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Risk of automated driving: Implications on safety acceptability and productivity

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A R T I C L E I N F O

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A B S T R A C T

Autonomous Vehicles have captured the imagination of our society and have promised a future of safe and efficient mobility. However, there is a need to understand behaviour and its consequences in the use of autonomous vehicles. Using paradigms of behavioural and experimental economics, we show that risk attitudes play a role in acceptability of autonomous vehicles, productivity in autonomous vehicles and safety under risk of failures of autonomous systems. We found that risk attitudes and age have a significant impact on these. We believe these findings will help provide guidance to insurance agencies, licensing, vehicle design, and policies around automated vehicles.

1. Introduction

Automated driving has been predicted to be transformational in improving safety and productivity on roads. However, there are several unknowns with regards to how drivers' will interact with automated vehicles, especially at moments requiring manual resumption of vehicle control. This is a situation involving risk, and understanding the relationship of drivers' attitudes and perception to this risk would significantly help inform insurance implications for drivers, vehicle designs and licensing for drivers.

A key issue with automated driving at this stage of its development is that it is not yet 100% reliable and safe (Martens and Beukel, 2013; Merat and de Waard, 2014). When automated driving fails or is limited due to the inability of on-board computer algorithms to make a safe decision, drivers will be expected to resume manual driving.

In order to study how drivers performed in response to failures in automation, Strand et al. (2014) undertook driving simulator experiments to understand differences in performance between driving in semi-automated and highly-automated vehicles. They found that driver's situational awareness reduced when the automation level increased, and drivers tended to exhibit slightly better control of vehicles under partial failures as compared to complete failures. These were further corroborated by a meta-analysis of 37 studies undertaken by De Winter et al. (2014), that found that failure in highly automated driving resulted in longer response times and higher (near-) collision rates as compared to semi-automated systems. Focusing on semi-automated driving system, Naujoks et al. (2015) conducted a driving simulator experiment to evaluate whether allowing longer time of hands-off driving would impair driving performance. They found that extending the permitted hands-off driving from 10 s to 120 s had no impact on driving performance.

In addition, familiarity and experience of technology has been found to improve performance of drivers, more specifically in their ability to properly control a vehicle during an automation failure (Larsson et al., 2014). Hergeth et al. (2017) found that drivers' prior familiarization with takeover requests during conditional automated driving significantly improved their performance in the first takeover situation. This positive impact of familiarity was less significant in subsequent takeover situations. Furthermore, the authors found that exposure to repeated disengagements led to lower trust towards the automated driving system. Koustanaï et al. (2012) concentrated on the forward collision warning (FCW) system. They compared the performance of drivers who had been trained to use FCW on a driving simulator, drivers who only read an FCW manual, and drivers who had no contact with FCW. They found that drivers who gained familiarity with FCW through a simulator performed better than others. This indicated the positive impact of familiarity on driving performance with assisted driving systems.

Traffic density and predictability of system failures were also found to affect drivers' performance in regaining control of autonomous vehicles during system failures. Gold et al. (2016) identified that traffic density could influence drivers' takeover performance during automated driving through a driving simulator experiment. They tested three traffic density conditions, i.e. 0, 10, and 20 vehicles per kilometer.

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Higher traffic density led to longer takeover times and worse takeover quality. Merat et al. (2014a) also found that driver's ability to regain control of the vehicle was better when the system disengagement was more regular and predictable than variable. This suggests that predictability in failures improved situational awareness and expectations which helped improve reaction times, while experience with automated driving helped drivers control the vehicles better in the event of a failure.

There is also evidence that drivers would be involved in more non-driving tasks in autonomous vehicles (Carsten et al., 2012; Llaneras et al., 2013) as compared to semi-automated driving. Drivers' propensity to be involved in non-driving tasks was also found to be higher in light traffic conditions than heavy traffic conditions (Jamson et al., 2013). However, several studies emphasized the negative impact of non-driving tasks on takeover performance and ability to react during critical events (Merat et al., 2014b; Gold et al., 2015; Merat et al., 2012). There is no research evaluating performance in non-driving tasks and productivity in automated driving conditions.

Disengagements from automatic driving are risky situations for drivers. There is significant evidence that risk attitudes and perceptions play an important role in the safety performance of drivers' driving non-automated vehicles (Dixit, 2013; Dixit et al., 2014). As shown in Table 1, there have been studies that have evaluated the impact of various factors on takeover performance in automated driving and involvement in non-driving tasks, however, there is currently no study that has quantitatively captured drivers' risk attitudes (as described in an economic sense) and evaluated its implications on safety and productivity in automated vehicles. Further, to the best of our knowledge, there is no research that has studied factors influencing the willingness to engage in the autonomous driving mode.

Understanding the role of risk attitudes in the context of automated driving would not only help in designing insurance products that improve welfare of drivers (Harrison and Ng, 2016), but also help in designing vehicles, licensing procedures and information provision to influence perceptions.

To address this gap, we undertake a driving simulator experiment where we study the impact of risk attitudes calibrated using lottery choices, demographics such as age, and perceptions of safety of automated vehicles on reaction times, productivity as measured by the amount of non-driving task the drivers were involved in, and acceptability to engage automated driving. The next section describes the experimental design and the data collection procedure. This is followed by the section reporting the models and findings from these experiments. The paper then concludes with discussion of the implications of these findings.

Table 1
Evidence in Literature on Autonomous Driving.

	Takeover Performance	Involvement in Non-Driving Tasks
Familiarity through driving	+	•
Familiarity through reading	≈	•
No familiarity	≈	•
Increase in automation level	−	+
Traffic density	−	−
Predictability of system failure	+	•
Extending hands-off duration	≈	•
Involvement in non-driving task	−	•

*A +, − and ≈ indicates a positive, negative and no correlation between factors and observed behavior respectively.

