasking available had higher reaction time than the ones that didn't have multi-tasking
 430 option available .

431 3.10. Binary Logit Model Results

432 The initial results of the binary Logit model estimation based on the data gathered from the
 433 pilot study are presented in this section. The parameter values are not finalized, but provide us with

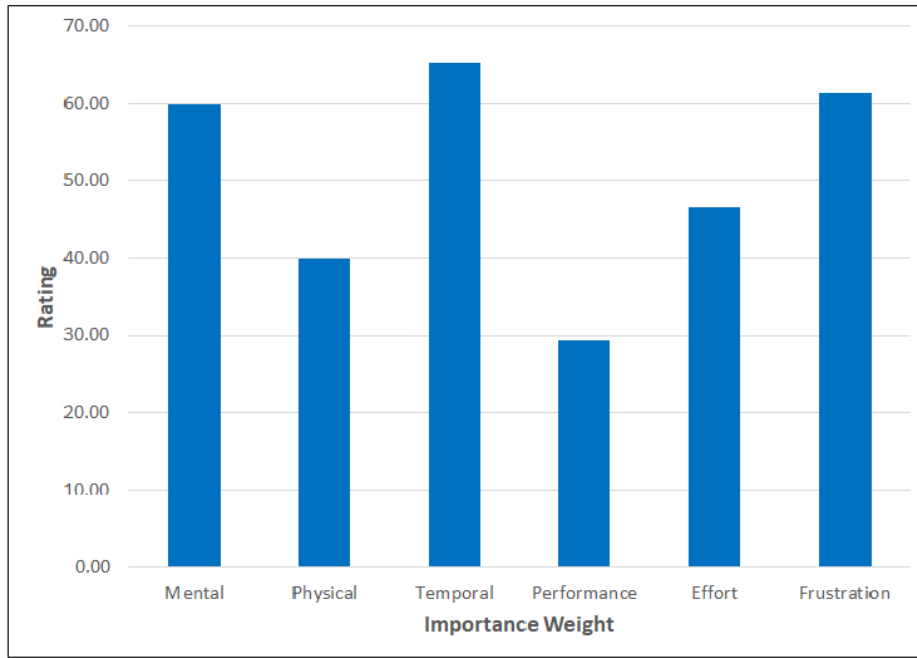
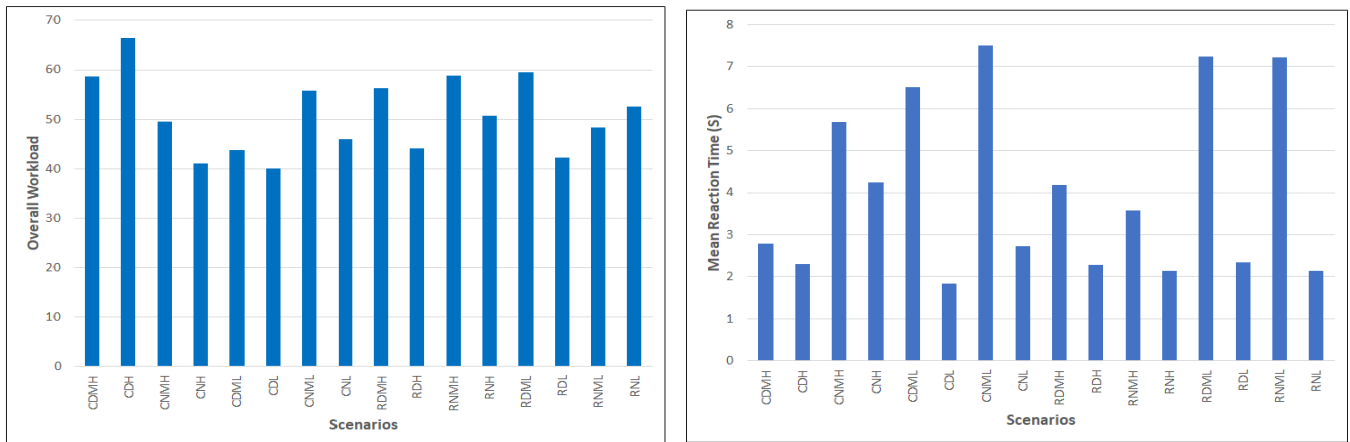


Figure 6: Composition of weighted mental workload score.



