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A Path towards Sustainable Vehicle Automation: Willingness to Engage in Level 3 Automated Driving

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Abstract: This paper describes a driving simulator study exploring driver willingness to engage in automated driving. The study aimed to explore factors that may influence willingness to engage (WTE) in automated driving and willingness to resume control (WTRC) in Level 3 automated vehicles during everyday driving. Automated driving is an emerging technology that promises a range of benefits. The first step towards sustainable automated driving is the successful introduction of Level 3 automated vehicles. This study investigates key factors that influence the driver's willingness to engage in automated driving in a Level 3 automated vehicle. A purpose-built driving simulator was used. Forty participants were exposed to driving situations of differing complexity in both manual and automated driving modes, and their willingness to engage or disengage automated driving and perception of safety were recorded. Results demonstrated a strong negative effect of perceived situation complexity on willingness to engage in automated driving. Other significant factors that determine drivers' willingness to engage in automated driving were trust in automation and driving enjoyment. The identification of perceived situation complexity as a significant factor in drivers' willingness to engage the automated driving vehicle control mode was the major finding of this research. This finding suggests that it is possible to improve the rate of uptake and sustainability of automated driving with external interventions (technological, regulatory and publicity).

Keywords: vehicle automation; situation complexity; willingness to engage; perceived safety; simulation

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1. Introduction

Driving is a very complex activity. A wide range of skills and abilities are required for safe driving [1], often while conditions are not ideal. It is not always the case that the driver is trained, experienced, rested, well-behaving and free of distractions. Moreover, there are other participants in the traffic system with their own imperfections. Interactions between traffic entities are many, not always predictable, and require a long time to learn and master. The number of vehicles on the roads is continuously increasing, making driving even more complex [2,3].

In addition to increasing traffic density, drivers are subjected to the introduction of new information, communication and entertainment technologies inside the vehicle. As a result of these trends, the driving task has increased in complexity and faces new challenges [4]. Problems with a surge of in-vehicle information technologies relate to the introduction of secondary tasks that compete with the primary driving task, potentially causing excessive workload and distraction [5,6]. An increase in the mature-age driving population in developed countries also represents a problem as they are particularly susceptible to an increase in driving task complexity. Loss of cognitive and physical abilities occurs in this group which, in the desire to maintain independence, continues to engage in driving despite being more prone to accidents [7]. Deaths of road users older than 65 years increased by 2.2% annually over the last decade in Australia [8].

It can be concluded that the development of automated cars promises new hope for traffic safety. However, it also raises important research questions about human factors regarding the acceptability of that technology, sustainability, driver trust, intentions of use, ease of use, and even optimisation of the human–machine interface [9–11]. Despite such concerns, it is generally accepted that the social benefits of automated vehicles will outweigh likely disadvantages as part of a sustainable transport system [12].

The Society of Automotive Engineers (SAE) developed a taxonomy that identifies different levels of vehicle automation [13], which has been widely accepted in the literature. The levels identified range from 0 (no automation) to 5 (full automation). The current level that is commercially available is considered to be 2 (driver assistance).

Early deployment predictions for Level 3 automation (referred to as conditional automation) have proven to be overly optimistic, suggesting the issue is more complex than previously assumed. It has been proposed that highly automated vehicles be allowed on roads once they are judged to be safer than an average human driver [14]. However, the more realistic scenario is that the safety benefits of automated vehicles will need to be supported by evidence as being significantly safer. It is predicted that until automated vehicles (AVs) are completely reliable and safe under all conditions, the human driver will remain responsible for safe driving [15]. Legal prerequisites, precise geolocation/map data, robust monitoring of the driver's state for handing over control, connectivity between vehicles, road users and infrastructure, and the optimal interaction between automated and non-automated vehicles were identified as "major enablers for the safe and efficient operation of automated transport" [16] (p. 3).

Level 3 vehicle automation is on the verge of becoming mainstream from a technological point of view. As it continues to develop and becomes more accessible, it may follow the path of the Anti-lock Braking System (ABS) [17] and Electronic Stability Control (ESC) [18], which became mandatory in 2003 and 2013, respectively, for all new cars sold in Australia, after the effectiveness of these technologies was demonstrated on roads [19–25].

Therefore, this research was conducted under the assumption that, in the foreseeable future, all new vehicles would have Level 3 automation capability, mostly because this technology would become an affordable part of the standard vehicle kit. Under this scenario, all drivers of new vehicles would be able to choose vehicle control mode, even if vehicle automation was not an important feature for some drivers. There is still a significant gap between the available level of automated driving technology and current regulations, which prevent the legalisation of Level 3 automated vehicles. Crossing this final hurdle requires a better understanding of how automated vehicles will be used, and identifying all possible issues and problems with it. This research aimed to contribute to that knowledge.

Some of the commonly researched topics related to automated vehicles are the transfer of control, benefits and disadvantages of AVs, and behavioural adaptation to AVs [26]. The literature search identified a lack of simulator-based studies that exposed drivers to Level 3 AVs and that investigated issues associated with everyday driving. In particular, there is a lack of research on the factors that influence a driver's use of vehicle automation.

Therefore, this study aimed to explore factors that may influence willingness to engage (WTE) in automated driving and willingness to resume control (WTRC) in Level 3 AVs during daily, non-critical driving. Results of previous research suggest that more demanding driving situations are likely to be associated with higher WTRC and lower WTE. Situation complexity, traffic density and driving speed were identified as some of the factors affecting the difficulty of the driving task [27], and were utilised in the current study to manipulate driving complexity.

This study exposed participants to a variety of situations that represented different levels of driving task demands. Three external factors from the range of factors that influence WTE, as identified by the adapted theoretical framework and findings from previous research, were found to be suitable for manipulation in experimental scenarios and selected as the independent variables for the study. They were: driving mode, situation complexity and driving speed.

The driving mode represented two experimental conditions, manual driving and automated driving. Two distinctive levels of situation complexity (SC) were selected, low SC and high SC. These levels were presented in the form of five events in the simulator drive. One event represented low complexity and the other four high complexity. The Free (free driving) event was selected to represent a low-complexity condition as driving task demands were minimal. The free driving situation can be defined by having the free choice of lane, velocity is not affected by other cars, and there is comfortable time headway [28]. Four events were selected to represent high SC in the study: rain and fog (RF), oncoming car (OC), give way (GW), and vehicle following (VF). These four high-complexity events represented a wide variety of situations instead of relying on different levels of complexity of a single event. However, each of these four events made the driving task more demanding in comparison with the low-complexity event. The GW event forced the participant (driver) to make a gap-acceptance decision at an unsignalised intersection. The driver had to decide when to enter the intersection as there were multiple opportunities presented. The VF event aimed to expose participants to a borderline short time headway situation and therefore increased driving task demands. A mean threshold between risky and comfortable time headway (TH) in simulated driving was found to be between 1.5 and 2.0 s [29]. Therefore, TH was set to 1.5 s to increase the driver's perception of risk without making the driving task appear unrealistic. The RF event aimed to expose the driver to low visibility and deteriorated driving conditions. Fog is recognised as one of the most dangerous conditions for drivers, and several studies confirm that such conditions contributed to the increase in driving task demands [30,31]. Finally, the purpose of the OC event was to expose participants to a latent hazard that never materialised. Latent hazards are traffic situations that experienced and alert drivers recognise as situations that have a high likelihood to develop into acute threatening situations, despite their harmless appearance at first sight [32]. The driver faced a potentially safety-critical event in which the oncoming vehicle signalised the intention to overtake, despite safe overtaking not being possible in the current situation. The third independent variable was speed, where higher driving speed was associated with an increase in driving task demands.