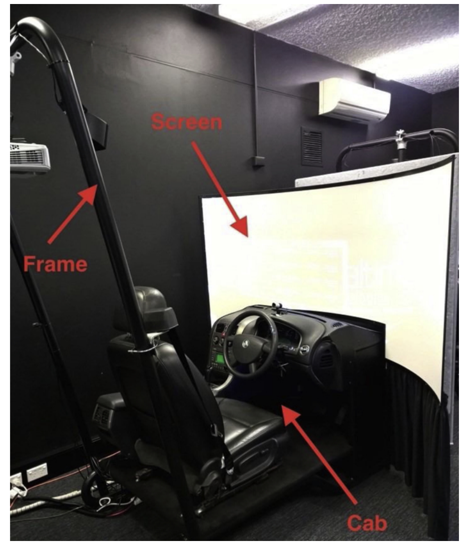

Fig. 1. Driving Simulator Setup.

2. Experiment design

This research utilized the TRAvel Choice Simulation Laboratory (TRACSLab) at UNSW Sydney to study driver behavior in an automated vehicle with a human driver in the loop. The study specifically aimed to identify the factors influencing decisions in an automated driving environment, with the possibility of the autonomous system failing and requiring the human driver to regain control of the vehicle. This section describes in detail the driving simulator setup, recruitment protocol for the subjects as well as the experimental protocol.

2.1. Driving simulator setup

TRACSLab is a multi-participant connected driving simulator laboratory located at UNSW Sydney and the University of Sydney. It consists of 10 driving simulators and one bicycle simulator which can be connected in a same virtual environment. In this experiment, we used one driving simulator and developed an autonomous driving module.

As shown in Fig. 1, the driving simulator includes a cabin with a screen and a projector to render the virtual environment to the participant. The inputs are from the brake pedals, accelerator pedals, and the wheel are fed into a computer, which then appropriately renders the graphics and the simulated traffic.

The autonomous system is engaged by pressing a button on the right, which is attached to the turn signal switch. The autonomous module, when enabled, overrides the inputs from the physical driving interface (steering wheel, pedals etc.) and makes driving decisions based on contextual information about the dynamics of the environment and other road users'. This module can conduct car following, lane changing and overtaking manoeuvres. The participant can press the same button again to disengage the autonomous system and take control of the vehicle.

The driving environment was modelled as a stretch of 2-lane motorway with low traffic flow and no pedestrians, with urban areas at the beginning and the end, shown in Fig. 2. The participant started at a carpark and finished at another carpark. The speed limit was 50 km/h in urban areas, while the arterial road connecting the urban areas with the motorways had a speed limit of 80 km/h, and the motorway had a speed limit of 110 km/h. As a common rule, all participants were instructed to obey speed limit and traffic rules while driving in the simulator environment, or their drive would be considered invalid. In addition, vegetation and road side infrastructure were placed in the

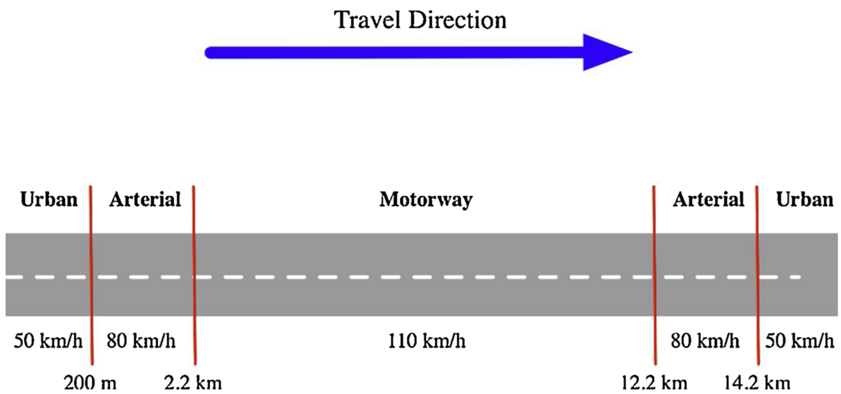

Fig. 2. Illustration of the Road Network.

virtual environment to replicate realistic motorway conditions.

A failure was considered to be a holistic one in which the autonomous system is unable to determine that the system itself has failed, and the driver needed to take over control of the vehicle. This is in line with disengagement and failures being reported by autonomous test vehicles on Californian roads (Dixit et al., 2016).

2.2. Subject recruitment

Participants were recruited through emails to UNSW staff and students, GoGet carshare members, as well as public advertisements on Gumtree, an online classifieds and community website. Only people over 18 years of age were eligible to participate in this study, and this requirement was clearly stated in the consent form. The show-up fee for each participant was $15 and their final payment could range from $15 to $60. The final payment depended on the participants' choices and performance in the driving tasks. A total of 80 participants took part in the experiments, although four participants did not complete all the tasks due to simulator sickness or other reasons. Further, driving simulator data from five of the participants were lost due to errors in the systems data capture. Therefore, data from a total of 71 participants was complete and valid for analysis.

Table 2 describes the demographics of these participants. The participants in this study covered a wide range of demographics. The participants were aged between 19–66 with a mean of 28.62 and a standard deviation of 11.10. The driving experience of these participants also covered a wide range. The shortest experience since obtaining a driving license was 3 months, while the longest was 50 years. 41% of the participants did not use personal cars for commuting, and 18% of them drove daily to work.

The recruited participants were heterogenous with respect to household income levels, with 20.51% from low-income households (annual household income under AU$25,000), 53.85% from medium-income households (annual household income from AU$25,000 to AU $100,000), and 25.64% from high-income households (annual household income over AU$100,000). In addition, 55% of the participants held a bachelor or higher degree, and 23% were currently working. These demographic statistics of participants are consistent with those of overall population in Sydney. As such, the outcomes drawn from this experiment can reflect Sydney residents' driving behavior in automated driving.

