1 Drivers' Evaluation of Different Automated Driving Styles: Is 2 It both Comfortable and Natural?

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15 **Précis**

16 This study investigated the subjective evaluation of three automated driving styles, in terms of their
17 comfort and naturalness. Results showed a distinction between these two concepts, which is also
18 influenced by participants' risk-taking personality trait, and the different road environmental factors
19 they experienced.

20 Abstract

21 **Objective:** This study investigated users' subjective evaluation of three highly automated driving
22 styles, in terms of comfort and naturalness, when negotiating a UK road in a high-fidelity, motion-
23 based, driving simulator.

24 **Background:** Comfort and naturalness are thought to play an important role in contributing to
25 users' acceptance and trust of automated vehicles (AVs), although not much is understood about
26 the types of driving style which are considered comfortable or natural.

27 **Method:** A driving simulator study, simulating roads with different road geometries and speed
28 limits, was conducted. Twenty-four participants experienced three highly automated driving styles,
29 two of which were recordings from human drivers, and the other was based on a machine learning
30 (ML) algorithm, termed Defensive, Aggressive, and Turner, respectively. Participants evaluated
31 comfort or naturalness of each driving style, for each road segment, and completed a Sensation
32 Seeking (SS) questionnaire, which assessed their risk-taking propensity.

33 **Results:** Participants regarded both human-like driving styles as more comfortable and natural,
34 compared with the less human-like, ML-based, driving controller. Particularly, between the two
35 human-like controllers, the Defensive style was considered more comfortable, especially for the
36 more challenging road environments. Differences in preference for controller by driver trait were
37 also observed, with the Aggressive driving style evaluated as more natural by the high sensation
38 seekers.

39 **Conclusion:** Participants were able to distinguish between human- and machine-like AV controllers.
40 A range of psychological concepts must be considered for the subjective evaluation of controllers.

- 41 **Application:** Insights into how different driver groups evaluate automated vehicle controllers are
- 42 important in designing more acceptable systems in the future.
- 43 **Keywords:** highly automated driving, driving style, comfort, naturalness, sensation seeking

44 1. Introduction

45 With higher SAE level AVs (SAE International, 2016), drivers will inevitably lose the controllability of
46 the vehicle, and the role of human drivers will shift from active controllers of the vehicle, towards
47 passive observers and passengers (Elbanhawi et al., 2015; Kaber & Endsley, 2004). There are several
48 subsequent concerns that might hinder the deployment of these vehicles, such as users' experience
49 of comfort inside the AV (Elbanhawi et al., 2015). Comfort is crucial for an AV's implementation, as it
50 is found to be correlated with trust and acceptance (Paddeu et al., 2020; Siebert et al., 2013),
51 important elements for encouraging public uptake of these new forms of mobility (Madigan et al.,
52 2016).

53 Although there is currently no commonly agreed definition for comfort in this context, some
54 suggestions exist. Under the context of automated driving, Hartwich et al. (2018) summarised driving
55 comfort as *'a subjective, pleasant state of relaxation given by confidence and an apparently safe*
56 *vehicle operation, which is achieved by the removal or absence of uneasiness and distress'* (p. 1019).

57 For automated vehicles, however, comfort is not simply limited to physical aspects of the vehicle,
58 such as good seat design (Ebe & Griffin, 2001), or acceptable levels of engine noise, and vehicle
59 vibrations (Qatu, 2012). These features are mentioned in studies of traditional, manually operated,
60 road vehicles, and also in other domains, for example, cabin noise in aircraft (Pennig et al., 2012).
61 Since the vehicle is no longer controlled by a human, it is important that its "driving behaviour", and
62 how it negotiates different road geometries, and traffic conditions, is considered pleasant, and rated
63 positively by the user, ensuring it feels comfortable and safe (Elbanhawi et al., 2015; Summala, 2007).
64 Other, more psychological, terms and concepts used in this context include ensuring the AV is
65 considered reliable, and familiar, avoiding any sudden surprise behaviours, which are shown to

66 enhance the acceptance, satisfaction and perceived safety of AVs (Carsten & Martens, 2018; Ramm
67 et al., 2014).