Two dependent variables were measured: (1) WTE observed during manual drives or WTRC observed during automated drives; and (2) perception of safety (POS) during all drives. Both dependent variables were subjective and self-reported with a questionnaire. Based on the reviewed literature the following hypotheses were formulated:

- An increase in SC has a negative effect on WTE and a positive effect on WTRC;
- An increase in SC has a negative effect on POS;
- Higher POS is negatively associated with WTE and positively associated with WTRC.

This paper first presents the methods used, then outlines the results and discusses the findings.

2. Materials and Methods

This section describes the methodology used and the experimental design of the driving simulator study. The study used a 2 × 2 × 2 factorial design (Table 1). The independent variables were speed (low/high), driving mode (manual/automated) and SC (low/high). Dependent variables were WTE or WTRC and POS.

Table 1. Independent variables and conditions.

Factors (IVs)	Conditions
Speed	Low/High
Driving mode	Manual/Automated
Situation complexity	Low/High

The experiment used the simulation freeze technique. During each freeze of the simulation, participants were asked to complete a questionnaire item. The use of this technique has been reported in several simulation studies, such as the measurement of situation awareness during the takeover performance in automation [33] and the use of an adaptive cruise control system [34]. Although simulation freeze was somewhat artificial [35], task performance is not affected by the number and duration of freezes [33].

Forty participants were involved in the study: 30 males and 10 females, ranging in age from 18 to 79 years, with a mean age of 40.35 years and a standard deviation of 16.26 years. The mean number of years of driving experience was 21.55 with a standard deviation of 16.15 years. Participants were recruited from Monash University (undergraduate students, post-graduate students and staff), outside the university using personal contacts, the Monash University Accident Research Centre (MUARC) participant database, and advertising on social media. Participants were required to have either a full driver license or a second-year probationary license. They were also required to drive at least 5000 km per year. Apart from the aforementioned criteria, participants were not specifically recruited according to any demographic characteristics or specific attitudes towards automated driving. Participants were offered AUD20.00 each. Ethics approval was obtained from the Monash University Human Research Ethics Committee.

The experimental research was conducted in a purposely built MUARC Automation simulator, which was previously validated for behavioural research examining the human factors of vehicle automation [27]. The simulator consisted of a car seat and standard controls mounted on a rigid frame (Figure 1). The simulated vehicle was equipped with an automatic transmission. Visuals were presented on three 46″ high brightness bezel-less displays. Each display had a resolution of 1080p and the image refresh rate was 60 Hz. The driver and the passenger both had a horizontal field of view of 140° and a vertical field of view of 45°. The sound was presented via left, right and centre satellite speakers and a subwoofer for reproducing low-frequency effects.

Figure 1. Automation driving simulator.

A 10″ tablet was used to administer questionnaires. The tablet was mounted on the right side of the simulator dashboard for easy access.

A conservative driving style was adopted for the presentation of automated drives. This was done to minimise the potential for adverse reactions to automated driving. The experimental scenario itself needed to minimise opportunities for conflicts between the participant's preferred driving style and the automated driving style; for example, avoiding sharp bends or overtaking situations.

Four scenarios were developed. Scenarios 1 and 2 were created in an urban environment with a 50 km/h speed limit. The road had two lanes and three intersections. Scenarios 3 and 4 were created on a highway in a country environment with a speed limit of 90 km/h.

This speed limit was chosen as the highest speed limit allowed on highways in Victoria, Australia. Each drive lasted approximately seven minutes. During each drive, participants were exposed to five distinctive events. The events were one low-complexity event (Free) and four high-complexity events (GW, RF, OC and VF). A schematic showing the order of events on a 50 km/h road is shown in Figure 2 and the order of events on a 90 km road in Figure 3.

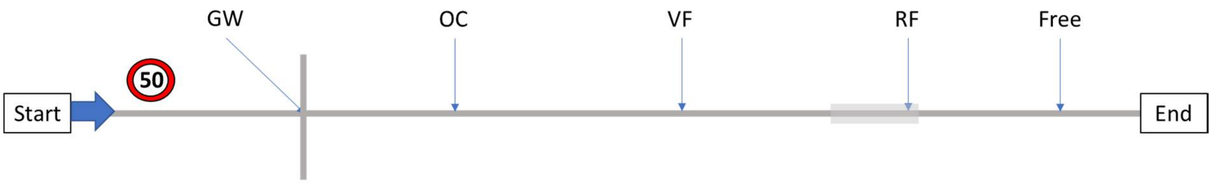


Figure 2. Events in 50 km/h drives.

Figure 3. Events in 90 km/h drive.

Two drives were presented in manual driving mode (Scenarios 1 and 3) and two in automated driving mode (Scenarios 2 and 4). During manual drives, participants were required to control car speed and steering. In automated mode, participants were free of the physical component of the driving task. All experimental scenarios with associated conditions and order of events are presented in Table 2. Scenarios were presented in counterbalanced order.

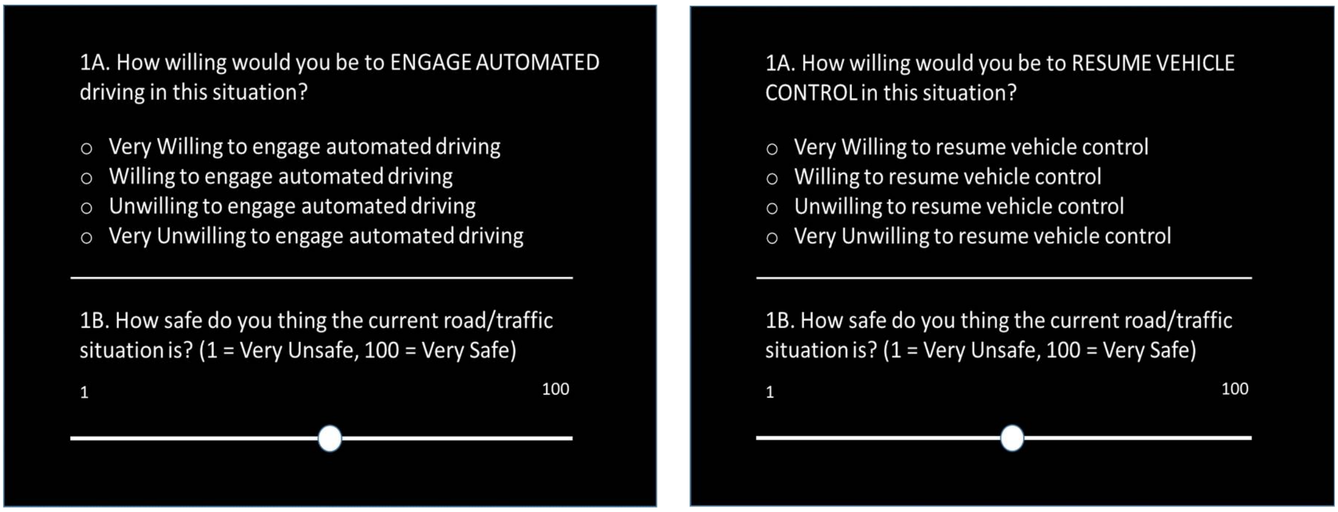
Table 2. Study experimental scenarios.

