Transportation Research Part F: Psychology and Behaviour 90 (2022) 1–14

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers

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A B S T R A C T

Achieving optimal performance in human-machine systems, such as highly automated vehicles, relies, in part, on individuals' acceptance and use of the system, which is in turn affected by their enjoyment of engaging with, or experiencing, the system. This driving simulator study investigated individuals' real-time subjective evaluation of four different Automated Vehicle (AV) driving styles, in different environmental contexts. Twenty-four participants were recruited to manually drive a contextually rich simulator environment, and to experience human-like and non-human-like AV driving styles, as well as the automated replay of their own manual drive. Their subjective real-time feedback towards these driving styles was analyzed. Our results showed that participants gave higher positive feedback towards the replay of their own drive, compared to the other three controllers. This difference was statistically significant, when compared to the high-speed controller (named as Fast), particularly for sharp curves. With respect to the replay of their own drive, participants gave higher negative feedback when navigating an Urban environment, compared to Rural settings. Moreover, changes in roadside furniture affected individuals' feedback, and this effect was more prominent when the vehicle was driving closer to the edge of the road. Based on our results, we conclude that individuals' perception of different AV driving styles changes based on different environmental conditions, including, but not limited to, road geometry and roadside furniture. These findings suggest that humans prefer a slower human-like driving style for AV controllers that adapts its speed and lateral offset to roadside objects and furniture. Investigating individual differences in AV driving style preference showed that low Sensation Seeking individuals preferred the slower human-like controller more than the faster human-like controller. Consideration of this human-centered feedback is important for the design of future AV controllers, to enhance individuals' ride experience, and potentially improve acceptance and use of these vehicles.

1. Introduction

The introduction of Automated Vehicles (AVs) to the market is becoming more of a reality, with SAE Level 2 (Society of Automotive Engineers, 2018) systems already available in some vehicles, such as General Motor's Cadillac Super Cruise (Cadillac, n.d.) and Audi's Drivers Assistance Plus (Audio-mediacenter, 2017). Currently, the main focus of most vehicle manufacturers is on addressing the technical challenges associated with developing safe and reliable automated vehicles for deployment on the road. However, although safety is one of the most important aspects of vehicle design, ensuring that future automated vehicles are used, and accepted, by

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https://doi.org/10.1016/j.trf.2022.07.018
Received 10 May 2022; Received in revised form 18 July 2022; Accepted 26 July 2022
Available online 17 August 2022

consumers also relies on creating a comfortable ride experience for the on-board user (Bellem, Thiel, Schrauf, & Krems, 2018; Lee, Liu, Domeyer, & DinparastDjadid, 2019; Voβ, Keck, & Schwalm, 2018). The challenge with automated vehicles that do not consider the users' experience and personal preferences in the design process is not just that they create an unpleasant experience for the occupant, for example leading to motion sickness (Diels & Bos, 2016), but that they may affect the trust, acceptance, and consistent use of the system, by both drivers, and other road users (Price, Venkatraman, Gibson, Lee, & Mutlu, 2016; Siebert, Oehl, Höger, & Pfister, 2013). This lack of engagement and acceptance by the user can defeat the benefits of such innovations, including the safety benefits that can be achieved from system engagement.

The effect of an individual's perception of a system, and their acceptance and use of that system, has long been established in other domains, including, but not limited to, aviation and manufacturing (Lee & See, 2004; Muir, 1994; Parasuraman & Riley, 1997; Riley, 1989). For example, using a general model of mixed-initiative human–machine systems, Riley (1989), suggests that incompatibility between users' assessment of a situation, and the behavior of the machine, can lead to an override of automation by users, if they trust their own judgement and capabilities more than that of the automation.

Similarly, studies on driver assistance systems have consistently shown that systems that are considered annoying by users, such as some lane departure warning/prevention systems, are engaged less often, than, for example, forward collision warning systems, mainly due to the higher false alarm rates of the former (Braitman, McCartt, Zuby, & Singer, 2010; Eichelberger & McCartt, 2014; Reagan, Cicchino, Kerfoot, & Weast, 2018).

However, there are currently very few studies, and limited available knowledge on how changes to the driving style of automated vehicles are perceived by users, and how/if this affects their ride experience, and ultimate acceptance of these vehicles. Studies in manual driving suggest that drivers have a range of different driving styles, from calm or defensive, to aggressive or assertive (Eboli, Mazzulla, & Pungillo, 2017; Ekman, Johansson, Bligård, Karlsson, & Strömberg, 2019; Murphey, Milton, & Kiliaris, 2009; Yusof et al., 2016). Here, driving style can simply refer to how drivers choose to drive a vehicle, or the driving habits that they obtain with more driving experience (Elander, West, & French, 1993). Preference for a particular style is related to certain vehicle maneuver parameters, including speed, acceleration, jerk, time headway, gap acceptance, and safety margins, which differ in different driving environments, based on road type and geometry, as well as level of traffic. It can be argued that, in the future, automated vehicles may use this knowledge about the factors that affect driving style, to develop algorithms that provide a driving experience adapted to drivers' preferences. In addition, when examining individuals' perceptions of, and experiences with, automated vehicles, previous research has shown that personality traits such as locus of control and sensation seeking are crucial elements to examine in this context, because they can assist with the personalization of the driving experience offered by future AVs (Bellem et al., 2018). However, there is currently a gap in the research regarding whether these traits also affect drivers' perception of, and preference for, the different driving styles depicted by automated vehicles.

In terms of understanding how different driving styles are rated by users, Yusof et al. (2016), used longitudinal, lateral, and vertical acceleration of the vehicle to define three AV driving styles in a test track-based study, categorized into: i) assertive (driving above designated speed limit), ii) defensive (described as less risky driving), and iii) a "Light Rail Transit" (LRT) style (which had smaller acceleration and deceleration values, compared to manual driving). They studied individuals' feedback, in terms of comfort, safety, and pleasantness of each of the driving styles, using three 5-point Likert scale questions. Four driving environments were included in this study: driving over a speed hump, leaving and approaching a junction, and navigating a curve. Participants were also divided into two groups, based on their Sensation Seeking scores (Zuckerman, 1984): defensive (scores 0–9), and assertive (scores 10–20). Results showed that both groups provided significantly more positive feedback towards the defensive style of driving, for the speed hump maneuvers. They also showed that for the curve navigation maneuver, both groups preferred the defensive style more than the aggressive style, in terms of comfort. Finally, for the acceleration maneuver at junctions, defensive drivers preferred the defensive style and LRT more than the assertive style, in terms of comfort, pleasantness, and safety. The authors concluded that, overall, a defensive AV style was more preferable, compared to the other styles, for both the aggressive and defensive driver groups in their study.

Using a driving simulator study, Hartwich, Beggiato, and Krems (2018) report an age-related effect on subjective feedback towards three different automated driving styles, which included one replay of each individuals' own manual drive, and two replays of other individuals' manual drives. Results showed that younger drivers (25–45 years) rated their own driving style as more comfortable, whereas those aged over 60 years were more positive about the driving style of others. These authors suggest that older drivers prefer a style that compensates for any age-related changes in their own driving style, which again highlights the value of considering individual differences and driver characteristics, when designing automated controllers. Similar conclusions are made by Basu, Yang, Hungerman, Sinahal, and Draqan (2017), who found that, on average, individuals prefer a more defensive driving style to an aggressive style, their own driving, and a distractor style (a different participant's style).