68 One, relatively unexplored, concept in this context is “naturalness” of the AV’s driving behaviour,
69 which has been linked to the familiarity of the AV’s manoeuvres, for the user. Here, the familiarity of
70 AV movements, rendered by mimicking human-like vehicle controls, is expected to fulfil human users’
71 anticipation of an AV’s behaviours, and result in positive subjective feedback (Butakov & Ioannou,
72 2015; Hartwich et al., 2018). Moreover, Elbanhawi et al. (2015) suggest that naturalness of
73 automated driving is an important determinant of comfort. However, some empirical studies have
74 shown that familiar automated driving manoeuvres do not always lead to higher subjective comfort
75 (Hartwich et al., 2018), which suggests that more knowledge is needed on the link between these
76 two concepts, since they will likely contribute to acceptance of future AVs.

77 From a technical perspective, there are a large number of automated driving styles that could be
78 generated for such investigations. Taking motion planning as an example, the generated driving
79 behaviour of AVs could be robotic, with algorithm-optimised trajectories, based solely on sensory
80 information provided by lasers, radars and cameras, to adapt to the environment (e.g., Urmson et al.,
81 2008). Alternatively, these may mimic a human driver’s average behavioural patterns, by training
82 models, based on real human driving data (e.g., Hajiseyedjavadi et al., submitted; Rehder et al., 2017;
83 Wei et al., 2019). Personalisation of driving styles can also be achieved by using users’ own driving
84 style in the model development loop (e.g., Menner et al., 2019).

85 Studies on manual driving suggest that participants’ reported levels of comfort are also linked to the
86 vehicle’s “driving style” (Ellinghaus & Schlag, 2001, cited in Bellem et al., 2018), which is defined as
87 the driving habits of the driver, such as their preferred speed, threshold for overtaking, headway
88 distance, and tendency to violate traffic regulations (Elander et al., 1993). In highly automated

89 vehicles, the use of such driving styles has been reported to enhance driving comfort of passive users
90 (Bellem et al., 2018).

91 Research has revealed the existence of several driving styles, associated with different character
92 traits of human drivers, loosely linked to defensive (less sudden acceleration and deceleration) and
93 aggressive (higher acceleration and more sudden braking) driving behaviours (Murphey et al., 2009).

94 Results also suggest that different automated driving styles are sometimes found to be preferred by
95 different groups of users, when evaluated in terms of comfort, safety and pleasantness, although

96 findings are inconclusive. For example, a more defensive driving style, with slower lane changing
97 features, and lower acceleration, was favoured by most participants, when compared with a higher-

98 acceleration, more assertive, driving style (Rossner & Bullinger, 2020). Moreover, Hartwich et al.
99 (2018) found that familiar driving styles (a replay of participants' own driving) were more favoured

100 by younger drivers (25-35 years), while faster and unfamiliar automated driving styles (that of the
101 younger drivers) were preferred by older drivers (65-84 years). Therefore, Hartwich et al. (2018)

102 suggest that solely mimicking drivers' personal manual driving habits may not be suitable for all age
103 groups. Using a more comprehensive set of vehicle kinematics, Bellem et al. (2018) manipulated the

104 initiation time and strength of acceleration and jerk of three manoeuvres on the highway (i.e., lane
105 changes, accelerations and decelerations). These authors recommend a number of configurations for

106 comfortable driving experiences, such as minimising jerk for acceleration and deceleration
107 manoeuvres, lowering acceleration, and providing action feedback, which is when maximum

108 acceleration is applied at the early stages of a lane change manoeuvre.

109 As outlined above, most of the existing studies considering users' responses to different driving styles
110 of AVs have compared different replays of drivers' manual driving performance. To date, there has

111 been little comparison of user preferences for machine- versus human-like AV driving styles. An

112 important consideration here is the balance between what is expected from users about the
113 acceptable driving style of an AV, compared to that of a human driver. For example, studies have
114 shown that an AV controller that precisely follows the lane centre, is considered more competent,
115 compared to those with less accurate lane-tracking and more lateral drifts from the centre lane (Price
116 et al., 2016). Therefore, from a human factors perspective, more research is warranted to understand
117 what types of driving styles and behaviours of machine- and human-like driving are considered more
118 comfortable and natural, and whether these are linked to the particular driving environment being
119 negotiated by the AV.