Scenario	Speed Limit	Control Mode	Event 1	Event 2	Event 3	Event 4	Event 5
1	50 km/h	Manual	GW	OC	VF	RF	Free
2	50 km/h	Automated	GW	OC	VF	RF	Free
3	90 km/h	Manual	RF	Free	VF	OC	GW
4	90 km/h	Automated	RF	Free	VF	OC	GW

Each event contained a question point. At pre-determined locations within each event, the simulation would freeze for 10 s, manifesting as a sudden stop in travel, absence of car engine sound and a still speedometer. Figure 4 illustrates the frozen simulator drive during the RF event. During each simulation freeze, participants entered their ratings for WTE or WTRC and POS. After 10 s, the simulation would continue until the following event until all five events had been presented and ratings entered.

Each question point had two parts. Part A of the question required the participant to rate WTE during manual driving (Figure 5a) or WTRC during automated driving (Figure 5b). Ratings were provided on a four-point scale (1 = Very unwilling, 2 = Unwilling, 3 = Willing, 4 = Very Willing). Part B of the question rated POS of the current situation. The POS score was entered using a sliding scale, ranging from 1 for very unsafe to 100 for very safe.

Figure 4. An example of a question point (RF event).



(**a**) (**b**)

Figure 5. Example of questions: (**a**) manual drive (WTE and POS); (**b**) automated drive (WTRC and POS).

Before the simulator drives, participants were given a brief introduction to automated vehicles explaining different levels of vehicle automation, with an emphasis on Level 3 automation and choice of control mode since they would be experiencing Level 3 automated driving in the simulator. Participants were then presented with a definition of willingness and an explanation of an experimental task. They were instructed that Level 3 automation was capable of handling all situations during the experimental drives, but they had to be alert if there was a takeover request. Following practice drives, four experimental scenarios were presented in a counterbalanced order. During each drive, participants were instructed to observe road and traffic conditions. At each question point, participants would enter their ratings for WTE (during manual drives) or WTRC (during automated drives) and POS. Thereafter, each drive was completed.

3. Results

This section presents statistical models developed for the investigation of hypotheses outlined in the Introduction section.

3.1. Willingness to Engage Automated Control and Willingness to Resume Manual Control

The effects of experimental conditions on WTE/WTRC were analysed using the generalised estimating equation (GEE) method. The unstructured working correlated matrix was selected. For modelling the dependent variable, the ordinal logit model and cumulative logit link function were selected. The independent variables were speed (50 km/h and 90 km/h), and situation complexity (low and high). As the questions were different across manual and automated drives, two full factorial models, one for WTE and one for WTRC, were specified to allow examination of all possible main and interaction effects. All non-significant effects were removed from the model one at a time until only those effects that were significant at $p \leq 0.05$ remained. For each model, a table containing the parameter estimates (B coefficients) for the significant main effect of the level of complexity is provided. Also provided are the standard error of B, the confidence intervals (CI) of the Wald chi-square, the Wald chi-square value, whether the parameter attained significance, the exponential value of B (that is, the relative odds ratio), and the 95% confidence intervals for the relative odds ratio.

3.1.1. WTE Model

The final GEE model for WTE, observed during manual drives, was made up only of a significant main effect of the level of complexity ($\chi^2(4) = 34.50$, $p < 0.001$). There was no statistically significant effect of speed on WTE. The parameter estimates (B coefficients) for the significant main effect of level of complexity are provided in Table 3.

Table 3. WTE model parameter estimates.

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	df	Sig.		Lower	Upper
Event						
VF	9.507	1	0.002	0.439	0.260	0.741
RF	18.495	1	0.000	0.246	0.130	0.467
OC	27.390	1	0.000	0.147	0.072	0.301
GW	10.224	1	0.001	0.285	0.132	0.615
Free	.	.	.	1	.	.

These tests compared WTE ratings at the low-complexity event (Free) with WTE ratings at high-complexity events and WTE ratings at two different speeds. The results confirmed that WTE at the low-complexity event was statistically significantly different from POS at high-complexity events. The examination of Table 3 revealed that WTE for each high-complexity event was significantly reduced when compared with the Free event. Therefore, participants were significantly less willing to engage in automated driving during high-complexity events. The comparison of mean WTE scores is illustrated in Figure 6. To enable calculation of means, each WTRC category was assigned a value as follows: 1 for very unwilling, 2 for unwilling, 3 for willing and 4 for very willing.

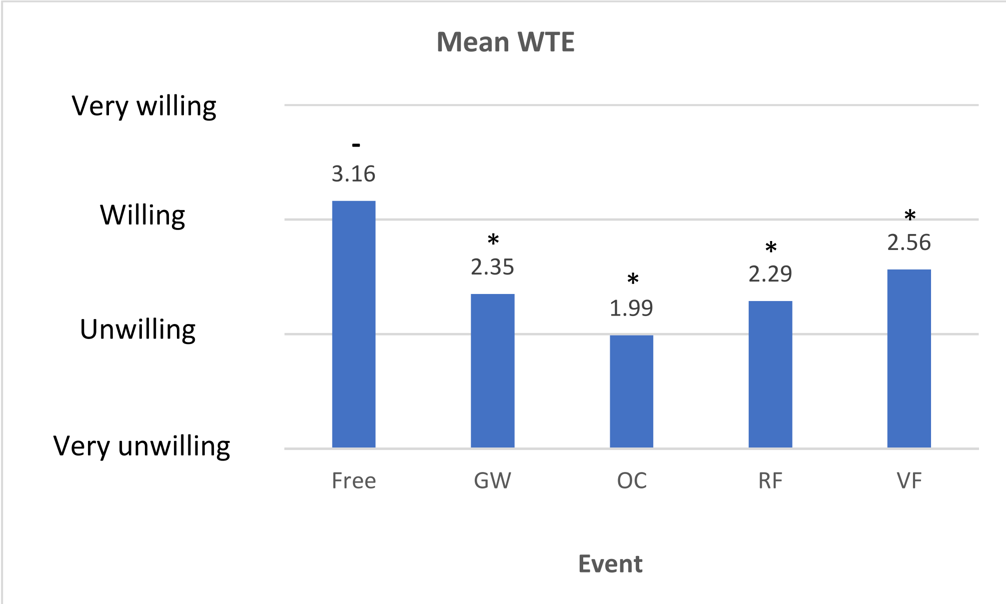


Figure 6. Mean WTE scores (* $p < 0.05$).