(a) Mental workload (NASA-TLX)

(b) Reaction time (DRT)

Figure 7: a) Mental workload vs. b) reaction time

Table 6: Descriptive statistics for reaction time & mental workload

Stats.	Reaction time (sec)	Mental workload (out of 100)
Mean	4.04	50.93
Standard deviation	2.09	19.78
Minimum	1.83	9.33
Maximum	7.50	92.33

434 an idea of what variables had the most impact on the choices of participants when it came to the
 435 preference of giving control to CAV en-route.

436 *3.10.1. Give-away experiment*

437 Table 7 presents the results of binary Logit model for the give-away experiments. As can be seen,
 438 the two main factors were heavy congestion when sky was clear and rain. With respect to rain, if the
 439 weather condition was rainy the variable was 1 and otherwise 0. As discussed before and as shown
 440 in Figure 5a, more participants gave control to CAV en-route under rainy weather condition which
 441 explains the positive sign of rain variable. These results are in-line with the de-briefing questionnaire
 442 where majority of participants noted that they were more inclined to give control to CAV under
 443 bad weather condition because of poor visibility. In regard to the variable clearsky-heavycongestion,
 444 when the sky was clear and the traffic congestion was heavy the variable was 1 and 0 otherwise.
 445 As can be seen from Table 7 and Figure 5a , the participants were less willing to give control to
 446 CAV when the weather condition was good, unless there was a heavy congestion. This explains the
 447 positive sign of the variable clearsky-heavycongestion. On the de-briefing questionnaire participants
 448 reported that when it was day light and light traffic condition they enjoyed driving but in heavy
 449 congestion they would rather give away control to CAV due to stop & go nature of traffic.

Table 7: Preliminary Binary Logit Model estimation results

Variables	Estimate	t-stat
ClearSky-HeavyCongestion (1,0)	1.40	2.10
Rain (1,0)	1.10	1.71
<hr/>		
# of Observations	36	
# of parameters tested	2	
Likelihood ratio test	8.401	
Adjusted Rho-square	0.088	

450 **4. Concluding Discussion**

451 In this study, we designed and conducted a stated preference experiment employing virtual im-
 452 mersive reality environment simulator to investigate the factors that affect the willingness of drivers
 453 to give control to CAV en-route and similarly the factors that affect their mental workload and
 454 situational awareness when it comes to taking control safely back from CAV when required.

455 This study was divided into four sections: pre-experiment questionnaire, learning session, vir-
 456 tual reality experiment and de-briefing questionnaire which included NASA-TLX questions to eval-
 457 uate participants mental workload. The pre-experiment questionnaire was used to collect socio-
 458 demographic characteristics of participants and their familiarity and perception of CAV. The results
 459 obtained showed that almost all the participants were familiar to some extend with the concept of
 460 CAV. The fear of equipment failure, liability, and giving full control were reported as three main
 461 factors negatively affecting their decision of buying CAV in the future. With the same token, they
 462 reported that in general they think CAV will make driving safer, less congested and reduce the need
 463 for finding parking space. Based on the results of the questionnaire, participants were more willing
 464 to give control to CAV under heavy traffic congestion, while driving on highways and while driving
 465 on unfamiliar networks. The purpose of the learning session was to familiarized participants with
 466 driving in virtual reality and at the same time reduce the effect of VIRE novelty on the choices of
 467 the participants.