120 Users' perception of an AV's driving style is known to be influenced by both objective and subjective
121 factors. For example, road furniture and geometry are known to influence ratings of safety and
122 comfort (Hajiseyedjavadi et al., submitted) and physiological response (Beggiato et al., 2019;
123 Radhakrishnan et al., 2020), while a number of studies have shown a correlation between personality
124 traits such as Sensation Seeking (Arnett, 1994) and preferred driving style. For example, in manual
125 driving; drivers with high sensation seeking scores are found to drive in a riskier and more aggressive
126 manner and at higher speeds, while low sensation seekers have a tendency to drive more slowly
127 (Louw et al., 2019; Taubman-Ben-Ari et al., 2004; Zuckerman & Neeb, 1980). However, results are
128 mixed regarding preferences for AV-driving styles. For example, Yusof et al. (2016) reported that both
129 assertive and defensive drivers, characterised by higher and lower sensation seeking scores,
130 respectively, showed a consistent preference for a defensive (and not assertive) AV driving style.
131 Therefore, in addition to considering user response to two human-like and one machine-like AV
132 controller, this study assessed the effect of road geometries and users' sensation seeking scores on
133 such evaluations.

134 1.1. Current study

135 This study is based on data collected from a driving simulator study within the UK-funded
136 HumanDrive project (TS/P012035/1); the main purpose of which was to develop, and evaluate,
137 advanced AV-controllers, imitating natural, human-like, driving styles. Two representative human-
138 like driving styles were recorded, and replayed to participants. Response to these was compared to
139 a machine-like, machine learning (ML)-built, driving style (Solernou et al., 2020).

140 The following research questions were addressed in the present study:

- 141 1. Are the three driving styles rated differently in terms of perceived comfort and naturalness?
- 142 2. Do environmental settings influence the comfort and naturalness of the three driving styles?
- 143 3. Do users' sensation seeking propensities affect their ratings of comfort and naturalness
144 towards the three driving styles?
- 145 4. Is a natural driving style also a comfortable driving style?

146 2. Methods

147 2.1. Participants

148 Twenty-four participants (12 male, 12 female) aged between 20 and 49 years ($M = 35.7$, $SD = 7.1$)
149 were recruited. All participants held a valid UK driving licence, with experience ranging from 2 to 27
150 years ($M = 14.7$, $SD = 7.8$). Reported annual driving distance ranged from 500 to 18000 miles ($M =$
151 7554.2 , $SD = 3982.7$).

152 All participants were recruited by using the University of Leeds Driving Simulator database, and all
153 provided informed consent to take part in the study. Each participant was compensated £30 for

154 taking part in the study. This study was approved by the University of Leeds Ethics Committee
155 (LTTRAN-086).

156 2.2. Apparatus

157 The high-fidelity, motion-based University of Leeds Driving Simulator (UoLDS) was used in the
158 experiment. The simulator's vehicle cab is based around a 2006 Jaguar S-type, housed within a 4m
159 diameter, spherical projection dome. There are eight visual channels rendered at 60 frames/s,
160 predominantly at a resolution of 1920×1200, providing a horizontal forward field of view of 270°.
161 The simulator also incorporates an eight degree-of-freedom electrical motion system. The
162 generated range of acceleration of the motion system is $\pm 5.0 \text{ m/s}^2$ (Jamson et al., 2007)

163 2.3. Experimental Design

164 A fully within-participant experimental design was used in this study to investigate participants'
165 subjective evaluation of three different automated vehicle driving styles, described below.
166 Participants were asked to use an eleven-point, Likert-type, scale, to rate how "comfortable" and
167 "natural" each automated drive felt, as it negotiated the same stretch of road, in six separate drives,
168 completed over two days.

169 2.3.1. Driving styles

170 A machine learning (ML) based controller, and two human-driven controllers were developed for
171 evaluation in this study. These controllers are described further below, and a diagram presenting the
172 development procedure is shown in Figure 1.