3.1.2. WTRC Model

The final GEE model for WTRC, observed during automated driving, was made up of a significant main effect of the level of complexity ($\chi^2(4) = 58.36$, $p < 0.001$) and a significant main effect of speed ($\chi^2(1) = 5.16$, $p = 0.023$). The WTRC model parameter estimates (B coefficients) for the significant main effects are provided in Table 4.

Table 4. WTRC model parameter estimates for event (SC) and speed.

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	Df	Sig.		Lower	Upper
Event						
VF	14.162	1	0.000	2.090	1.424	3.067
RF	34.271	1	0.000	6.227	3.376	11.486
OC	43.271	1	0.000	9.357	4.806	18.216
GW	32.164	1	0.000	5.106	2.907	8.970
Free				1		
Speed						
90 km/h	5.162	1	0.023	1.376	1.045	1.811
50 km/h				1		

An examination of Table 4 reveals that WTRC for each high-complexity event was significantly increased when compared with the Free event. Parameter estimates confirmed that WTRC at the low-complexity event was statistically significantly different from WTRC at every high-complexity event and significantly different between the two driving speed categories. In summary, participants were significantly more willing to resume manual control of the vehicle during high-complexity events and at a higher speed. The comparison of mean WTRC scores is illustrated in Figure 7.

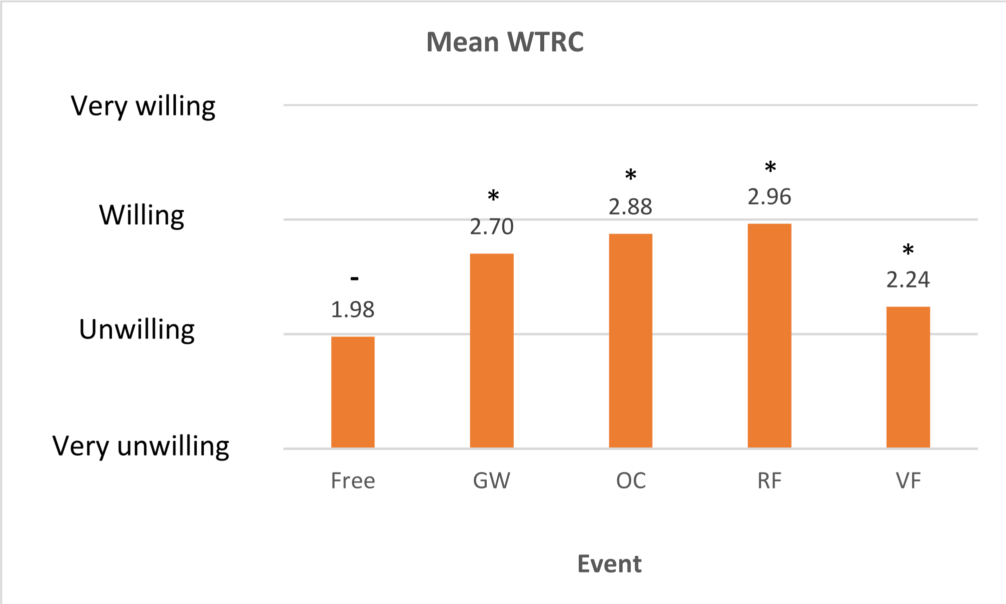


Figure 7. Mean WTRC scores (* $p < 0.05$).

3.2. Perception of Safety

The effects of experimental conditions on POS were analysed using the GEE model. The unstructured working correlated matrix was selected. For modelling the dependent variable, the linear model and identity link function was selected. The independent variables were speed (50 km/h and 90 km/h), driving mode (manual and automated) and situation complexity (low-complexity and high-complexity events). A full factorial model was specified to allow examination of all possible main and interaction effects, and non-significant effects were removed from the model one at a time until only those effects that were significant at $p \leq 0.05$ remained in the model. The final GEE model was made up of four significant effects: the main effect of situation complexity ($\chi^2(4) = 175.07$, $p < 0.001$), whereby POS for the low-complexity event was statistically significantly higher than POS for the high-complexity events; the main effect of driving mode ($\chi^2(1) = 5.15$, $p = 0.023$); and two significant interaction effects. The first interaction was between speed and situation complexity ($\chi^2(5) = 14.07$, $p = 0.015$) and the second interaction was between driving mode and situation complexity ($\chi^2(4) = 12.37$, $p < 0.015$).

The parameter estimates (B coefficients) for the significant main effect of levels of complexity and two statistically significant interactions are provided in Table 5. For each parameter, also provided are the B coefficient, the standard error of B, the 95% confidence intervals for the coefficients, the Wald chi-square value and whether the parameter attained significance.

Table 5. POS model parameter estimates.

Parameter	B	SE	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
Event							
VF	−13.846	2.420	−18.590	−9.102	32.722	1	0.000
RF	−40.279	2.999	−46.158	−34.399	180.277	1	0.000
OC	−32.255	3.287	−38.699	−25.811	96.242	1	0.000
GW	−19.922	3.179	−26.155	−13.690	39.249	1	0.000
Free	0	.	.	.	.	.	.
Driving mode							
Automated	2.885	1.247	0.440	5.331	5.347	1	0.021
Manual	0	.	.	.	.	.	.

Table 5. *Cont.*

Parameter	B	SE	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
Speed*Event							
90 km/h*VF	2.089	2.460	−2.733	6.911	0.721	1	0.396
50 km/h*VF	0	.	.	.	.	.	.
90 km/h*RF	−3.464	2.273	−7.920	0.992	2.322	1	0.128
50 km/h*RF	0	.	.	.	.	.	.
90 km/h*OC	−4.059	2.110	−8.195	0.076	3.701	1	0.054
50 km/h*OC	0	.	.	.	.	.	.
90 km/h*GW	1.784	2.359	−2.841	6.410	0.572	1	0.450
50 km/h*GW	0	.	.	.	.	.	.
90 km/h*Free	−5.487	2.728	−10.835	−0.139	4.043	1	0.044
50 km/h*Free	0	.	.	.	.	.	.
Driving mode*Event							
Automated*VF	10.749	3.453	3.981	17.517	9.689	1	0.002
Manual*VF	0	.	.	.	.	.	.
Automated*RF	1.727	3.163	−4.474	7.927	0.298	1	0.585
Manual*RF	0	.	.	.	.	.	.
Automated*OC	2.359	3.087	−3.692	8.409	0.584	1	0.445
Manual*OC	0	.	.	.	.	.	.
Automated*GW	6.187	3.292	−0.266	12.641	3.532	1	0.060
Manual*GW	0	.	.	.	.	.	.
Automated*Free	0	.	.	.	.	.	.
Manual*Free	0	.	.	.	.	.	.

3.2.1. The Main Effect of SC on POS

Results revealed that there was a statistically significant difference in POS ratings between the low-complexity event and each of the high-complexity events. Estimated marginal means of POS for each event, sorted in descending order, are illustrated in Figure 8. The POS score for the Free event was the highest, whereas the POS score for the RF event was the lowest. The model predicted a difference of 40 rating points between the POS score at the Free event and the POS score at the RF event.