2.3. Experimental protocol

The experiment involved the following main tasks: (1) a questionnaire (2) nine lottery choice tasks, and (3) five driving tasks, that is briefly described in Table 3. Participants were required to carry out all three sections. An entire experiment took approximately one hour and a half to complete.

The driving tasks were interspersed with non-driving tasks in the experiment, to mitigate issues related to motion sickness from continuous long exposure to driving in the driving simulator. Fig. 3 provides a step-by-step overview of the tasks presented to each participant.

The use of incentives in this study is an important point of departure from previous studies. Most previous studies provide participants with a fixed modest participation fee to take part in the driving simulator experiments (eg. Carsten et al., 2012; Merat et al., 2012; Koustanaï et al., 2012; Llaneras et al., 2013; Jamson et al., 2013; Larsson et al., 2014; Merat et al., 2014a, b; Gold et al., 2015; Naujoks et al., 2015; Hergeth et al., 2016). Though driving simulators provide significant immersion, the real-life consequences are not experienced. The weakness of the approach is the lack of actual consequences, which is likely to lead to both noise and biases in responses.[1] To overcome this we use methods from the Experimental Economics (EE) tool box[2] . EE simulates consequences through money, where people earn or lose money based on their actions and the state of the environment. Such tasks are called incentive compatible. In this study we designed incentive compatible tasks for the lottery choice as well as the driving tasks. The combination of EE methods with driving simulator has been published in earlier works by Dixit et al. (2014) and Dixit et al. (2015). Furthermore, the strength of employing such a methodology has been discussed in depth in Dixit et al. (2017). The experiment was approved by the UNSW human ethics committee in accordance with the experimental protocols presented under HC15382. Informed consent was obtained from all the participants.

2.3.1. Demographics questionnaire

A questionnaire was used to collect data on participants' driving experience (Section 1 in Fig. 3), demographics (Section 2 in Fig. 3) and attitudes towards new technologies and autonomous vehicles (Section 3 in Fig. 3). There were 22 questions, and the variables studied are shown in Table 2.

2.3.2. Lottery choice task

Nine lottery choice tasks were used to elicit the risk attitudes of participants. The monetary consequences of the lottery were implemented using methods from experimental economics (Dixit et al., 2017). We apply the lottery choice design to estimate risk attitudes because it is context-free and provides a revealed choice. Fig. 4 presents an example of a lottery choice task. Each lottery choice is a binary choice. The right lottery always yields a fixed outcome, and the left

[1] Such hypothetical response biases have been demonstrated in Cummings et al. (1999), Holt & Laury (2002), and Harrison & Rutström (2008)

[2] EE has grown exponentially and now includes several dedicated journals, the Economic Science Association with over 500 members, and four winners of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel (Reinhard Selten, Vernon L. Smith, Elinor Ostrom, Alvin E. Roth).

Table 2
Summary of Participant Demographics Variables.

Variable	Mean	Std. Dev.	Percent of Discrete	Data Type	Description
Age	28.62	11.10		Continuous	Age of participant
YearsDr	9.32	11.44		Continuous	Number of years since participant obtained driving license
EmpStatus	-	-	23%	Discrete	Binary variable, employment status of participant: = 1, if participant is currently working; = 0, otherwise
incHH	3.88	2.61		Discrete	Income level of household, 8 levels of income in total, higher level indicates higher income
CarUseWeekly	2.02	2.32		Continuous	Number of days in a week participant commutes to work/study by car
NspTic	0.24	0.51		Continuous	Number of speeding tickets participant has had in the last 5 years
nHH	2.40	1.44		Continuous	Number of people in the household
EducHH	3.97	0.23		Discrete	Highest level of education of household, 5 levels of education in total, higher level indicates higher education level
Educ	-	-	55%	Discrete	Binary variable, education level of participant: = 1, if participant has degree of bachelor or higher; = 0, otherwise

Table 3
Data Collection Method Summary.

Section	Purpose	Description
Demographics Questionnaire	Collect data of participants' experience and other demographics	A questionnaire with 22 questions in three sections
Lottery Choice	To elicit risk attitudes of the participants	Nine lottery choice tasks with monetary consequences
Driving Simulator Study	Collect data of driving behaviors	A driving simulator study on a motorway, that is 10 km long, with the drive lasting approximately 10 minutes. Five driving tasks were administered with monetary consequences.

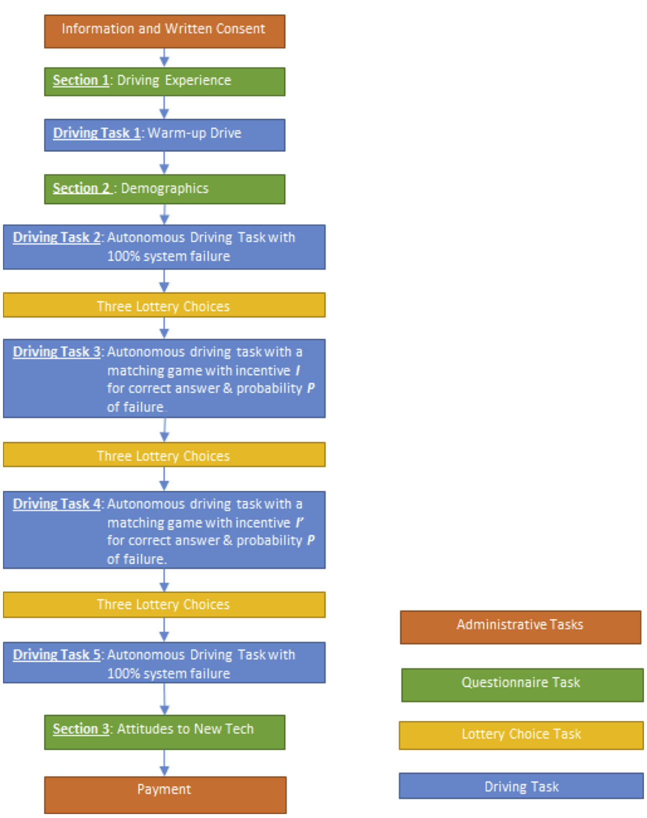

Fig. 3. Experimental Protocol.