Finally, Bellem et al. (2018), report the importance of the magnitude and onset of deceleration, acceleration, and jerk of automated vehicle controllers' actions on individuals' feelings of comfort. They state that an early, imminent, response from the automated vehicle controller, minimizing the controllers' jerk, and reducing deceleration at the start of a deceleration maneuver, was generally more preferable for their participants.

Therefore, although a number of recent studies have started to suggest how variations in vehicle control characteristics affect driver preferences and comfort levels, to our knowledge, there is currently a shortage of studies on how user response in an AV is affected by a wide range of road environments, which, by their nature, result in a variety of lateral and longitudinal maneuvers typical of a driving experience that must be depicted by future Automated Vehicles, especially relevant to navigation in more complex, European-style roads. In addition, there is currently little understanding of how individuals' feelings of safety and comfort in AVs, is affected by their personality traits, such as their propensity for risk taking.

To explore this idea further, the aim of the current study was to understand human drivers' preference for two AV controllers that imitated “human-like” driving styles, compared to a more robotic driving style, depicted by a Conventional AV controller, which rigidly tracked the center of the driving lane, minimizing deviation from the lane center, and unable to navigate around roadside objects. Drivers' response to these controllers was also compared to their preference for a replay of their own driving style. To understand how environmental conditions affected this preference, the controllers were operated in a comprehensive set of, UK-based, road environments, with different levels of complexity and geometry, and different roadside features, such as presence of parked cars, or grass and asphalt verges. Our human-like automated vehicle controllers were created on the assumption that human drivers control their vehicle states, including speed and lateral positioning, to keep their Time to Lane Crossing (TLC) above a minimum acceptable value (Boer, 2016). This assumes that drivers accept a range of longitudinal and lateral vehicle states, including speed and lateral offset, as long as these satisfy the minimum TLC value. This type of controller, therefore, produces a shift in lateral position that matches how humans adapt their trajectory in response to road geometry and road furniture. As outlined below, we used the above assumption to also create two versions of human-like controllers for evaluation. These controllers were created using data collected from a group of drivers negotiating the same stretch of road in manual driving, during a previous study. To assess users' preferences for these controllers, we used a simple button-pressing tool to collect real-time feedback from participants, as they experienced these controllers in an automated drive, within a motion-based driving simulator. Finally, the effect of driver personality on preference for the different controllers was examined, by investigating the link between participants' Sensation Seeking scores (Arnett, 1994), and controller preference.

We hypothesized a correlation between TLC and safety risk, such that driving conditions associated with a higher TLC, at slower speeds, and greater distance from the roadside would be favored by drivers. Moreover, we expected that increased complexity of the road environment, such as tighter road curvature would reduce drivers' comfort, and presence of roadside objects and furniture, which increased the likelihood of collisions, would reduce drivers' perceived comfort and safety. We assumed that, overall, drivers would prefer the driving style of human-like, over those of conventional, controllers. Finally, we anticipated individual differences in preference for the various vehicle controllers, based on their personality traits, as measured by the Sensation Seeking score.

2. Method

2.1. Participants

Twenty-four regular drivers (14 males, 10 females) were recruited for this study, using the University of Leeds Driving Simulator database. All participants had a minimum of 2 years' driving experience, with an average driving mileage of 6952.08 miles, per year (SD = 4799.99), and were aged between 23 and 87 years (M = 43.83, SD = 17.12). The study was approved by the University of Leeds Ethics Committee (LTTRAN-086). All participants were compensated £50 for their time in the simulator study. There were no participant drop-outs or severe simulation sickness effects throughout the study.

2.2. Apparatus

The University of Leeds Driving Simulator includes a full sized 2006 Jaguar S-type vehicle cab, placed inside a 4 m diameter, spherical projection dome. The dome is equipped with eight overhead projectors, rendered at 60 frames/s, predominantly at a resolution of 1920×1200 that subtend a horizontal forward field of view of 270°. The simulator has an eight degree-of-freedom electrical motion system, which consists of a hexapod, sitting on a $5 \text{ m} \times 5 \text{ m}$ XY rail system.

2.3. Experimental design and procedure

A within-subjects, repeated measures, experimental design was used to study participants' subjective evaluation of three different automated vehicle driving styles, as well as a replay of their own manual drive. Feedback was sought on the overall feelings of pleasantness, safety, and comfort experienced during the same sections of each drive, with each controller navigating the same environmental conditions.

The study was conducted over 2 days, due to the length of the experiment, and its potential negative effect on participants' fatigue levels. Each participant was presented with a written and verbal briefing of the study, upon arrival on the first day. They then provided a written informed consent to participate in the experiment, followed by completion of a set of questionnaires, described below. Participants started the study with a practice drive, to become familiar with the simulation environment, and vehicle controls, and in order to ensure they did not suffer any ill-effects from simulator exposure. The researcher accompanied drivers during this practice drive, which lasted about 10–15 min. Following this practice drive, the researcher left the simulator dome, and participants then completed a manual drive, where the participant was in full control of vehicle maneuvers. This drive always happened first, and was recorded, in order to be used as participants' “Replay” drive, see below. Participants then completed 2 of the four automated drives, with a short break in between each, followed by a short questionnaire asking about participants' perception of the AV controller they just experienced (results not reported here). Following data collection on day 1, arrangements were made for participants to return to the simulator, no more than a week later (M = 4.21 days, SD = 1.58), to complete two more automated drives. The order of the four automated drives was counter-balanced across participants.

For each of the four automated drives, the controller was in full control of the speed and lateral position of the vehicle, and the participant was an evaluator of the controller's behavior. Feedback about the pleasantness, safety, and comfort of the automated controller was provided, using an x-box response box (see below). Participants were also encouraged to provide any verbal feedback about the behavior of the controller, whenever they felt comfortable to do so (results not reported here). The duration of the manual drive and the Replay drive depended on participants' manual driving speed, and varied across participants. However, for the other three automated drives, the Slow controller had the longest duration, which was around 15 min, and the Fast controller had the shortest duration, which was around 13 min.

2.4. Road environment and scenarios

Based on a previous HumanDrive study (see Louw et al., 2019) a combination of six independent environmental factors were used to develop a range of road-based characteristics, and features, (each called a scenario), resulting in 37 scenarios that were navigated by the human driver and automated controllers in the five experimental drives (Table 1). Each Urban or Rural road section featured a particular width, curvature, and "road furniture" (e.g. asphalt, grass, hedges, bus stops), which affected vehicle lateral and longitudinal control metrics (i.e. lateral positioning, speed, acceleration, and jerk), and therefore, influenced driving demand and comfort. Fig. 1, provides the driver's view of some of the scenarios used in this study. Note, we did not target a full factorial design here, because some of the conditions in the urban environments did not necessarily exist in rural environments. The study did not include any other leading, or oncoming, traffic.