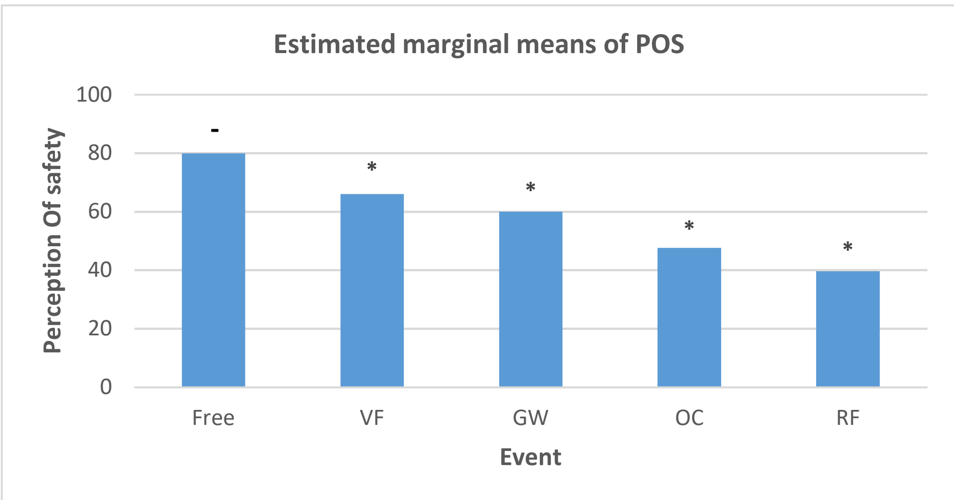


Figure 8. Estimated marginal means of POS for each event (* $p < 0.05$).

3.2.2. The Main Effect of Driving Mode on the Perception of Safety

The test compared POS in manual drives with POS in automated drives. The model suggested that predicted POS during automated driving was higher by 2.885 rating points compared to POS during manual driving. Although statistically significant, the difference between observed POS was not large.

3.2.3. Interaction Effect of Speed and Situation Complexity

Examination of parameter estimates (B coefficients) for the significant interaction effect of event*speed revealed that the statistically significant interaction of speed and SC was observed only for the Free event, and a marginally significant interaction was observed for the OC event. Estimated marginal means of POS for each event are illustrated in Figure 9.

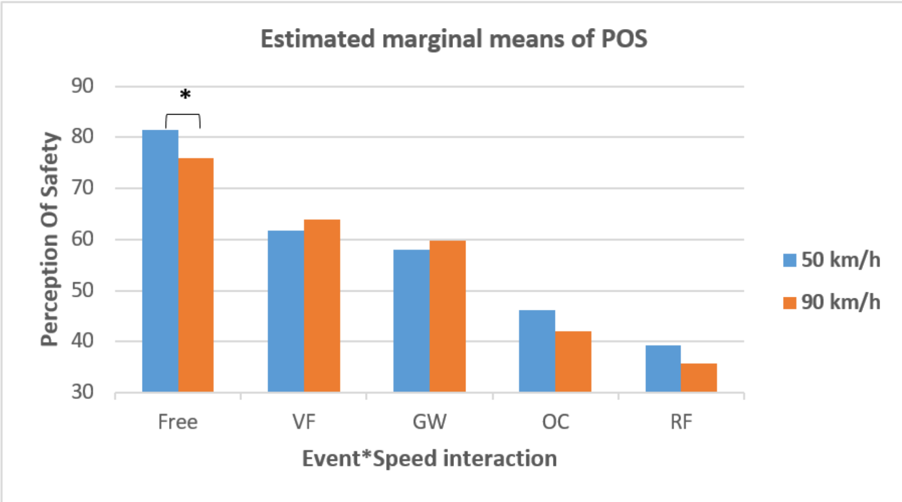


Figure 9. Estimated marginal means of POS for the interaction of event (SC) and speed (* $p < 0.05$).

3.2.4. Interaction Effect of Driving Mode and Situation Complexity

Examination of parameter estimates for this interaction of driving mode and SC revealed a significant effect of driving mode on POS for the VF event and a marginally significant effect of driving mode for the GW event. Estimated marginal means of POS for each event are illustrated in Figure 10. For both the VF event and the GW event, the estimated POS was higher in automated driving mode.

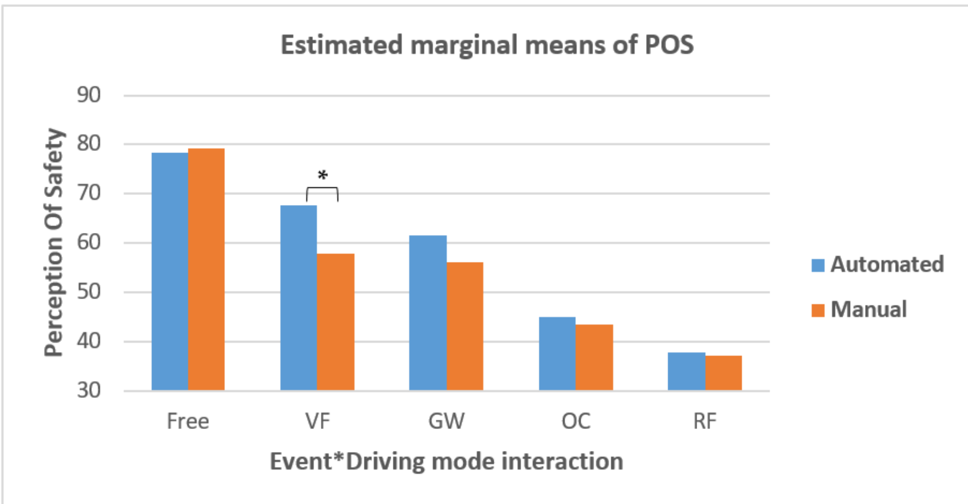


Figure 10. Estimated marginal means of POS for the interaction of event (SC) and driving mode (* $p < 0.05$).

3.3. Preference of Vehicle Control Mode

The preferred vehicle control mode is a variable derived from WTE and WTRC ratings. It allowed two separate datasets to be combined and, therefore, investigation of the effect of driving mode across both driving conditions. The new dependent variable (preference) was calculated according to the rules presented in Table 6. The logic behind these rules was that, if the driver in a current driving mode was very unwilling to change the driving mode, then a strong preference for the current driving mode was assigned to the new variable; conversely, if the driver was very willing to change the driving mode, a strong preference for the alternate driving mode was assigned to the new variable.

Table 6. Rules for calculating the preference of vehicle control mode.

Level of WTE/WTRC	Driving Mode	Preference of Vehicle Control Mode
Very unwilling (WTRC)	Automated	2 (Strong automated)
Unwilling (WTRC)	Automated	1 (Automated)
Willing (WTRC)	Automated	−1 (Manual)
Very willing (WTRC)	Automated	−2 (Strong manual)
Very unwilling (WTE)	Manual	−2 (Strong manual)
Unwilling (WTE)	Manual	−1 (Manual)
Willing (WTE)	Manual	1 (Automated)
Very willing (WTE)	Manual	2 (Strong automated)

The overview of proportions of driving mode preferences for all categories and events is illustrated in Figure 11. Each preference level is colour-coded, and counts are presented as percentages of the total number of selections for each category.