Figure 1. Overview of the development of the three AV controllers

The ML-built controller (Turner)

The ML controller was calibrated using a Recurrent Convolutional Neural Network (RCNN) that was capable of imitating the human driving behaviour, in terms of future yaw rate and speed demands. The RCNN was trained from data of 10 participants, from an earlier experiment of the project (see Solernou et al., 2020). This controller will be called the Turner controller from here on.

The human-like controllers (Termed Aggressive and Defensive controllers)

The two human-like controllers were recorded drives of human participants, collected before the main study took place, which were then replayed to participants of this study. Previous studies have shown a positive correlation between speed choice and sensation seeking (Louw et al., 2019) as well as risk-taking behaviour in manual driving (Ge et al., 2014; Oppenheim et al., 2016; Riendeau et al.,

2018; Ulleberg & Rundmo, 2003). To ensure that distinct differences in driving behaviour would arise between the two human-driven controllers, recruitment of participants used for the human-driven controllers was based on their sensation seeking scores.

Before recruiting participants for these replay drives, data from a previous study of the project was used to create clusters of driving behaviour (see Appendix 1). These participants were clustered into three main groups: defensive, moderate and aggressive drivers. There was a moderate, but insignificant, correlation between participants' sensation seeking scores, and cluster membership ($r(14) = .429$, $p = .143$). For example, we found that the aggressive driving cluster contained participants with higher sensation seeking scores. The absence of a significant correlation was likely due to the small sample size used in this study. Following this analysis, participants with higher sensation seeking scores from the aggressive cluster, and lower sensation seeking scores from the defensive cluster were contacted to participate in the replay recordings of the current study. In total, eight participants were recruited, four for each sensation seeking group (Table 1).

Table 1 - Descriptive statistics of the participants used for the replay recording phase

	Gender		Age		AISS score
	Male	Female	Mean	Std.	Mean
High sensation seeking	4	0	36.25	9.78	55.75
Low sensation seeking	2	2	52	6.73	45

Note. AISS scores were calculated based on drivers' responses to Arnett Inventory of Sensation Seeking (AISS; Arnett, 1994), and scores were the sum of all responses to in total of 20 questions, with a higher score means higher sensation seeking propensities.

During the recording process, each participant drove the experimental route three times. The process took approximately one hour. After the data collection, the clustering process was applied again for the new data, to confirm the obtained driving behaviours belonged to the previously identified

205 defensive and aggressive driver groups, respectively. Out of the eight participants recorded, the
206 manual driving data of two participants (one per sensation seeking group, with scores of 59 and 43,
207 respectively) which was closest to the median of the defensive and aggressive clusters, were selected
208 as the representative driving styles for our two human-like controllers. It is worth highlighting that
209 the selected drives were also checked to ensure that no unusual or unexpected manoeuvres existed
210 along the drive. For the rest of this paper, the higher sensation seekers' driving style will be termed
211 Aggressive, and the lower sensation seekers' driving style will be called the Defensive driving style.

212 2.3.2. Road Environment and Scenarios

213 The simulated driving scene was modelled from real stretches of road around North Bedfordshire in
214 the UK (Figure 2). Two loops, going North and South, were simulated, creating a virtual environment
215 covering around 12 miles of driving. In the present work, however, only the North loop was included
216 for the simulated drive, since it included the range of scenarios required for studying driver behaviour
217 in response to changes in speed and geometry, and shortened the overall drive. This section of road
218 was approximately 5 miles long, taking about 15 minutes to complete.

219 To understand user preferences for, and in response to, a wide range of road geometries and speed
220 profiles, the layout of the North loop contained a combination of high-speed (60 mph) rural sections,
221 with varying road curvature, and more built-up, village sections, at a speed limit of 40 mph (Table 2).

222

223

224 *Figure 2. Example of the simulated (top) and real (bottom) road environments*

225 **Table 2** - The speed limit and geometrical details of the simulated road.