2.5. Controllers

As outlined above, the 4 automated controllers used in this study included a Conventional controller, two, model-based, human-like controllers, and a Replay of each individual's manual drive, which are further described in Table 2. Participants experienced each controller once, in one of the four automated drives, and were asked to evaluate these controllers, as outlined below. The next section describes each controller, before illustrating how these were evaluated by users.

3. Conventional controller

The conventional controller used in this study was a non-human-like, robotic, controller that, like many of the production controllers currently available in vehicles, tracked the center of the lane, to navigate the vehicle, and was unable to negotiate the road-side objects, and obstacles, that partially blocked the road. Therefore, for this controller, we excluded the partially blocked road conditions from the drive (i.e. scenarios with road works, and parked cars). For this controller, a fixed lateral offset was added to the lane center, for occasions when the vehicle was approaching the center hatch, edge hatch, and pedestrian refuge. This fixed value was the median of the lateral offset observed for the middle portion of that road segment, derived from 35 drivers, who drove the same road environment in a previous HumanDrive study (Louw et al., 2019). When the Conventional controller arrived at these specific road segments, it picked up the corresponding value, and rigidly followed that fixed offset throughout the whole segment. Fig. 2a shows the lateral offset of this controller from the start to the end of the drive, where the horizontal axis is the road mileage, and zero on the vertical axis is the center of the lane of travel.

In terms of the longitudinal features, the conventional controller was set to drive at 5 different speeds, based on the particular road environment it was navigating. The speed in each environment was calculated as the average observed speed of all participants' manual drive, for that section. For example, it maintained a speed of 24.29 m/s in the straight sections of the Rural environment, and a speed of 18.24 m/s during the straight sections of the Urban parts of the drive. It also slowed down when negotiating the different road curvatures (100 m curve, 170 m curve, and 250 m curve), in each environment. The transition between the stepwise speed profiles was smoothed, to keep acceleration within an acceptable range during the drive, with a maximum deceleration of 2.05 m/s^2 and maximum acceleration of 1.04 m/s^2. Fig. 2b shows the speed and acceleration of this controller, as well as the speed limit (i.e. 60 mph and 40 mph), and the road type (i.e. Rural or Urban), from the start to the end of the drive.

4. Human-like controllers

As outlined briefly in the Introduction, the human-like controllers were tuned to drive within an acceptable boundary of the vehicle's states, including lateral position and speed, in a way that satisfied a minimum TLC, for each of the different roadway conditions. The assumption here was that navigation of a section of roadway by human drivers is typically within a range of acceptable vehicle states, rather than based on an optimized state. Therefore, any vehicle state inside this range is considered acceptable by human drivers

Table 1
The range of environmental factors used to create the simulated scenarios.

	Environmental Factors	Description
1	Road Type	Rural and Urban
2	Road Curvature Radius	Straight, 750 m,250 m, 470 m, 100 *m*
3	Road Curvature Direction	Right and Left
4	Road Width	Wide (3.65 m) and Narrow (2.90 m)
5	Road Furniture	Asphalt, Grass, Kerb, Hedge, Edge Hatch, Centre Hatch, Bus-Stop, Parked Cars, Work Zone, Pedestrian Refuge
6	Length of the Presented Road Furniture	Long (250 m), Short (20 m)

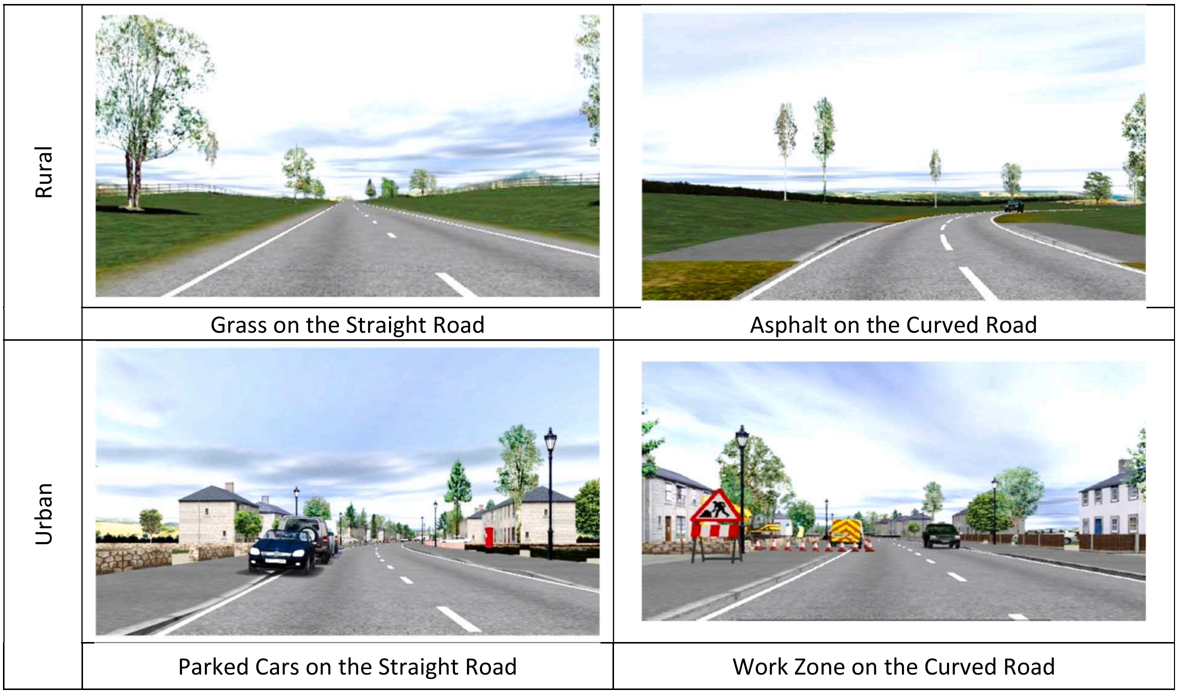

Fig. 1. Sample of scenarios used in the experiment.

Table 2
Description of the four Controllers.

	Controller Type	Description
1	Conventional AV*	Conventional controller, without human-like features
2	Slow Human-like AV*	Modelled controller, at low speed
3	Fast Human-like AV*	Modelled controller, at high speed
4	Replay	Playback of each individual's own manual drive

* AV: Automated Vehicle.

(Boer, 2016). Based on these assumptions, the human-like controllers always stayed within an acceptable boundary, which was created by using data from the manual drives of 35 participants, driving the same road in a previous study, see Louw et al. (2019).

In order to account for different speed preferences across individuals, two human-like controllers were created: the low-speed controller (termed Slow controller) was designed to reflect the median of the lower range of the observed speed (15 to 50 percentile) and the high-speed controller (termed Fast controller) reflected the median of the higher range (50 to 85 percentile) of the speed observed from all participants in our previous study. The data was captured across a moving window of 5 m, updated every half a meter.

These speed values lay within an acceptable speed boundary, as defined in Boer (2016). We also adjusted the lateral offset corridor for each speed, because the observed trend of speed and lateral offset from participants' manual driving data showed that, at high speeds, lateral offset decreased with an increase in speed. The rate of this change varied, based on the environmental condition. Therefore, for developing the high speed human-like controller, we considered a constant 2.5 cm shift of the offset boundary from the center, for every 1 m/s increase in speed.