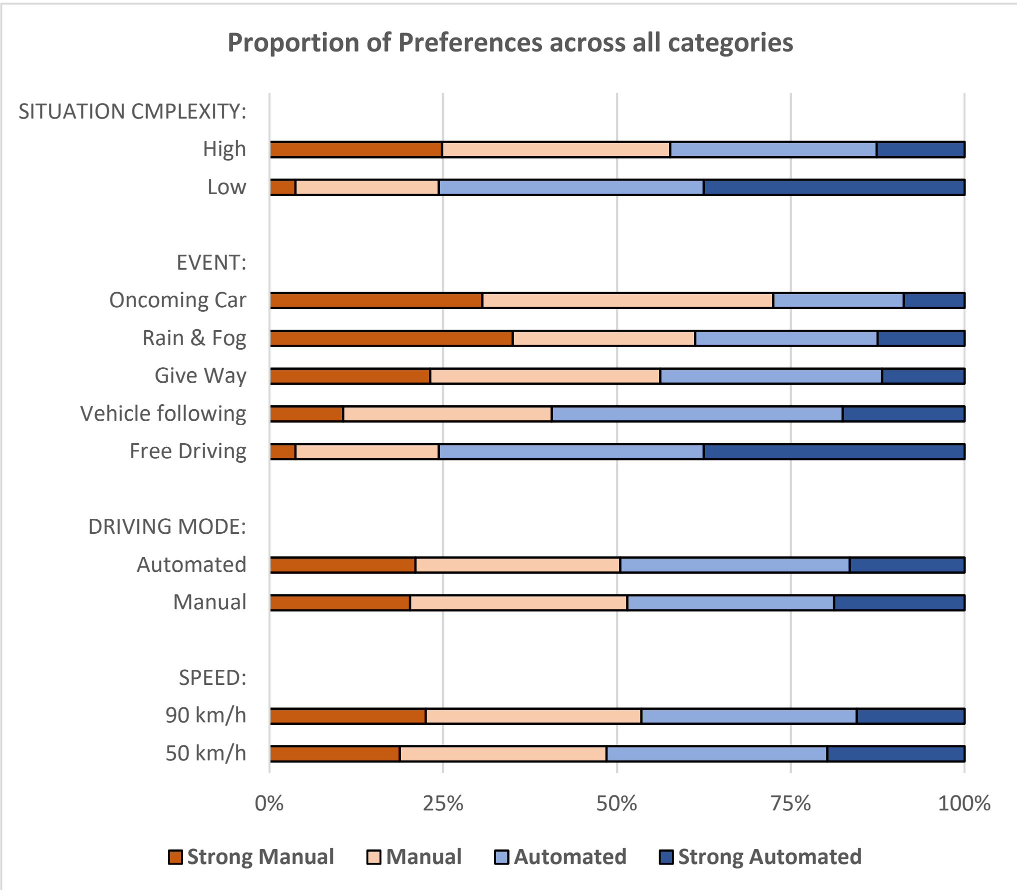


Figure 11. Distribution of the preferred vehicle control mode for each event.

The effects of experimental conditions on the preference of vehicle control mode were analysed using the GEE model. The unstructured working correlated matrix was selected. For modelling the dependent variable, the ordinal logit model and cumulative logit link function were selected. The independent variables were driving mode (manual and automated), speed (50 km/h and 90 km/h), and SC (low and high). A full factorial model was specified to allow examination of all possible main and interaction effects, and non-significant effects were removed from the model until only significant effects ($p \leq 0.05$) remained. The final GEE model for preference of the driving mode was made of a significant main effect for the level of complexity ($\chi^2(4) = 128.46$, $p < 0.001$), speed ($\chi^2(1) = 6.47$, $p = 0.011$), and the interaction effect between driving mode and level of complexity ($\chi^2(5) = 81.10$, $p < 0.001$).

The parameter estimates (B coefficients) for both significant main effects and the interaction effect are provided in Table 7. For each parameter, also provided are the standard error of B, the Wald chi-square value, whether the parameter attained significance, the exponential value of B (that is, the relative odds ratio), and the 95% confidence intervals for the relative odds ratio.

Table 7. Parameter estimates for the preference of the driving mode.

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	df	Sig.		Lower	Upper
Speed						
90 km/h	6.473	1	0.011	0.820	0.703	0.955
50 km/h	.	.	.	1	.	.
Event						
VF	10.184	1	0.001	0.507	0.334	0.770
RF	35.187	1	0.000	0.247	0.155	0.392
OC	109.046	1	0.000	0.125	0.084	0.184
GW	35.248	1	0.000	0.245	0.154	0.390
Free	.	.	.	1	.	.
Event*Mode						
VF*Auto	0.085	1	0.770	1.067	0.690	1.649
VF*Man	.	.	.	1	.	.
RF*Auto	31.207	1	0.000	0.530	0.424	0.662
RF*Man	.	.	.	1	.	.
OC*Auto	22.615	1	0.000	2.213	1.595	3.069
OC*Man	.	.	.	1	.	.
GW*Auto	0.545	1	0.460	1.129	0.818	1.558
GW*Man	.	.	.	1	.	.
Free*Auto	2.139	1	0.144	0.764	0.533	1.096
Free*Man	.	.	.	1	.	.

Driving speed had a small effect on the preferred driving mode, with the odds favouring manual driving mode at a higher speed. The odds of the preference of automated driving mode increased significantly with a higher level of SC. Parameter estimates for interaction between events and driving mode (event $\times$ driving mode) explained the absence of the main effect of driving mode on the preference. Only two interactions of driving mode with event were statistically significant, one with the RF event and the second with the OC event.

Comparison of beta coefficients revealed a crossover interaction which resulted in no overall effect of driving mode on preference. Encountering the RF event in automated driving mode significantly increased the odds of preference for manual control mode, when compared with experiencing the RF event during manual driving. Encountering the OC event in the automated driving mode had the opposite effect. When compared with manual driving, the odds of preference for automated control mode were significantly reduced. In summary, these results confirm the significant effect of complexity, speed and interaction effects of driving mode with two events (RF and OC) on POS.

3.4. Association of POS and WTE/WTRC

The correlation between POS and WTE/WTRC was tested with two GEE models, one for the dataset originating from automated drives and the second dataset from manual drives. In these models, POS outcomes were tested by willingness categories being used as predictors. For each model, the exchangeable working correlated matrix was selected. For modelling the dependent variable (POS), the linear model and identity link function were selected. The independent variables were WTE or WTRC. A main-effect-only model was specified for each dataset.

3.4.1. Effect of WTE on POS during Manual Driving

There was a significant main effect of WTE ($\chi^2(3) = 171.30$, $p < 0.001$) on POS (perception of safety). The model parameter estimates are summarised in Table 8, and indicate significant differences in estimated POS for each level of WTE. Beta coefficients indicate that an increase in the level of WTE is associated with increased POS.

Table 8. Parameter estimates of WTE for POS (manual driving).