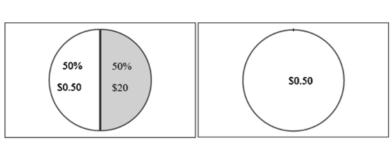

Fig. 4. Example of a Lottery Choice Task.

Table 4
List of Lotteries Presented to Participants.

Lottery	Left Lottery			Right Lottery ($)	EV_{Left}	EV_{Right}	ΔEV
	Low ($)	High ($)	P_{Low}				
1	0.5	20	0.5	8	10.25	8	2.25
2	0.5	20	0.7	1	6.35	1	5.35
3	0.5	20	0.9	4	2.45	4	−1.55
4	0.5	20	0.5	6	10.25	6	4.25
5	0.5	20	0.7	2	6.35	2	4.35
6	0.5	20	0.9	2	2.45	2	0.45
7	0.5	20	0.5	4	10.25	4	6.25
8	0.5	20	0.7	5	6.35	5	1.35
9	0.5	20	0.9	1	2.45	1	1.45

lottery is risky. Choosing the left lottery will lead to either a high prize or a low prize. The probability of getting the high prize is transparent to the participants, and varies across the nine lottery choice tasks. The entire set of the lottery choice tasks are tabulated in Table 4. In this table, EV_{Left} represents the expected value of choosing the left lottery, EV_{Right} the expected utility of choosing the right lottery, and ΔEV refers to the difference between the expected utility of choosing the left and the right lotteries. The expected value (EV) is the anticipated value for a lottery. The EV is calculated by multiplying each of the possible outcomes by its likelihood, and summing all of those values.

As shown in Fig. 3, the nine lottery choice tasks were presented to the participants throughout the experiment, i.e. three lottery choice tasks were given after each of the Driving Tasks 2, 3, and 4, respectively. At the end of the experiment, one of the nine lottery choice tasks were randomly chosen, and the participant received the pay-off from the realization of their chosen lottery.

2.3.3. Driving simulator task

Five driving tasks were undertaken in the driving simulator. Data on driver performance was collected with regards to: driver reaction time, lane variation, the time when automation was engaged, speed profile, as well as the dynamics of the automated and surrounding vehicles. During each of these driving tasks participants were instructed to engage the autonomous driving module as soon as they got on the motorway, which had a speed limit of 110 km/hr. They were also instructed to re-engage the autonomous driving module as soon as they found out that the system failed. The module would disengage once the motorway section finished, and the driver had to then control the vehicle.

Task 1 provided participants' driving experience in automated and normal driving scenarios, to familiarize themselves with the system. In Task 1 participants drove in the same driving environment that would be presented to them in later tasks, and could engage the autonomous system as they would in Tasks 2 to 5. In Task 2 the participants were informed that their automated system would have a certain random failure in the system during their drive. Task 5 was like Task 2, with the only difference being that participants entered Task 5 with experience from driving in previous tasks. Therefore, Task 2 is referred to as "Inexperienced Driving with Certain Failure" and Task 5 as "Experienced Driving with Certain Failure".

The choice to undertake a risky act can be attributed an individual's risk perception (i.e., the likelihood that an individual believes and associates to consequences) and their risk attitudes (i.e., an individual's predisposition to take risk). Though observing risky events such as lane changing and gap acceptance provide a good surrogate for risky behavior, it however does not allow us to determine whether this behavior is due to an individual's risk attitudes or risk perceptions. Moreover, in the case of autonomous vehicles the risk perception of the likelihood of failure of autonomous vehicles would be arbitrary and vague due to lack of sufficient experience with these vehicles, which would therefore cause problems in identifying whether these risky driving behaviors are due to risk attitudes or arbitrary perceptions.

The use of explicitly defined probabilities of failures in Task 3 and Task 4, ensures that any pre-conceived perceptions of the likelihood of failures do not play a role, and similarly explicitly defined monetary consequences ensures that individuals' perception over consequences don't play a role. It is possible that individual's might be extra vigilant with monetary consequences than non-monetary consequences, but the risk attitudes of an individual are the same when comparing the alternatives to be vigilant or non-vigilant. To control for different vigilance levels, different consequences for work ($0.05 and $0.10 for correct answers) and different risks (10% and 30% risk of failure) were implemented. Therefore, by implementing these controls we can isolate the impact of risk attitudes on individuals' propensity to take risky decisions.

In Tasks 3 and 4 participants were informed that there was a probabilistic chance of failure, which was either 30% or 10%. This probability of failure was assigned randomly to a participant, and remained constant between Tasks 3 and 4. To study the productivity of autonomous vehicles, as shown in Fig. 5 the participants were given a choice to engage in an incentivized shape matching activity (Fig. 6) during the automated driving in Task 3 and 4. The incentive rate for each participant in Task 3 was randomly assigned at the start of the experiment to be either AU $0.10 or AU $0.05 per correct match. The incentive rate in Task 4 for each participant was switched to the incentive rate that was not assigned in Task 3.