For the lateral control of the vehicle, a "corridor" was introduced, based on the same manual data of our previous study. Here, the controller followed the median of the offset corridor, and stayed within the left and right edges of the offset boundaries. The median of the offset was modelled with a mix of Sigmoid Gaussian models. However, it did not fit the median of the offset at some sections of the road geometry, due to short-lived changes, such as transition between a wide to narrow road section. For these sections, the observed median of the offset was used for the controller. The average width of the boundary was 0.586 m, with a standard deviation of 0.266 m along the whole road.

Fig. 3 shows the offset, speed, and its derivative, acceleration of the Fast and Slow controllers experienced by the participants from the beginning to the end of the drive, where the horizontal axis is road mileage. As described above, the Fast controller's speed (red line) was always higher than the Slow controller (blue line), and its offset (red line) was always further away from the edge of the road compared to the Slow controller (blue line). The accelerations of the Fast and Slow controllers are presented with magenta and green, respectively. Road types (i.e. Rural and Urban) and the speed limits (i.e. 60 mph and 40 mph) at each point through the drive are also

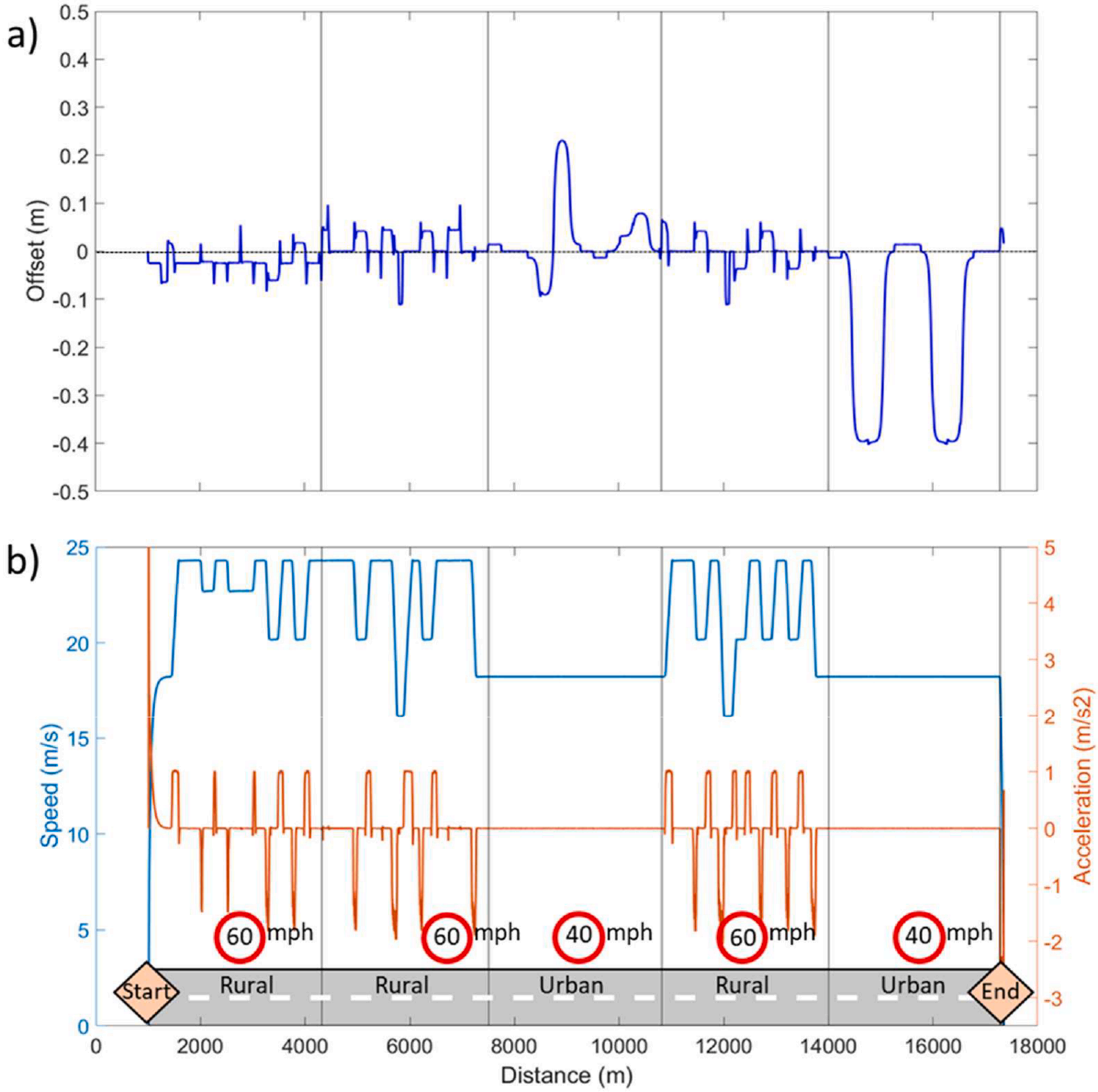

Fig. 2. Lateral and longitudinal characteristics of the Conventional AV controller: a) Lateral positioning (offset) and b) Speed and acceleration values.

shown. The figure shows how the speed, acceleration, and lateral offset of the controllers changed due to the presence of different environmental factors (described in Table 1).

5. Replay drive

As outlined above, after the practice drive, all participants drove the environment in manual mode. The data from this drive was recorded, and played back to each participant, as one of the automated drives. The offset, speed, and longitudinal acceleration of these individual Replay drives are shown in Fig. 3. Participants were not informed that they would experience a replay of their own drive, simply assuming they were evaluating another controller.

The offset and speed of the Replays of all the individuals are plotted in grey in Fig. 3. The zoomed in view is presented at the right side of the figure to better present the different Replay lines.

A summary of the vehicle metrics, including mean speed, root mean square (RMS) of lateral and longitudinal acceleration, and RMS of lateral jerk, of each controller is provided in Table 3.