Parameter	B	Std. Error	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
WTE							
Very willing	40.655	3.6361	33.529	47.782	125.015	1	0.000
Willing	37.656	3.2938	31.201	44.112	130.701	1	0.000
Unwilling	19.774	3.2534	13.398	26.151	36.943	1	0.000
Very unwilling	0	.	.	.	.	.	.

3.4.2. Effect of WTRC on POS during Automated Driving

There was a significant main effect of WTRC ($\chi^2(3) = 166.21$, $p < 0.001$) on POS. The parameter estimates are summarised in Table 9, and indicate significant differences in estimated POS for each level of WTRC. Beta coefficients indicate that an increase in the level of WTRC is associated with a reduction in POS.

Table 9. Parameter estimates of WTRC for POS (automated driving).

Parameter	B	Std. Error	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
WTRC							
Very willing	−42.971	3.7217	−50.265	−35.677	133.314	1	0.000
Willing	−19.647	3.5343	−26.574	−12.720	30.901	1	0.000
Unwilling	−8.300	3.3700	−14.905	−1.695	6.066	1	0.014
Very unwilling	0	.	.	.	.	.	.

In summary, these results confirmed a strong association between WTE/WTRC and POS. An increase in the level of WTE was associated with increased POS, whereas an increase in the level of WTRC was associated with a reduction in POS. Combined plots of estimated marginal means of POS for levels of WTE and WTRC are presented in Figure 12.

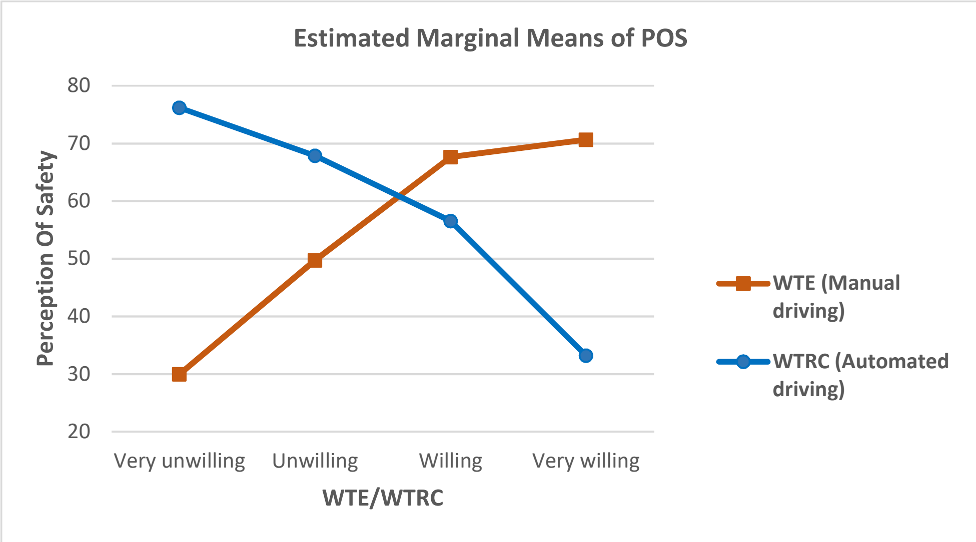


Figure 12. Summary of estimated marginal means of POS for levels of willingness.

4. Discussion

This study examined the key factors that influence drivers' willingness to engage in Level 3 automated vehicles under everyday driving situations. All study hypotheses were supported by the results. The level of SC had a significant effect on both WTE and WTRC. The general effect of an increase in SC on WTE was negative, meaning that drivers were less willing to engage in automated driving in more complex situations, whereas the effect on WTRC was the opposite. Although no other studies that investigated WTE or WTRC in Level 3 automated vehicles were identified, support for these findings can be found in an increased willingness to use Adaptive Cruise Control (ACC) in less complex driving conditions [36].

A significant effect of speed was observed only during automated drives. During automated driving, higher speed (90 km/h) increased the odds of WTRC. This result can be explained by the comparison of driving task workloads during automated driving and manual driving. As discussed previously, the driving simulator was not validated for speed. Deficiencies in the perception of absolute speed and, to a lesser extent, relative speed, may have minimised the effect of the speed difference. It was concluded that, since drivers were relieved of operational vehicle controlling tasks during automated drives, they had more internal resources available [37] and were able to perceive and process the difference between the high speed and the low speed.

A strong effect of SC on POS was observed, with high SC resulting in lower POS. This finding was indirectly supported by the suggestion that feelings of risk can behave as a surrogate for driving task difficulty [38]. Since measurement of safety is often opposite to the measurement of risk [39], it can be concluded that POS decreases with an increase in driving task difficulty. All four high-complexity events recorded significantly lower ratings of POS in comparison with the low-complexity event (Free). A possible correlation/association between SC and POS for individual events was suggested.

The POS during automated driving was higher than that observed during manual driving. The effect was statistically significant although not large. During manual drives, participants had to control a relatively unfamiliar vehicle while compensating for limitations in the simulation visuals. In comparison, during automated drives participants were relieved of these tasks. It may be assumed that automated driving presented lower driving task demands compared to manual driving. Results showed that, for automation-inexperienced drivers, the perceived driving workload was similar for both driving modes. As the majority of participants in the study were automation-inexperienced, it was no surprise that the difference in POS was relatively small. However, the effect was statistically significant, suggesting that the automation was successfully presented as confident, assured, and steady driving in terms of longitudinal and lateral control, resulting in slightly higher POS. A similar observation was made based on a study of effects of ACC, which reported that more homogenous speeds achieved by ACC contributed to better traffic safety [40].

The significant effect of SC on the preference of driving mode was not surprising since the dependent variable was derived from WTE and WTRC, which were both strongly affected by the level of SC. Overall, participants preferred manual vehicle control mode when facing a more complex situation. Interestingly, the preference for manual control was the highest for events that can be classified as less predictable and not completely under the driver's control (OC and RF). Unlike VF and GW events, where the driver perceives enough information about the situation to react, OC and VF events deliver incomplete information sets, forcing the driver to take some risks. This suggests that certainty may play an important role in the preference of vehicle control mode. For example, visibility is reduced in the RF event, denying driver information of what is beyond the visible range. In the OC event, the driver is denied certainty about the overtaking car's intentions.

Moreover, there was a statistically significant increase in the preference for manual driving mode for the high-speed condition. The main effect of the driving mode was not significant; however, several interesting observations were made after examining parameter estimates for the interaction between driving mode and SC for each event. Two of the events, the RF event and the OC event, revealed statistically significant interactions with driving mode. In the case of the RF event, the drivers' preference for manual vehicle control was more likely to be lower when experiencing this event during automated driving compared to experiencing it during manual driving. It was concluded that the majority of participants accepted that the automated system was capable of handling on-road conditions. During the RF event, the automated system maintained the same speed under the assumption that functional AV would be equipped with a range of sensors capable of "seeing and feeling" the road better than human drivers. For example, thermal imaging has the potential to penetrate fog further than visible light cameras [41], in addition to other sensors (e.g., road friction sensor) and technologies (e.g., near-field communication) that might be employed in future automated vehicles. This example emphasised the importance of training and exposure to the use of automated driving.