Therefore, this ensured a total of two treatments: (a) two probability treatments of 10% and 30%, and (b) two incentive treatments for productivity of $0.10 and $0.05 per correct match. The participants were randomly and equally allocated to each of the treatments associated with failure probabilities and incentive rates as shown in Table 5. Due to this randomization of treatment, the impact of experience can be studied when comparing results from Task 3 and Task 4 in the pooled data. Later when describing the results, Task 3 is referred to as "Inexperienced Driving under Risk" and Task 4 is referred to as "Experienced Driving under Risk".

Fig. 5. Driving Simulator Task.

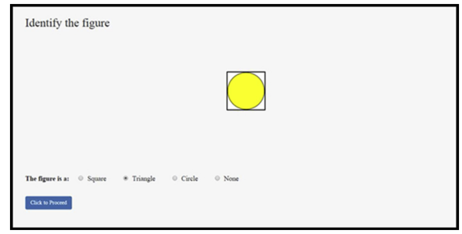

Fig. 6. Incentivized Shape Matching Task.

Table 5
Number of Subjects in Each Treatment.

	Failure Probability	
	10%	30%
Task 3		
$0.05/correct answer	14	15
$0.10/correct answer	25	16
Task 4		
$0.05/correct answer	24	15
$0.10/correct answer	14	15

3. Modelling risk attitudes

The risk homeostasis theory was originally first put forth by Wilde (1982). There has been a significant body of literature that has provided evidence for this theory (e.g. Recent work by Ba et al., 2016). In his seminal work, Wilde (1982) stated that:

> "The level of risk at which the net benefit is expected to maximize is called the target level of risk in recognition of the realization that people do not try to minimize risk (which would be zero at zero mobility), but instead attempt to optimize it. Risk homeostasis theory posits that people at any moment of time compare the amount of risk they perceive with their target level of risk and will adjust their behaviour in an attempt to eliminate any discrepancies between the two." (Wilde, 1982, 89–90)

This framework is operationalized in economics based on expected utility theory, where individuals maximize their expected utility. Within expected utility theory the risk attitudes capture how individuals' make choices under risk, and in some sense, can be interpreted as the adjustment an individual undertakes to eliminate the discrepancy between the perceived risks and the target risk. This approach has been validated in an earlier work by Dixit (2013), in which using the risk homeostasis theory and expected utility theory a fundamental traffic flow model was derived.

The economic framework with risk attitudes is extensively used in pricing insurance. Therefore, it is critical to evaluate the impact of risk attitude on user's driving behavior during automated driving. Risk attitude is estimated using data collected through the lottery choices. The demographics were then used to model heterogeneity in risk attitudes.

3.1. Maximum likelihood estimation

A Constant Relative Risk Aversion (CRRA) utility function was used to elicit participants' risk attitudes. The CRRA utility function has been previously applied to a driving simulator study which investigated the impacts of risk attitudes and subjective beliefs on crash propensity

(Dixit et al., 2014). In that study, a CRRA utility function was used to elicit and capture the heterogeneity in risk attitudes. Since this study also aims to study the impact of subjects' risk attitudes and perceptions on drivers' decisions in automated driving, the approach of Dixit et al. (2014) is applied to this study. The CRRA utility function is given by:

$$U(x) = \frac{x^{1-r}}{1-r} \tag{1}$$

where x is the income and r is the risk attitude. Under CRRA utility, risk neutral behaviour corresponds to $r = 0$, risk loving behaviour when $r < 0$ and risk averse behaviour when $r > 0$. The risk attitudes captured by the parameter "r" were estimated over the lottery choices using maximum likelihood estimation, assuming Expected Utility Theory.

The lottery choice task was a binary choice, where subjects could choose between the Left lottery or the Right lottery. For each lottery choice scenario, the left lottery choice consisted of a low outcome of \$0.50 with a probability of p and a high outcome of \$20 with probability *1-p*. The Right lottery had a certain value \$*C*. The value of p and C varied between choice tasks, shown in Table 4. Therefore, the expected utility (*EU*) for the left and right lotteries can be written as follows.

$$EU_{Left} = p \times U(0.50) + (1-p) \times U(20) \tag{2}$$

$$EU_{Right} = U(C) \tag{3}$$

A latent index ∇EU is defined as the difference in expected utility between the left and right lotteries, which is then normalized by a structural noise parameter. The parameter μ accounts for behavioural errors, and is referred to as the Fechner error or the inverse of the scale parameter. As μ gets larger the choice between alternatives becomes more random.

$$\nabla EU = (EU_{Left} - EU_{Right})/\mu \tag{4}$$

The log-likelihood for the lottery choices,

$$\ln L(r, \mu: X) = \sum_i [\ln(\Phi(\nabla EU) \times \boldsymbol{I}(Left)) + \ln((1-\Phi(\nabla EU_L)) \times \boldsymbol{I}(Right))] \tag{5}$$

where, $\boldsymbol{I}$ is an indicator function which takes a value 1 when the condition is satisfied, and zero otherwise; $\Phi(\nabla EU)$ is the probability of obtaining ∇EU. The argument in the indicator function is the participants' lottery choice, i.e. Left or Right. $\boldsymbol{X}$ is a vector of individual characteristics based on responses to the questionnaire.

To estimate the impact of socio-demographic characteristics upon risk attitudes, the analysis was generalised to allow the core parameter r to be linear functions of $\boldsymbol{X}$. The model is extended to be $r = r_o + \alpha \boldsymbol{X}$, where r_o is a fixed parameter, and α is a vector of effects associated with the socio-demographic variables represented by $\boldsymbol{X}$. The maximum likelihood model used the "cluster (*by participant*)" command in Stata to treat the residuals from the same person as being potentially correlated. It then corrects for this fact when calculating standard errors of estimates.