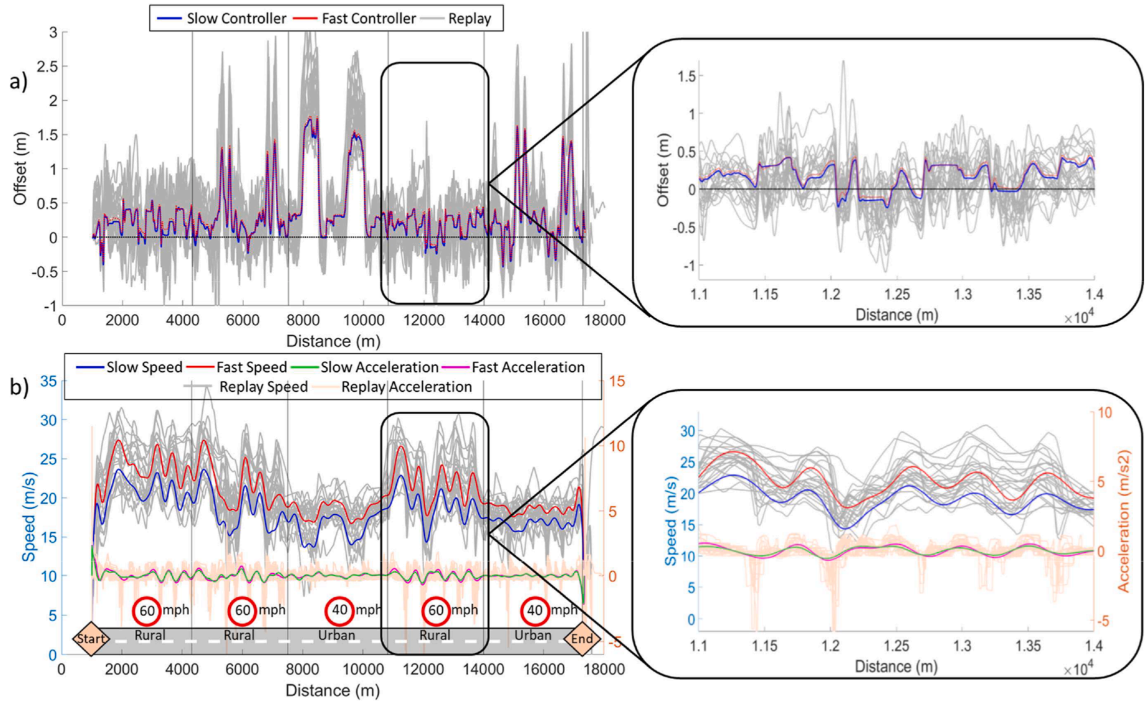

Fig. 3. Lateral and longitudinal characteristics of the Slow and Fast human-like AV controllers, and the Replays: a) Lateral positioning (offset) and b) Speed and acceleration values.

Table 3
Summary of Vehicle Metrics for the Automated Controllers.

	Mean Speed (m/s)	RMS Lat. Acc. (m/s^2)	RMS Long. Acc. (m/s^2)	RMS Lat. Jerk (m/s^3)
Slow	18.50	1.00	0.13	0.29
Conventional	20.79	1.29	0.11	0.23
Fast	21.14	1.32	0.18	0.41
Replay	20.63	1.34	0.19	0.64

5.1. Subjective feedback

Participants were asked to evaluate the automated vehicle controllers, by actively observing the behavior of each controller, as it navigated through different sections of each drive. Feedback was provided using two buttons on an x-box handset, which participants placed on their lap, see Fig. 4. To control the timing of responses across participants, a short auditory "beep" was triggered after every change of the designed environmental factors (Table 1), which required immediate feedback from participants. The timing between these auditory triggers was not fixed, so that participants could not predict its activation. The right button of the handset was pressed in response to "*Yes, I found the behavior of the controller safe/natural/comfortable*", which were all associated with a pleasant affect, and the

Fig. 4. Handset device used to capture participants' real-time feedback (left) held by the driver (right).

left button in response to "*No, I did not find the behavior of the controller safe/natural/comfortable*", which were all associated with an unpleasant affect. Participants were also free to press these buttons at any other time throughout the drive, and were also encouraged to provide verbal comments about the behavior of the auto controller, if they so wished (not reported here).

5.2. Questionnaires

In addition to the above subjective responses, drivers provided feedback via a set of questionnaires, which were administered after each of the automated drives. They also completed a set of personality trait questionnaires that included the Traffic Locus of Control (Özkan & Lajunen, 2005), the Driving Style Questionnaire (Elander et al., 1993), and the Arnett Inventory of Sensation Seeking (Arnett, 1994), administered after the practice drive, after the manual drive, and at the start of the 2nd day, respectively. However, analyses did not reveal any relationship between the subjective responses, and the former two questionnaires, therefore, only results from the Sensation Seeking scores are reported here.

6. Results and discussion

6.1. Experimental variables

The design of the study included multiple vehicle controllers, and scenarios with different levels of environmental factor (see Table 1), which, when combined, created a series of unique experimental conditions. Participants' subjective evaluation of each of the four controllers' driving style was analyzed using the average number of button presses (positive, negative) per experimental condition. The total number of times a participant pressed a button in an experimental condition, divided by the number of exposures to this experimental condition was the score used in the analysis. Note that participants could press the button multiple times within one experimental condition, resulting in an average greater than 1. The resulting data was a random and continuous variable, either skewed towards one, or zero. Hence, we used Compound Poisson distribution to describe the data, for both positive and negative presses.

Each unique experimental condition was assigned an independent dummy variable in our analysis, described below. The presence of a unique experimental condition was coded as 1, and its absence 0. When it was 1, the number of positive button presses were collected to compute the total for that condition.

The independent variables included the range of environmental factors (e.g. Urban and Rural road types, road width, road curvature, furniture, etc.), and the four controllers (Table 2), as well as individual drivers' characteristics, based on their Sensation Seeking score.

An initial inspection of the number of button presses across participants indicated that one participant had a markedly number of higher button presses in all experimental conditions, compared to other participants. Thus, the data from this participant was excluded from the analysis. The analyses in this manuscript are, therefore, based on data from the remaining 23 participants.

Using IBM SPSS Statistics Version 25, the Compound Poisson exponential dispersion model, with log link function was estimated,

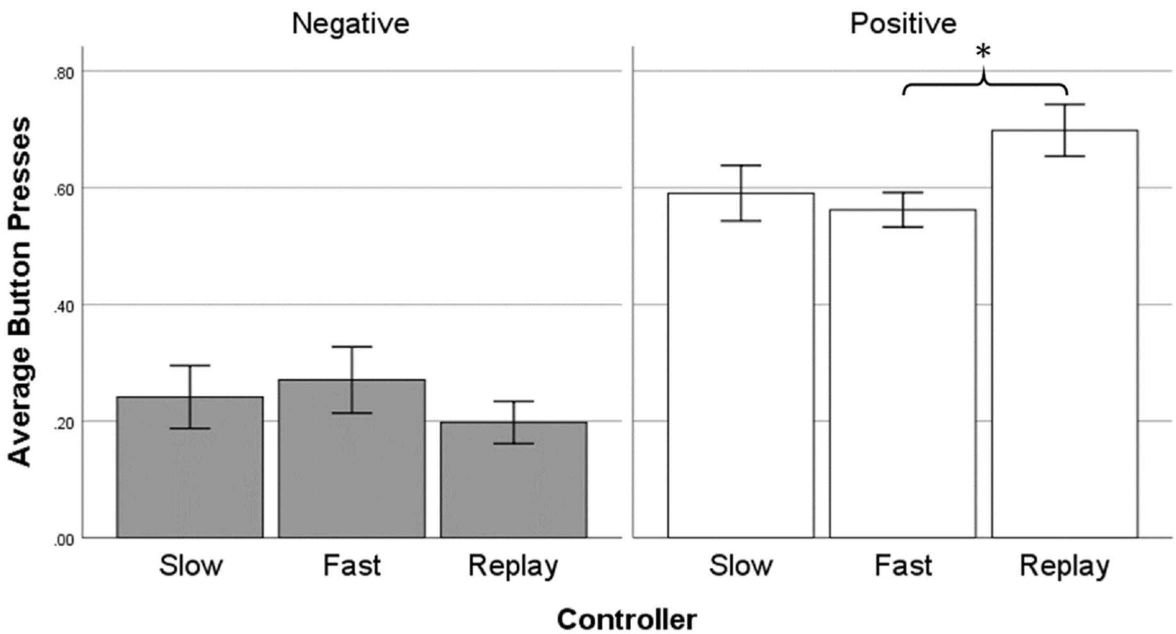

Fig. 5. Average positive and negative button presses for each controller (*p < 0.05). Error bars represent ± 1 standard error.

applying Generalized Estimating Equations (GEE). Use of GEE accounted for the correlated nature of the data, caused by the repeated measure design in this experiment. The model provided an estimate for the average population of participants. A set of post-hoc pairwise comparisons with Bonferroni corrections were conducted, to compare the average button presses across pairs of experimental conditions (i.e. our independent variables) in the model. The confidence interval was set to 0.05 for all analyses reported from this study.