Zone	Curve radius	Curve direction	Road type	Speed limit (mph)	Road context
1	300-800m	Left	Rural	60	Kerb + grass and the bridge in the middle of the area
2	Straight	Straight	Rural	60	Kerb + grass with hedge far from the road edge
3	<150m	Left	Rural	60	Kerb + grass and trees far from the road edge
4	<150m	Left	Rural	60	Kerb + grass with hedge quite far from the road edge
5	300-800m	Right	Rural	60	Kerb + grass with hedge quite far from the road edge
6	<150m	Right	Village	40	Kerb + grass and some structures far from the road edge
7	<150m	Left	Village	40	Kerb + grass
8	200-300m	Right	Village	40	Kerb + grass and hedge around 1-2m from the road edge
9	Straight	Straight	Village	40	Kerb + grass and fence quite close to the road edge
10	150-200m	Right	Village	30	Kerb + pavement and village structures far from the road edge
11	150-200m	Right	Village	30	Parked cars zone
12	300-800m	Right	Village	30	Kerb + grass and village structures
13	200-300m	Left	Rural	40	Grass, bushes and trees not close to the road edge
14	300-800m	Right	Rural	40	Grass and hedge far from the road edge
15	<150m	Right	Rural	60	Grass and trees far from the road edge
16	<150m	Left	Rural	60	Hedge at the road edge
17	150-200m	Right	Rural	60	Grass and hedge far from the road edge
18	300-800m	Left	Rural	60	Grass and bushes around 2m from the road edge
19	Straight	Straight	Rural	60	Fence around 1-2m from the road edge
20	Straight	Straight	Rural	60	Hedge at the road edge and an intersection at the end of the section
21	na	na	University	30	Mini roundabout and road markings
22	<150m	Left	University	30	Parked cars zone
23	300-800m	Left	University	30	Kerb + pavement
24	Straight	Straight	University	30	Kerb + pavement

226

227 2.4. Variables

228 The dependent variables were comfort and naturalness of the driving experience, for each controller.
229 A search of the literature at the time of study design revealed an absence of a formal, and universally
230 agreed, description for the two terms. To ensure that the same term was understood by all
231 participants, we therefore used a small expert group within the project team to define the two terms,
232 and included this information in the participant briefing sheet:

- 233 i. Comfortable driving was defined as '*a driving style that does not cause any feeling of*
234 *uneasiness or discomfort*';
- 235 ii. Natural driving was defined as '*a driving style that is closest to your own driving*'.

236 Participants evaluated each controller, in two ways: (i) after each drive, participants were asked to
237 provide an overall rating, based on their entire driving experience., and (ii) throughout the drive,
238 immediately after they heard a short auditory beep, which was played via the car's speakers,
239 corresponding to 24 relevant sections in the drive (Table 2). They were taught to use a Likert-type
240 scale for guiding their responses, providing a number between -5 (Extremely
241 Uncomfortable/Unnatural) and +5 (Extremely Comfortable/Natural) (Figure 3).

242 Participants also completed the Arnett Inventory of Sensation Seeking questionnaire (Arnett, 1994)
243 after they finished the last drive. This questionnaire includes twenty items, and four response options
244 for each item, ranging from 1 (does not describe me at all) to 4 (describes me very well). Reverse-
245 worded items were further reverse-coded. We used the sum score of these items to characterise
246 sensation seeking tendency, with a higher score indicating a higher sensation seeking tendency.

Figure 3. The Comfort and Naturalness scales used in the study

2.5. Procedure

To reduce the effect of fatigue on participants, the study was conducted over two separate days (M=6.75 days apart, SD=2.17), with data collection lasting about 1.5 hours on each day. Participants evaluated the three driving styles twice: once in terms of comfort, and once in terms of naturalness, with half of the participants evaluating in terms of comfort on day 1, and the other half on day 2, (Figure 4).

Upon arrival on the first day, each participant received a written and verbal briefing of the study, including how to use the subjective scale, and provided their written consent to take part in the experiment. They then started the simulator experiment with a practice drive in manual driving, followed by a practice ride in an automated driving mode. A researcher accompanied participants

259 during the practice session, which lasted 20-30 minutes. Following the practice drive, the researcher
 260 left the simulator dome, and the participant started the first of three experimental drives, one for
 261 each controller. The order of the three automated driving styles was counterbalanced across
 262 participants, and participants left the simulator dome after each drive, to reduce fatigue effects. After
 263 the second day's experiment, participants were asked to complete a set of questionnaires, including
 264 the sensation seeking questionnaire. The data from the other questionnaires is not reported here.