468 Two different sets of experiments were implemented in VIRE. In the first set of experiments,
469 participants were asked to drive on a 2km stretch of multi-lane highway with the option of giving
470 control to CAV anytime en-route (taking control back when desired). In the second set of exper-
471 iments, participants were being driven on the same stretch of highway by CAV, however at some
472 point en-route due to sensor failure they were asked to take back control and safely pass the acci-
473 dent ahead. Auditory and visual warnings were used to bring back the focus of the participants to
474 driving. Different weather, traffic and lighting conditions were tested for both set of experiments.
475 While being driven by CAV, participants were also provided the option of multi-tasking (i.e. playing
476 game on the smartphone). The results from the VIRE experiment contradicted with the ones from
477 the pre-experiment questionnaire in the sense that VIRE results showed that participants were more
478 willing to give control to CAV en-route when the congestion was low as opposed to when it was
479 highly congested (pre-experiment results). The aforementioned discrepancy shows the value of hav-
480 ing visual image and immersive experience as opposed to just mental image provided by traditional
481 SP surveys. Based on participants' feedback on the de-briefing questionnaire, they enjoyed giving
482 control to CAV when it was low congestion because they liked being driven on an open road instead
483 of being stuck behind traffic. Those who gave control when congestion level was high mentioned that
484 they did it because switching to CAV took away the hassle of stop and go for them.

485 The results from the VIRE experiment also showed that bad weather conditions and poor visibility
486 played an important role on the decision of participants to give control to CAV. Participants were
487 less inclined to give control to CAV when it was rainy, mentioning that they didn't trust CAV. In line
488 with the study conducted by [Djavadian et al. \(2019\)](#), it was shown in this study that multi-tasking
489 also played a significant role in giving control en-route, with participants switching to auto-pilot 35%
490 of the times more when multi-tasking option was available. Although it is worth mentioning that
491 some participants they refrained themselves from using multi-tasking when it was rainy, citing that
492 they preferred instead to keep their eyes on the road.

493 In the case of taking back control from CAV, the average mental workload calculated using
494 NASA-TLX index was 50.60 (scale 0-100) with temporal demand, mental demand and frustration
495 having higher weights. Using detection response task technique, in this case reaction time to the
496 auditory and visual warning the average reaction time was 4.04 seconds. The reaction time was
497 lower and success rate was higher under scenarios where congestion level was low and multi-tasking
498 was not available suggesting that multi-tasking and congestion level playing major role on drivers'
499 situational awareness. There was the discrepancy between the subjective workload (NASA-TLX)
500 results and the objective one (DRT). In general scenarios that had lowest reaction time they had
501 higher workload (rainy night and no multi-tasking)

502 There are several directions that can be taken in future studies. First and foremost, the laboratory
503 experiment will be conducted with larger and more heterogeneous sample size. The results from de-
504 briefing questionnaire showed that participants were more willing to give control to CAV en-route
505 if the trip was longer and if they had the option of taking control back whenever they wanted. In
506 general, the participants were split with regards to their decision to trust CAV at night and rain.
507 In the future study, we will look into extending trip length and providing the option of taking back
508 control once the control is giving to CAV. Although auditory and visual warnings were provided to
509 participants, some participants were not able to successfully take over the control from CAV because
510 they forgot to pull the trigger to assume control and instead they intuitively pressed the brake pedal.
511 They noted that aside from warnings, they would prefer to receive clear instructions as what to
512 do when they have to take back control. In future studies, the effect of giving clear directions will
513 be examined. In this study, NASA-TLX was used to subjectively measure mental workload and
514 situational awareness. In the future, Galvanic Skin Response (GSR) sensors will be used to measure

515 emotional arousal of the participants objectively when they have to take control from CAV.

516 The project results will be of interest to car manufacturers, to design CAVs in a way that will
517 have maximum safety and driver acceptance, increasing market share. Also, the results will be of
518 benefit to traffic information providers, traffic management centers, city planners, and municipalities,
519 allowing them to target the right audience and apply traffic management strategies using CAVs in
520 situations that will result in higher acceptance and efficient use of transportation system. In general,
521 participants were more successful in taking control back safely in subsequent trials as opposed to
522 their first trial. In fact, those who experienced the take control scenario were more vigilant in their
523 subsequent experiments, even in the give control scenario. This points to the idea that knowledge
524 about CAVs is not sufficient and that consumers need to have the opportunity to experience being
525 driven by CAV and taught how to take back control safely. This can be done by providing pilot
526 studies using virtual reality or test CAVs.

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