The results are reported in three stages. The first aim of the analyses was to investigate if there was an effect of controller type on drivers' positive and negative subjective feedback. The second goal was to establish the effect of the different environmental factors on these measures, and whether these were different for the different controllers. The third goal was to understand the correlation between drivers' Sensation Seeking scores, and their subjective feedback about the driving style of the automated controllers.

The binary button-press approach used in this study was chosen because it allowed rapid response by participants, in real time. However, it can be argued that this method limited the range of possible responses likely to be associated with the emotional affects experienced by drivers. In other words, the rich driving environment experienced may not have been sufficiently captured by a binary approach, in that a negative button press was perhaps not the direct opposite of a positive button press. Therefore, the positive and negative presses were analyzed separately.

6.2. *Subjective evaluation of the controllers*

As outlined above, the drive with the Conventional controller did not include any blockage scenarios, which meant that the overall feedback for this controller was likely to be different to that of the other three drives. Therefore, this part of the analysis only compared subjective feedback to the Replay and human-like controllers.

Fig. 5 shows the estimated means of button presses for each controller. Overall, the number of positive presses was found to be higher than the negative presses, for all the controllers, suggesting that they were generally able to negotiate the different environments in a pleasant, safe, and comfortable manner. The Replay driver had the highest number of positive presses and lowest number of negative presses among the controllers which is in line with Rossner and Bullinger (2019).

Multiple comparison tests, using Bonferroni corrections, were conducted, to investigate whether there were any significant differences in feedback for each of the controllers, as shown in Table 4.

Results showed no statistically significant difference between the number of negative presses across controllers. However, drivers provided a significantly ($p < 0.05$) higher number of positive button presses for the Replay of their own drive ($M = 0.697$, $SD = 0.0436$), compared to the Fast human-like controller ($M = 0.563$, $SD = 0.047$), Fig. 5. This finding is partially supported by results from Dettmann et al. (2021), who studied individuals' subjective ratings of comfort, enjoyment, and acceptance of different automated vehicle driving styles, which were prerecorded playbacks of another group of drivers. Their results showed that young drivers in their study preferred automated driving styles that were similar to their own. We outline what aspects of the Replay controller were preferred over the Fast controller, in the next section.

6.3. *Effect of environmental factors on subjective response*

The environmental factors manipulated in the drives included geometry of the road (straight, different curvatures) and presence of different types of road furniture (asphalt, grass, hedge, parked cars etc.), for the two main road categories: Urban and Rural. The interaction between AV controllers and environmental factors was explored to understand whether the controllers were perceived differently in the various road conditions. The next section describes overall participant response to the Urban and Rural road sections, followed by an analysis of how the different types of road furniture affected participant evaluation of each controller. This allowed us to understand the effect of each road factor on participant preferences, in isolation, and, therefore, what contextual adaptations of speed and lateral offset should be incorporated by an AV controller.

7. Response in Urban and Rural road sections

A range of road geometries, speed limits, and roadside objects were used to create a rich set of UK-based Urban and Rural roads in our simulated world. The Rural environment did not include any hatched sections, bus stops, or pedestrian refuges, but did include a range of curve radii. On the other hand, only one road curvature was included in the Urban environment, which was densely populated with a range of road-based objects and furniture.

Table 4
Pairwise comparisons of the mean button presses, across controllers.

	Negative Feedback Mean Difference (95 % Confidence Interval)	Positive Feedback Mean Difference (95 % Confidence Interval)
Slow-Fast	−0.0283 (-1.288,0.072)	0.029 (-0.062,0.119)
Slow-Replay	0.044 (-0.054,0.142)	−0.106 (-0.256,0.044)
Fast-Replay	0.073 (-0.0542,0.199)	−0.135 (-0.254,-0.015)*

* $p < 0.05$.

The GEE model showed that both positive and negative responses were significantly higher than zero, for all the controllers (Fig. 6). Across controllers, there was no significant difference in the number of negative responses for the Rural environment. However, for the Urban environment, the Slow human-like controller received more negative feedback ($M = 0.244$, $SD = 0.054$), compared to the Replay drive ($M = 0.120$, $SD = 0.034$, $p < 0.05$). Post hoc tests, using Bonferroni corrections, also showed that the Replay drive received more negative feedback ($p < 0.05$) in the Rural environment ($M = 0.247$, $SD = 0.044$), compared to the Urban environment ($M = 0.120$, $SD = 0.034$), while the human-like controllers were perceived equally, in terms of negative button presses, for these two road types. The higher number of negative responses for the Replay controller in the Rural environment is likely associated with the higher speed of travel or curvature of this road section, both of which are absent in urban settings. Human drivers' negotiation around parked cars is also seen to be more acceptable by the evaluators, who provided more negative responses for the human-like controllers in the urban section, compared to that of the Replay controller.

Positive feedback was not significantly different across the two road types, or across controllers. Overall, the observed effects of controller and environment were consistent across positive and negative feedback (i.e. translated as opposite), such that, for example, the Replay drive received higher negative, and lower positive feedback, in the Rural environment, compared to the Urban environment.

The absence of a difference in preference for the two human-like controllers was disappointing, although the Fast controller does seem to have received marginally less positive feedback overall, and especially for the urban sections, suggesting that the road blockages caused by the parked cars, for example, were perhaps negotiated less comfortably by this controller, than the sharp curves of the Rural sections. Overall, however, these results show clearly that drivers preferred a direct replay of their own drive, more than the "artificially" created human-like controllers.

8. Response in different environment sections

Analyses were conducted to explore what vehicle state adaptations (i.e. speed and lateral positioning) are needed, when navigating different road environments with different road furniture and geometry, to create a favourable experience for individuals on board an AV.