3.2. Heterogeneity in risk attitudes

We chose these demographics variables (age, driving experience, household income level, education level, employment status, etc.) because these are commonly investigated individual-level factors that may affect drivers' driving behavior (Dixit et al., 2014; Arbis et al., 2016).

The estimates of the risk attitude are presented in Table 6. Risk attitudes are significantly influenced by participants' age, years holding a driving license, household income level and education level at a 5% statistical significance level. Positive coefficients for age and household income level imply that an increase in these values results in individuals' being more risk averse. Variables related to driving experience and individual education level have a negative coefficient, indicating that increase in levels for these variables result in individuals' being less risk averse.

Table 6
Estimation Results of Risk Attitude.

Variable	Coef.	Std. Err.	z	P > |z|
Risk Attitude (r)				
Age	0.040	0.014	2.800	0.005
YearsDr	−0.038	0.014	−2.740	0.006
EmpStatus	−0.118	0.084	−1.410	0.158
incHH	0.038	0.018	2.140	0.033
CarUseWeekly	0.013	0.015	0.840	0.401
NspTic	0.008	0.084	0.100	0.921
nHH	−0.064	0.043	−1.480	0.139
EducHH	0.010	0.063	0.170	0.869
Educ	−0.171	0.078	−2.180	0.029
Constant	−0.319	0.334	−0.960	0.339
Log Fechner (LNmu)				
Constant	0.190	0.095	2.010	0.045

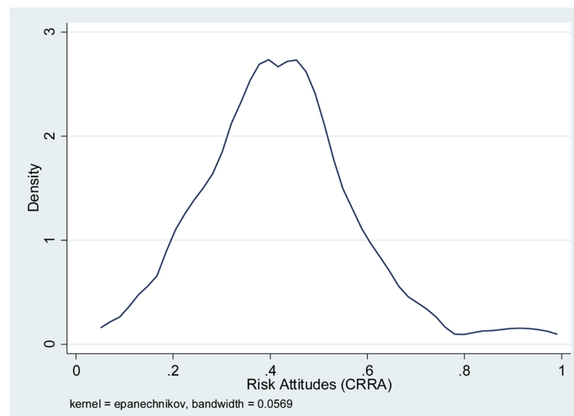

Fig. 7. Kernel Density of Risk Attitudes among Participants.

Since each of the 80 participants made choices on 9 lottery scenarios, the model was estimated over 720 (= 80 × 9) data points. The above model was used to predict the heterogeneity in individual risk attitudes and its impacts on people's behavior within an automated driving environment. The distribution of individual risk attitudes is shown in Fig. 7.

To evaluate the impact of risk attitudes on the outcome variables, the above model was used to predict back the risk attitudes for each user using the standard non-linear prediction command called "predictnl" in STATA. The non-linear prediction provides an estimate of the mean and standard deviation for each individuals' risk attitudes.

It is important to note that the risk attitudes predicted for an individual is a distribution, represented by the mean and standard deviation. Any correlation analysis undertaken should account for this. We use a simulation approach to account for this, for each individual we simulate 1000 points from the distribution of their risk attitudes. These simulated points are then correlated with the variables of interest. In Psychometrics studies, a coefficient from 0.1 to 0.29 is defined to imply a weak correlation, from 0.3 to 0.59 implies a medium correlation, and greater than 0.6 indicates a strong correlation (Psychometric Resource Centre, 2017).

4. Results and discussion

Currently, automated driving is not devoid of risks. Therefore, risk attitudes could play an important role on in reaction times to take control of the vehicle which in turn affects safety, productivity and

Table 7
Descriptive Statistics on Reaction Times.

Driving Task	Label	Obs.	Mean (Sec)	Std. Dev.(Sec)
Task 2	Inexperienced Driving with Certain Failure	71	1.57	0.35
Task 5	Experienced Driving with Certain Failure	71	1.62	0.32
Task 3	Inexperienced Driving under Risk	14[a]	1.58	0.39
Task 4	Experienced Driving under Risk	14[a]	1.46	0.34

[a] The reaction times in Tasks 3 & 4 were observed only during failures that were probabilistic.

acceptability. We study the underlying relationships empirically.

4.1. Reaction times

User's ability to control the vehicle in the event of failure in the automation system is a critical factor in understanding safety in automated vehicles. The reaction time is defined to be the time the user first controls the vehicle after the failure occurs. In the experiment, there were four tasks where reaction times were collected from the participants, i.e. Task 2, Task 3, Task 4 and Task 5. The descriptive statistics of the reaction times are provided in Table 7. Based on a *t*-test, no statistically significant differences were observed in average reaction times across the four driving tasks. Furthermore, no statistically significant impact of incentives and failure probabilities were found on the reaction times.

Risk averse individuals are expected to be more attentive and therefore are more likely to react quicker. A comparison of the relationship between reaction times and risk attitudes for certain failures and probabilistic failures are shown in Fig. 8.

A careful consideration of the figure reveals that in the case of inexperienced driving with probabilistic failure (Tasks 3) there is a negative correlation, while in the case of certain failure (i.e. Tasks 2 & 5) no underlying correlation was found. More specifically, the correlation coefficients between risk attitudes and reaction times in Tasks 2 and 5 with certain failure are 0.11 and -0.19 respectively, indicating risk attitudes do not have a significant impact on reaction times.

The negative correlation between risk attitudes and reaction times are more pronounced when system failure is uncertain to the drivers (-0.39 in Task 3), but such correlation again drops to minor once participants get experience of driving under risk (-0.04 in Task 4). However, a sensitivity testing based on removing the three outliers that occur when the coefficient of risk aversion r is greater than 0.66, increases these correlations to 0.67 and 0.41 for inexperienced and experienced automated driving respectively. This is shown in Table 8. This result highlight that risk averse people are quicker in their reaction times. Once they get familiar with driving autonomous vehicle under risk, this correlation between reaction times and risk attitudes reduce.