265

266 *Figure 4. The overall experimental procedure, including the order of drives.*

267 3. Results

268 The main aim of the analyses was to assess users' evaluation of the three automated controllers, in

terms of comfort and naturalness. Participants' subjective feedback about the driving styles adopted by the controllers was provided in two ways: (i) an overall evaluation of the controller, after finishing the entire drive, and (ii) 24 responses, based on the 24 auditory beeps throughout each drive, which prompted a response for each of the different driving zones. Two statistical tests were used: the Wilcoxon signed-rank test was used for the overall evaluation provided at the end of each drive, and the Generalised Estimating Equation (GEE) (Liang & Zeger, 1986) was used for the 24 individual evaluations provided during the drive (see configurations of GEE in Appendix 2).

3.1. Subjective evaluations of the driving styles

Table 3 shows results of the Wilcoxon signed-ranks test on matched-pairs, and Figure 5 shows box plots of overall comfort and naturalness evaluation of the three driving styles.

Regarding overall comfort, the Wilcoxon test showed significantly higher evaluation for the Defensive controller, compared to the Aggressive and the Turner controllers (both $p < .001$). There was no significant difference between the Aggressive and Turner controllers ($p = .49$). Regarding overall naturalness, the Wilcoxon test showed a significantly higher evaluation for the Defensive controller, compared to the Turner ($p < .001$), and a higher evaluation than the Aggressive controller ($p = .02$). A significantly lower score for the Turner than the Aggressive controller ($p = .01$) was also revealed.

Figure 5 shows that the evaluation of the Defensive driving style was relatively consistent across participants. By contrast, the evaluation for the Aggressive and Turner controllers was more variable, with a bimodal pattern observed in response to naturalness of the Aggressive, and the comfort and naturalness of the Turner. To understand this further, we conducted additional analyses by taking participants' personality trait into account.

290 **Table 3** - Wilcoxon signed-rank test results for overall comfort and naturalness

Comfort (overall)			
Driving style	z	p	r
Defensive vs Turner	4.27	0.000*	0.87
Defensive vs Aggressive	4.11	0.000*	0.84
Aggressive vs Turner	0.70	0.490	0.14
Naturalness (overall)			
Driving style	z	p	r
Defensive vs Turner	3.67	0.001*	0.75
Aggressive vs Turner	2.44	0.010*	0.50
Defensive vs Aggressive	2.25	0.020*	0.46

291 Note. * p < .05. Orders of paired comparison are based on z values.

292
293 *Figure 5.* Evaluation of each controllers' driving style, in terms of its overall comfort (left) and overall
294 naturalness (right). Horizontal lines inside each box represent the median values. Whiskers denote a
295 distance of 1.5 times interquartile range (IQR) above the upper quantile up to the largest observation,
296 or below the lower quartiles up to the smallest value. Grey dots represent data points (with small
297 variations added to the position to avoid overlapping), while black points represent outliers.

298

Table 4 presents the GEE results for the repeated ratings of comfort and naturalness. Regarding comfort, the probability of reporting high levels of comfort was significantly higher for the Defensive controller, compared to both the Turner (OR = 7.21, $p < .001$), and Aggressive controllers (OR = 4.01, $p < .001$). Comfort ratings were also slightly higher for the Aggressive, than the Turner, controller (OR = 1.80, $p = .04$). Regarding naturalness, both the Defensive, and Aggressive controllers were more likely to be rated more natural, when compared to the Turner controller (OR = 4.98, $p < .001$; OR = 2.59, $p = .002$). The Defensive controller also had a higher probability of being assessed as more natural than the Aggressive driving style (OR = 1.92, $p = .01$).