Here, since we did not have a full factorial design, we compared feedback between scenarios that were different for only one factor (e.g. only different in curve radius) for the environmental factors described in Table 1 (i.e. road width, curvature, furniture, etc.). Curve direction was not included in the analyses, since we did not expect a significant effect of left versus right curve direction. We identified 38 sets of meaningful pairwise comparisons of comparable scenarios (i.e. sets of two or more), that differed in one environmental factor, which we call the target factor (e.g. a set of wide Rural road sections, with 250-meter long kerbs, and 3 different curve radii). A set of pairwise comparisons, with Bonferroni corrections, were conducted to capture the effect of the target factor on feedback, for each controller. Each significant result means the change of the target factor significantly affected (either reduced or increased) feedback towards the controller. Results are outlined and discussed separately for the effect of road curvature (Table 5) and road furniture (Table 6). The lack of a full factorial design also meant that if a condition is absent from Table 5 or Table 6, it may be either due to

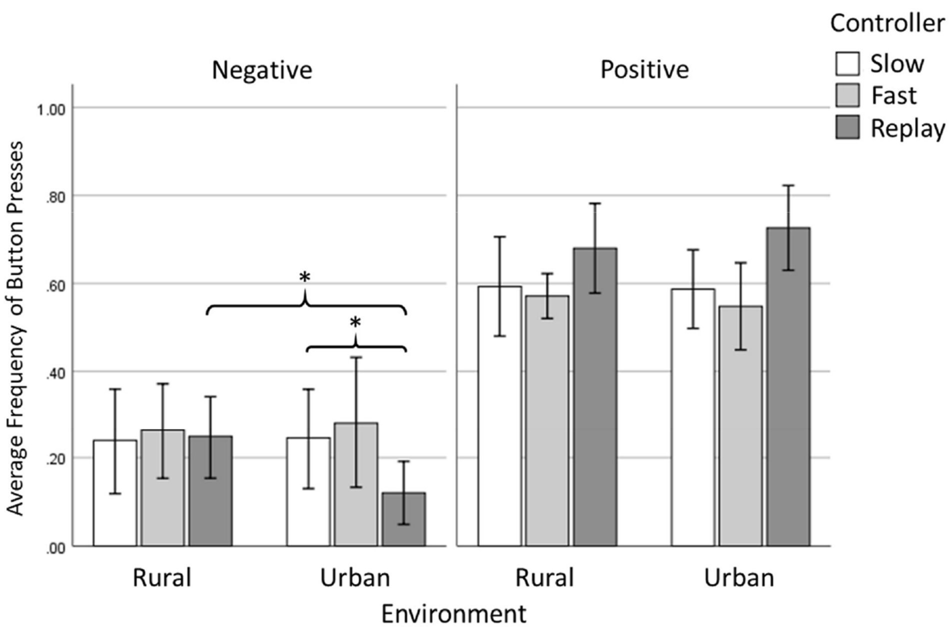

Fig. 6. Average positive and negative button presses for each controller in the Rural and Urban environment (*$p < 0.05$). Error bars represent ± 1 standard error.

Table 5
Mean difference of negative feedback across cases with different road curvature. (Only reporting cases with p-value < 0.05).

Environmental Factors					Controller			
Env.	Curve*	Furniture	Width	Length of the Road Furniture	Slow	Conv.	Fast	Replay
Rural	170	Kerb	Narrow	Long	0.2826	–	–	–
Rural	Straight	Kerb	Narrow	Long				
Rural	170	Kerb	Wide	Long	–	−0.4348	–	–
Rural	250	Kerb	Wide	Long				
Rural	250	Kerb	Wide	Long	–	0.413	–	–
Rural	Straight	Kerb	Wide	Long				
Rural	170	Hedge	Narrow	Short	–	–	0.413	–
Rural	Straight	Hedge	Narrow	Short				
Rural	100	Hedge	Narrow	Long	–	–	0.4565	–
Rural	Straight	Hedge	Narrow	Long				
Rural	100	Kerb	Narrow	Short	–	–	0.4348	–
Rural	Straight	Kerb	Narrow	Short				

* the changing factor.

Table 6
Mean difference of negative feedbacks across cases with different road furniture (Only reported cases with p-value < 0.05).

Environmental Factors					Controller			
Env.	Curve	Furniture*	Width	Length of the Road Furniture	Slow	Conv.	Fast	Replay
Rural	170	Asphalt	Narrow	Long	−0.44	−0.3043	–	–
Rural	170	Kerb	Narrow	Long				
Urban	750	Bus-stop	Wide	Short	−0.3696	–	–	–
Urban	750	Ped-refuge	Wide	Short				
Urban	Straight	Blockage	Wide	Long	0.3913	–	–	–
Urban	Straight	Edge-hatch	Wide	Long				
Urban	750	Center-hatch	Wide	Long	–	–	0.6522	–
Urban	750	Edge-hatch	Wide	Long				

* the changing factor.

insignificant differences, or because a condition was not present in that section. In this section, only results from the negative button presses are explored in depth. An analysis of the positive button presses, and comparisons between positive and negative button presses are not discussed in this study, due to the complexity of their relationship, which would also increase the length of the paper.

Results showed that road curvature and road furniture (but not road width) were the only factors that significantly affected the number of negative button presses. Table 5 shows the significant mean differences of negative feedback, for each road curvature, per controller. Six experimental conditions, out of a total of 22 pairs, were significant, for at least one of the controllers. For each case in Table 5 and 6, the values seen in the Controller columns are the mean difference in negative feedback for the corresponding pair (i.e. mean of negative feedback for the first row, minus the mean of negative feedback for the second row).

Results showed that the main significant differences were observed for the Rural (and not Urban) sections, which may be due to the higher speed limit of the former. In addition, a decrease in curve radius (i.e. a sharper curve), increased negative feedback for the Fast and Slow controllers when they were negotiating the narrow curves, but not so for the Conventional controller. This may be because the human-like controllers cut the corners of the curve, whereas drivers actually preferred a controller that followed the center of the lane, such as that achieved by the Conventional controller. The Fast controller was also found to be particularly unpleasant when it negotiated the narrow curves surrounded by high hedges, illustrating the combination of higher speeds, sharper narrow curves and visual feedback of the high hedges was particularly unpleasant. Overall, these results suggest that the speed of a controller at curves needs to match an individual's preferences.

In terms of the effect of road Furniture on negative feedback, 4 conditions, out of a total of 41 compared pairs, were significant, for at least one of the controllers (Table 4). The number of negative button presses were found to be lowest for the Fast controller, and highest for the Slow controller. This is likely because the Slow controller drove closer to the road edge, and therefore closer to the roadside objects, with results showing that an increase in the height profile of roadside Furniture (such as kerbs versus asphalt), or presence of elements on the side of the road (such as parked cars) increased the negative feedback for the Slow controller. On the other hand, since the Fast controller drove closer to the center of the road, the only observable effect for this controller was seen for the central furniture, i.e. the Centre hatch, which likely increased discomfort due to the visual stimulation created by a highly textured road center, enhancing the perception of speed (Godley, Triggs, & Fildes, 2004).

8.1. The correlation between Sensation Seeking scores and subjective button presses

Since previous studies have shown a relationship between certain driving behaviors (such as preferred speed) and Sensation Seeking score (Louw et al., 2019; Yusof et al., 2016), we investigated whether individual drivers' feedback towards the controllers was linked to their Sensation Seeking (SS) score.

We used the Arnett Inventory of Sensation Seeking (SS) questionnaire, a widely used 20-item Likert-scale questionnaire, to measure participants' SS. The SS score of our 23 participants ranged from 27 to 71 (M = 50.70, SD = 8.42). These scores were used to divide participants into 4 groups (quantiles), and analyzed for both negative and positive responses, using the GEE model, with post hoc pairwise comparison of means, with Bonferroni corrections.