An even stronger effect of driving mode was observed for the interaction with the OC event. When the OC event was experienced during automated drives, the preference for manual vehicle control was likely to be significantly higher compared to such preference observed during manual driving. This suggests that participants disagreed with how the automated system reacted to this situation. A feasible explanation may be that, when experiencing an increase in driving task demands, drivers would attempt to compensate by reducing speed [42], whereas when the OC event was encountered during automated driving the speed was not reduced.

A very strong association of POS and WTE/WTRC was confirmed. Therefore, it was concluded that POS can be used as a predictor of a driver's WTE/WTRC. Although no comparable studies that measured POS in AVs were found, some similarities can be identified with the results of surveys on AVs. Assuming that the measurement of safety is opposite to the measurement of risk [39], the association of POS and WTE/WTRC was indirectly supported by finding that risk perception had a significant impact on the interest in using an automated vehicle [43].

Several practical implications for the acceptability of the AVs were identified. Findings such as the effects of the driving mode in the rain and fog conditions emphasised the importance of education and training before using AVs. Drivers need to know what AVs can and cannot do, and to be trained to accept AV behaviour. Driving in more complex situations could benefit the most from automation since the processing and reaction times of an automated system are much quicker than human reactions and advanced sensor technologies can gather more information than a human driver. Moreover, this information (what the system sees and plans to do) needs to be conveyed to the human driver in real-time. This would provide a more complete information set, compensating for uncertainty and generating trust and confidence in automation. This will be a task for human–machine interface (HMI) designers. The driver's comfort will have an important role in the acceptance of AVs. It is quite possible that some, most likely older, drivers would not be able to adapt to certain aspects of high-level automation driving; for example, platooning with extremely short time headways. As POS had a strong association with WTE/WTRC, the automation system needs to prevent or moderate all driving situations that may lead towards subjectively high POS to facilitate acceptance of automated vehicles.

This study investigated aspects of driver behaviour in Level 3 automated vehicles in non-critical situations. For many years the main research focus here was on critical situations such as the transition of control due to automation failure. However, non-critical driving represents a vast majority of driving experience and deals with a very broad range of human factor issues. A strong negative effect of situation complexity on WTE and a strong association between POS and WTE mean that if drivers of Level 3 automated vehicles perceive that a driving situation is complex, they would be less willing to use vehicle automation since they feel safer when manually controlling the vehicle. If drivers' perceived level of complexity is reduced, they are likely to be more willing to engage in automated driving. Since better-trained drivers are more capable of dealing with more complex situations [44], driver training is one way to reduce perceived situation complexity by developing automatic information processing [45], resulting in driving situations being seen as more transparent and predictable. Therefore, improving drivers' cognitive and perceptual skills will help increase engagement with vehicle automation.

As perceived situation complexity was found to have such a strong effect on WTE and choice of vehicle control mode, manipulation of this perception may be utilised to influence the choice of how and when vehicle automation is used by drivers. Simplification of complex driving situations or a reduction in perceived complexity may increase WTE, and, therefore, facilitate exposure to automated driving. This can be applied to roads, traffic regulation systems, other infrastructure and AV HMI. For example, HMI design is able to influence driver behaviour [46]. There are already some guidelines for reducing the complexity of the automated system [47]. Advanced technologies such as augmented reality can be utilised [48]. Visibility in fog may be enhanced by superimposing a 3D model of a driving scene created from outputs of sensors that are not affected by these conditions [49], using a head-up display (HUD). Similar and much more complex systems are already implemented in later generations of jet fighters, such as the F-35 [50]; therefore, it is a matter of time before they become used in civilian applications.

Conversely, the presentation of increased complexity is highly likely to have the opposite effect. One practical application of an increase in perceived complexity may be its application in providing a subtle mechanism to keep the driver "in the loop". Hence, active manipulation of perceived SC has the potential to influence the choice of vehicle control mode and achieve optimal safety benefits.

The effects of speed on patterns of the selection of AV control mode would be more effectively explored in a higher-fidelity simulator that has been validated for absolute speed perception. The effects of automated driving style on a driver's willingness to use automated driving mode need to be further explored due to issues of driver comfort and motion sickness. Although an ordinal scale for WTE/WTRC was selected, a linear scale (similar to the one for POS) for recording WTE/WTRC scores would allow a more precise statistical analysis of several hypotheses on WTE/WTRC.

Several limitations were identified in the course of the study and data analysis; however, despite these limitations, it was concluded that none of the main findings was significantly affected. The simulator was not validated for the absolute perception of speed. Regardless, speed was included as one of the independent variables of the study design in the hope that relative speed differences would be easily perceived.

These results were obtained after only a single session in the driving simulator. Most of the participants experienced Level 3 automated driving for the first time during this session. In addition, only a few participants experienced some forms of driving with new technologies such as ACC and Lane-Keeping Assist (LKA). Therefore, it is not surprising that, when facing the novelty of automated driving, they preferred the familiarity of being in control of the vehicle; for example, a bias towards manual control during initial interactions with the system [51]. The findings of this study can therefore be applied to issues that users will face when Level 3 automated vehicles are initially deployed.

5. Conclusions

This research assumed that, in the foreseeable future, all new vehicles will have Level 3 automation capability, Therefore, all drivers of new vehicles may be able to freely choose to engage and disengage vehicle automation as desired. Before this research, no peer-reviewed publications had explicitly investigated drivers' willingness to engage automation, a new behavioural phenomenon that became meaningful in Level 3 AVs. Moreover, only a small number of unrelated papers touched on non-critical driving in the context of vehicle automation.

In the experiment presented in this paper, WTE was found to be a reliable predictor of the choice of the vehicle control mode in Level 3 AVs. The study results demonstrated that, when facing more complex everyday driving situations, drivers indicate a preference to control the vehicle manually, rather than engage the vehicle's automation. Similarly, when the driving situation was perceived as less safe, for example entering an unsignalised intersection with other vehicles being involved, participants preferred to control the vehicle themselves, rather than delegate the driving task to automation. This means that drivers of Level 3 AV fundamentally trusted themselves more than the automated system in complex or less safe driving situations, and revealed a strong association between WTE/WTRC and POS. This indicates that a range of education and awareness measures will need to be implemented to improve drivers' knowledge of the capabilities of vehicle automation, particularly its ability to cope with complex driving environments. Further research in this area is also recommended, such as replicating the current findings using simulation or on-road studies with objective driving performance measures, and expanding the demographic characteristics of the sample, particularly to include more female drivers. Research currently being undertaken by the authors is examining the actual choice of the vehicle control mode using objective measures in a driving simulator; a further research extension would then be a naturalistic study on a test track or a public highway to further explore the actual vehicle control mode choice.

This research was conducted at a pivotal stage in automotive history as the number of vehicles equipped with Advanced Driver Assistance Systems is growing and such systems are becoming more capable of replacing the human driver. Once the floodgates to conditional automated driving are open, drivers of Level 3 automated vehicles will have a choice of vehicle control mode. The initial success and long-term sustainability of vehicle automation will depend largely on whether this technology meets the needs and expectations of users. This research shows that indirect manipulation of WTE can be utilised to improve user acceptance and uptake of vehicle automation.

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