Table 4 - GEE model parameter estimates and odds ratios for repeatedly reported comfort and naturalness

Comfort					
Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Defensive vs Turner	1.975	0.238	68.847	0.000*	7.206
Defensive vs Aggressive	1.388	0.234	35.111	0.000*	4.007
Aggressive vs Turner	0.587	0.285	4.258	0.039*	1.799
Naturalness					
Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Defensive vs Turner	1.606	0.232	48.113	0.000*	4.980
Aggressive vs Turner	0.953	0.305	9.745	0.002*	2.593
Defensive vs Aggressive	0.653	0.255	6.560	0.010*	1.921

Note. * $p < .05$. Orders of paired comparison are based on the odds ratios.

To further understand whether subjective evaluation was due to any differences in the driving styles of the controllers, the vehicle kinematics, including the speed and lateral offsets of all three controllers, were inspected (Figure 6 and Figure 7). The interpretations provided in this section were based on visual observations of the controllers' kinematic characteristics only, and no formal analyses were conducted. Figure 6 shows that, overall, speed was higher in the Aggressive driving style, compared to the other two controllers. The Defensive and Turner controllers had similar increasing

316 or decreasing trends in speed, for the same road sections, with smoother patterns (i.e., less frequent
 317 and gentler fluctuations in speed) seen for the Defensive controller. There was not much difference
 318 in the observed lateral offset of the three controllers (Figure 7).

319
 320 *Figure 6. The speed profiles of the controllers*

321
 322 *Figure 7. The lateral offset profiles of the controllers*

323 3.2. The effect of road environment on subjective evaluation

324 As shown in Table 2, the simulated road included a range of road environments divided into five main
325 categories: (i) road type, (ii) speed limit, (iii) road context, (iv) curve direction, and (v) curve radius.
326 For simplicity, only two categories were included in this analysis, as follows:

- 327 i. road type (rural and village), which differed by posted speed limit (60 mph vs 40 mph), and
328 roadside furniture (see Table 2);
- 329 ii. curve radius (five levels, varying from straight sections to curves of less than 150m).

330 Road type was included as the representative of speed limit and road context, supported by the
331 strong ($r = 0.88$, $p < .001$) and medium ($r = -0.05$, $p < .001$) correlation between road type and the
332 two categories (speed limit, road context), respectively. The University road type was excluded from
333 analysis, due to the small number of sections falling into this category. The direction of a curve was
334 also not included as a factor, as it was not expected to have a significant influence on results. It is
335 worth mentioning that the number of road sections in each level outlined above was not equal, since
336 the road was a replication of the real world.

337 Figure 8 shows the average comfort and naturalness ratings for the three driving styles, for the
338 different road sections. An overall pattern was observed, such that, with increasing curve radius,
339 there was a mild reduction in both comfort and naturalness ratings for all controllers, especially in
340 the Rural areas. This pattern was not apparent in the Village areas, apart from two unexpected
341 fluctuations. Inspection of the vehicle-based metrics showed a high speed for the Aggressive
342 controller in the 200-300 Curve Radius section, and a suddenly changing speed of the Turner in the
343 300-800 Curve Radius section (for further evaluation of these, see Appendix 3).

346

347 *Figure 8.* Mean evaluation scores for comfort (left) and naturalness (right) for each driving style, for
 348 the different road environments. Error bars indicate standard error of the data.

349 Table 5 shows the results of the GEE models, which showed that the effect of driving style, on comfort
 350 and naturalness ratings, was significant for both the Rural and Village road sections (all $p < .001$). In
 351 the Rural sections, which had a generally higher speed limit than the Village sections, there was less
 352 difference in odds ratios between the Aggressive and the Turner controllers for the gentler roads (i.e.,
 353 Straight and Curve Radius 300-800), but this difference was more prominent for the shaper road
 354 sections (i.e., Curve Radius 150-200, and 200-300). It is also worth highlighting the preference for the
 355 Defensive controller over the Turner, where the odds ratios are seen to be larger with increasing road
 356 curvatures. However, these differences in controllers were not observed for the sharpest Rural

357 section (i.e., less than 150).

358 In the Village sections, where the controllers negotiated the road at a lower speed, the observed
359 pattern with curvature outlined above, was not as apparent. This may be because all controllers
360 negotiated the curves at a relatively low speed, thus reducing the effect of Curve Radius. Overall, the
361 Defensive controller remained the most comfortable and natural, compared to the Aggressive and
362 Turner controllers, indicated by the odds ratios for all Village sections. In contrast, not much
363 difference was seen in the evaluation for comfort and naturalness between the Aggressive and
364 Turner controllers, for the Village sections.