Once again, the Conventional controller is not included in this cross-controller comparison, since the absence of work zones, and parked cars for this controller meant that its comparison with the other controllers was not appropriate. Results are discussed with respect to the two extreme quantiles: Q1 and Q4, as the scores in the middle quantiles (Q2 and Q3) were not significantly different from each other. The mean sensation seeking scores for the low (Q1) and high (Q4) sensation seekers were: 40.8 (SD = 7.0) and 61.4 (SD = 5.4), respectively.

As shown in Fig. 7, the low Sensation Seekers (Q1) provided more negative feedback to the Fast controller (M = 0.317, SD = 0.122), compared to the Slow (M = 0.180, SD = 0.120), or Replay (M = 0.154, SD = 0.073) controllers. However, the difference was only statistically significant between the Fast and the Slow controllers. The negative feedback provided by the high Sensation Seekers (Q4), was generally lower, and, although not statistically significant, less negative feedback was provided for the Fast controller (M = 0.129, SD = 0.047), compared to the Slow (M = 0.162, SD = 0.042) and Replay (M = 0.171, SD = 0.042) controllers. Therefore, although the low sensation seekers seem to have preferred the more cautious, Slow controller or their own Replay drive, this difference was not observed for the high sensation seekers. These results support Bellem et al. (2018) hypothesis that there may be a link between driving style and personality trait, although these authors did not find such a trend in their own study. Further research is therefore required, to clarify the reason for such differences between our study and theirs.

9. Final conclusions and study limitations

This study investigated individuals' preferences for four different Automated Vehicle (AV) driving styles, including a conventional robotic controller, two model-based human-like controllers, and a replay of each individual's recorded manual drive. Evaluation of each automated controller was provided using a simple real-time button press technique, in response to the controllers' navigation along a comprehensive range of simulated UK-based roadway environments.

Overall, drivers seemed to favor a replay of their own drive, compared to the modelled human-like controllers. Results also showed that drivers' feedback towards the AV controllers was largely affected by a combination of the speed and lateral positioning adopted by the controllers, which explains the differences in response provided for the different controllers, for each type of roadway environment. For example, feedback towards the high speed human-like controller was found to be especially sensitive to road curvature, especially in rural sections, such that negative feedback increased as the curve became sharper. On the other hand, the slow speed human-like controller was found to be unpleasant for sections with road-side objects and furniture, especially if these were at a height, because, compared to the other controllers, this controller drove closest to the edge of the road. In agreement with other studies in this context (Louw et al., 2019; Yusof et al., 2016), our results showed a correlation between individuals' sensation seeking scores, and their preference for the different driving styles, with the low sensation seeking individuals feeling particularly uncomfortable during the drive with the high-speed controller.

The findings from this study indicate that the design of AV driving style affects individuals' experience and level of comfort, with a complex influence from factors such as speed of travel, road curvature and road-side objects. Our results indicate that to enhance individuals' experience with AVs, controllers should adopt a speed that is similar to, or lower than, individuals' manual driving speed, and that it is particularly important for the appropriate speed to be adopted during negotiation of curves. In addition, AV controllers should assume a sufficiently large lateral offset from the roadside, to avoid the negative effect of roadside furniture on individuals' experience.

Regarding study limitations, this study only included static environmental features (i.e. road geometry, road furniture, and speed limit), and did not investigate the effect of surrounding traffic, or other road users, on participants' evaluations, which is clearly an important factor, if AVs are to be incorporated successfully into the current, mixed, traffic system.

In addition, participants' exposure to each driving style was quite limited in this study. Previous studies have established a correlation between familiarity, and trust and acceptance of AVs (Gold, Körber, Hohenberger, Lechner, & Bengler, 2015; Hergeth, Lorenz, Krems, & Toenert, 2015). Therefore, it will be interesting to investigate how evaluation of driving styles changes with longer term exposures. Finally, while the binary response method provided acceptable results, knowledge on the best method to use for such evaluations is currently limited and future studies should consider the value of a continuous measurement techniques, such as Likert-type scales, sliders (Schwanitz, Wittkowski, Rolny, Samel, & Basner, 2013), or knobs (Cleij et al., 2017).

CRediT authorship contribution statement

Foroogh Hajiseyedjavadi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Erwin R. Boer:** Conceptualization, Methodology, Validation, Writing – review & editing. **Richard Romano:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision. **Evangelos Paschalidis:** Methodology, Validation, Investigation. **Chongfeng Wei:** Validation. **Albert Solernou:** Methodology, Software, Investigation, Data curation. **Deborah Forster:** Conceptualization. **Natasha Merat:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration.

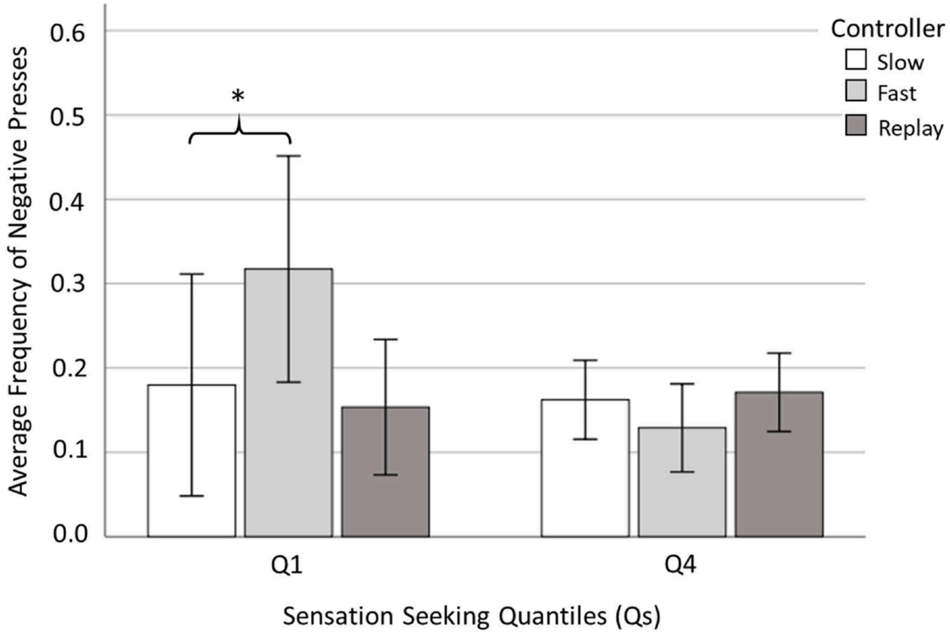

Fig. 7. Average negative button presses from each Sensation Seeking group toward each controller (*$p < 0.05$). Error bars represent ± 1 standard error.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgement

The work described in this paper was undertaken in connection with the HumanDrive project, co-funded by the Centre for Connected and Automated Vehicles (CCAV) and Innovate UK, the UK's innovation agency (TS/P012035/1). This paper is published with permission from the HumanDrive consortium: Nissan, Hitachi, Horiba MIRA, Atkins Ltd, Aimsun Ltd, SBD Automotive, University of Leeds, Highways England, Cranfield University and the Connected Places Catapult.

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