Table 8
Sensitivity analysis on correlations between reaction times and risk attitudes.

Reaction times	ra	ra < 0.66
Inexperienced driving task under risk	−0.39*	−0.67*
Experienced driving task under risk	−0.043	−0.41*
Overall	−0.28*	−0.59*

*indicates statistical significance at 95% confidence interval.

4.2. Acceptability

Drivers' acceptability towards autonomous vehicle dictates how quickly they are likely to trust and engage the automation system. Acceptability of automation is measured by the time taken to first switch on the automation system, where acceptability for automation is inferred to be higher if they start the automation system faster. Table 9 presents the summary of the first switch on time of the four tasks. Though on average Tasks 2 and 3 have much longer average starting times, they also have the higher standard deviations, which could be attributed to inexperience. The *t*-test results of the comparison between Tasks 2 and 5, as well as Tasks 3 and 4 are 6.06 and 3.39 respectively, showing significant differences were found in the time to engage the automation between experienced and inexperienced scenarios.

A careful analysis of the correlations between the times of fist engagement between all the tasks are shown in Table 10. Except for the case between Task 2 and Tasks 3–5, as well as Task 4 and Task 5, there were no statistically significant correlation were observed. This suggests the existence of some underlying systematic factors that could explain these strong correlations.

Individuals were also asked about their perception of automated vehicle safety, to which they could answer that it was safe for all, safe for the occupant, safe for other road users and don't know. A further

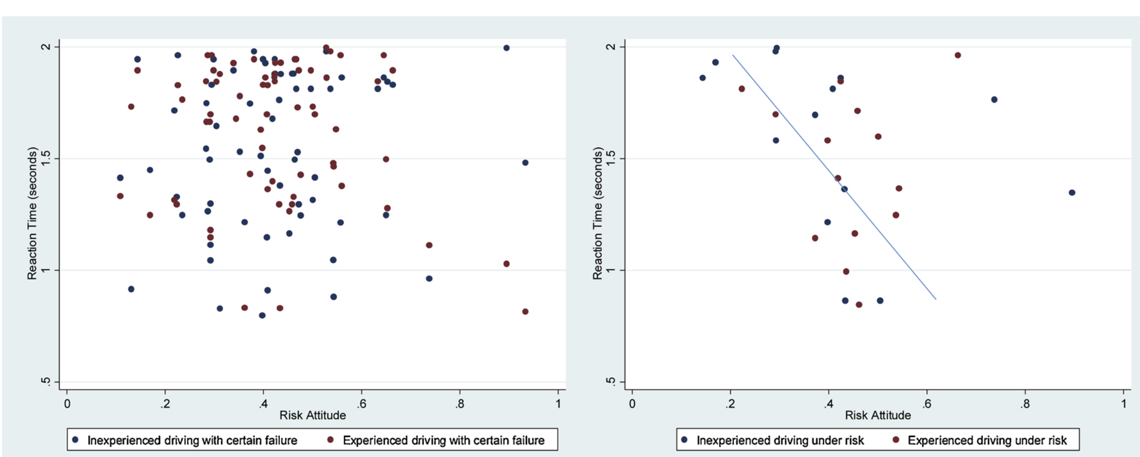

Fig. 8. Relationship of Reaction Times with Risk Attitudes.
A comparison between Certain Failure (Task 2&5) vs. Probabilistic Failure (Task 3&4).

Table 9
Summary of First Time to Engage in Tasks.2–5.

First time to engage (seconds)	Mean	Std. Dev.	Min	Max
Task 2	294.730	84.011	197.390	623.275
Task 3	299.322	143.386	195.318	740.582
Task 4	242.711	32.538	188.645	332.580
Task 5	234.406	34.506	164.082	370.597

Table 10
Correlations in first time to engage in Task.2–5.

First time to engage	Task 2	Task 3	Task 4	Task5
Task 2	1			
Task 3	0.6796*	1		
Task 4	0.3883*	0.1736	1	
Task 5	0.2447*	0.0854	0.6454*	1

*indicates statistical significance at 95% confidence interval.

Table 11
Correlations in first time to engage with risk attitudes and perceptions.

First time to engage	Risk attitudes	Risk attitudes and not knowing (24)
Task 2	0.05	0.35*
Task 3	−0.08	0.31*
Task 4	−0.04	0.25
Task 5	0.05	0.37*

*indicates statistical significance at 95% confidence interval.

analysis exploring the impact of the risk attitudes shows no significant impact on its own on the first time to engage (Table 11). However, individuals who did not know what the safety impact of automated vehicles (24 participants) were found to have a medium positive correlation between risk aversion and the time to first engage the automated functionality (Table 11). That is, risk averse individuals who were unable to assess the safety of automated vehicles took longer to engage the automated driving. This clearly demonstrates that perceived ambiguity had significant impact on engaging the automated driving functionality.

4.3. Productivity

One of the key drivers for automated vehicles is the possibility of increasing productivity. When automation system takes over the driving, drivers are free to engage in non-driving tasks that can contribute to activities related to labor and leisure. Productivity is measured as the amount of a secondary task an individual will undertake.

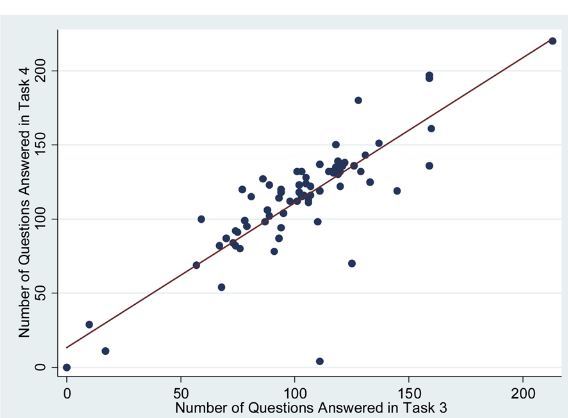

Fig. 9. Number of Shape Matching Questions Attempted in Task 4 and Task 3.

Table 12
Correlations Between Age and Risk Attitudes.

Variables	# Shapes in Task 3	# Shapes in Task 4
Age	−0.35*	−0.32*
Risk Attitudes	−0.31*	−0.30*

*indicates statistical significance at 95% confidence interval.

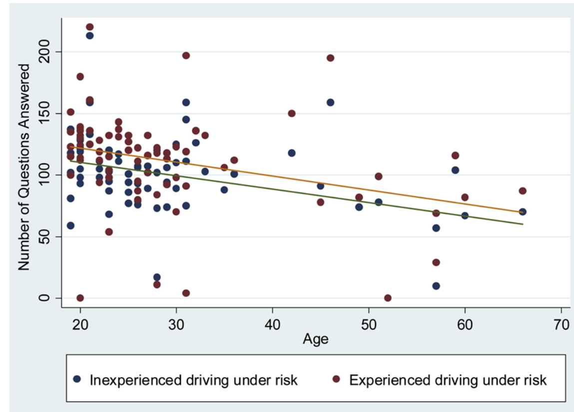

Fig. 10. Relationship between Age and Productivity.

As described in Section 2 on experimental protocols, participants could engage in an incentivized shape matching activity in Tasks 3 and 4. Fig. 9 plots the number of questions answered in Task 3 and Task 4. A strong positive correlation of 0.86 was observed. This suggests that there are underlying factors that are influencing the ability to be engaged in secondary tasks.

A correlation analysis reveals that age and risk attitudes play an important role in productivity during automated driving. Risk averse individuals were found to be less productive in both driving tasks under risk. The correlations are presented in Table 12. Driver's age was found to be negatively correlated with productivity, shown in Fig. 10. This indicates that younger individuals are more likely to complete secondary tasks. This confirms that age has a negative impact on productivity.

As observed in Table 10, risk attitudes were found to have a medium negative correlation in both Tasks 3 and 4. This hypothesis is confirmed by Fig. 11, which shows that risk-averse individuals have lower productivity. In summary, risk averse individuals and older individuals are less likely to be productive in other tasks in an automated vehicle.

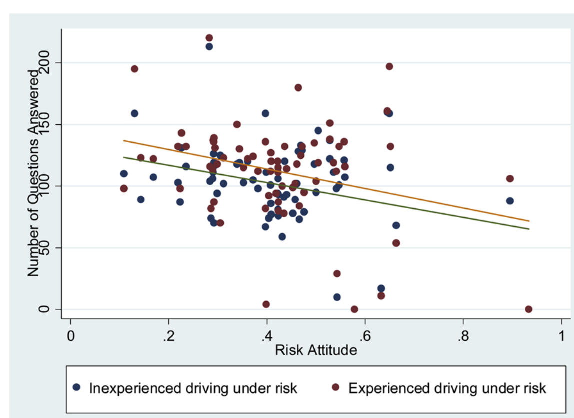

Fig. 11. Relationship Between Productivity and Risk attitudes.

Table 13
Relationships Observed in this Study.

	Reaction Times in Certain Failure	Reaction Times in Probabilistic Failure	Productivity under Probabilistic Risk	Acceptability
Risk Aversion	≈	Medium $^{-}$ (− 0.39)	Medium $^{-}$ (− 0.31)	≈
Risk Aversion and not knowing safety impact of automated vehicles	•	•	•	Medium +(0.32)
Experience	≈	≈	High + (+ 0.86)	Low $^{-}$(-0.26)
Age	≈	≈	Medium $^{-}$ (− 0.34)	≈

*A +, $^{-}$ and ≈ indicates a positive, negative and no correlation between factors and observed behavior respectively. Low degree of correlation is defined to have correlation coefficient between 0 and ± 0.29, medium degree of correlation is between ± 0.3 and ± 0.49, and high degree of correlation is between ± 0.5 and ± 1.

5. Conclusion

The trials and introduction of automated vehicles has accelerated, and is anticipated to have significant impact on safety and productivity. However, there is currently very limited understanding on the implication of demographics and preferences on automated vehicle safety and productivity.

Age was another important factor found to have a significant negative impact on productivity. As age becomes larger, individuals were found to be less productive. This suggests that older individuals might be more involved in evaluating the performance of the automated driving.

Risk averse individuals who were unable to assess the safety of automated vehicles took longer to engage the automated driving. This implies that perceived ambiguity had significant detrimental impact on time required to engage the automated driving functionality.

The findings and relationships shown in Table 13, between risk attitudes and age with acceptability, reaction times and productivity could have a significant impact on insurance, licensing, vehicle design, regulations and planning for a safe, efficient and productive advent of automated vehicles. For instance, insurance companies should evaluate customers' risk attitudes based on their personal information, and then determine the optimal pricing for each individual. Vehicle design companies should take into consideration the heterogeneity in reaction times when designing warning systems. Transport authorities should also evaluate drivers' risk attitudes before approving autonomous vehicle licenses. This study provides the starting point to inspire governments, transport authorities, and autonomous vehicle industry to consider risk attitudes when making regulations, designs and strategies.

This study utilized data collected from 71 valid subjects in the driving simulator, this is by far larger than any published studies on automated driving using driving simulator or actual field trials. However, we do believe that this study needs to be replicated to provide robust evidence, as well as, further experiments with more participants from various socio-demographic backgrounds would also provide more robust insights.

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