365 **Table 5** - The GEE model parameter estimates and odds ratios, for **comfort** and **naturalness** in rural and village roads with different curvatures

Environment	Curvature	Comfort						Naturalness					
		N	Driving style	Coefficient	SE	Sig	OR	N	Driving styles	Coefficient	SE	Sig	OR
Rural	Straight	216	Defensive vs Turner	1.662	0.326	0.000*	5.270	215 ^b	Defensive vs Turner	1.709	0.347	0.000*	5.522
			Defensive vs Aggressive	0.969	0.293	0.001*	2.636		Aggressive vs Turner	1.569	0.365	0.000*	4.801
			Aggressive vs Turner	0.693	0.366	0.058	1.999		Defensive vs Aggressive	0.140	0.253	0.580	1.150
	300to800	288	Defensive vs Turner	1.926	0.289	0.000*	6.860	288	Defensive vs Turner	1.316	0.307	0.000*	3.727
			Defensive vs Aggressive	1.350	0.290	0.000*	3.856		Aggressive vs Turner	1.141	0.342	0.001*	3.129
			Aggressive vs Turner	0.576	0.310	0.063	1.779		Defensive vs Aggressive	0.175	0.301	0.561	1.191
	200to300	72	Defensive vs Turner	2.812	0.483	0.000*	16.650	72	Defensive vs Turner	4.067	0.624	0.000*	58.356
			Aggressive vs Turner	1.422	0.506	0.005*	4.146		Aggressive vs Turner	2.441	0.667	0.000*	11.486
			Defensive vs Aggressive	1.390	0.411	0.001*	4.016		Defensive vs Aggressive	1.625	0.453	0.000*	5.081
	150to200	72	Defensive vs Turner	2.800	0.496	0.000*	16.446	72	Aggressive vs Turner	2.728	0.677	0.000*	15.295
			Aggressive vs Turner	1.561	0.522	0.003*	4.764		Defensive vs Turner	2.670	0.458	0.000*	14.439
			Defensive vs Aggressive	1.239	0.488	0.011*	3.452		Defensive vs Aggressive	-0.058	0.547	0.916	0.944
	less150	288	Defensive vs Turner	1.667	0.252	0.000*	5.295	287 ^c	Defensive vs Turner	1.784	0.303	0.000*	5.955
			Defensive vs Aggressive	0.966	0.277	0.000*	2.627		Aggressive vs Turner	1.159	0.415	0.005*	3.185
			Aggressive vs Turner	0.701	0.269	0.009*	2.016		Defensive vs Aggressive	0.626	0.265	0.018*	1.869
Village ^d	Straight	72	Defensive vs Turner	1.859	0.459	0.000*	6.415	72	Aggressive vs Turner	0.958	0.410	0.020*	2.607
			Defensive vs Aggressive	1.342	0.441	0.002*	3.828		Defensive vs Turner	0.083	0.5525	0.880	1.087
			Aggressive vs Turner	0.516	0.427	0.227	1.676		Defensive vs Aggressive	-0.875	0.508	0.085	0.417
	300to800	72	Defensive vs Aggressive	2.934	0.767	0.000*	18.796	72	Defensive vs Aggressive	3.667	0.542	0.000*	39.121
			Defensive vs Turner	2.480	0.425	0.000*	11.936		Defensive vs Turner	1.917	0.513	0.000*	6.798
			Aggressive vs Turner	-0.454	0.554	0.412	0.635		Aggressive vs Turner	-1.75	0.800	0.029*	0.174
	200to300	71 ^a	Defensive vs Turner	3.591	0.514	0.000*	36.255	72	Defensive vs Turner	3.917	0.692	0.000*	50.233
			Aggressive vs Turner	2.159	0.529	0.000*	8.662		Aggressive vs Turner	2.75	0.660	0.000*	15.643
			Defensive vs Aggressive	1.432	0.552	0.009*	4.186		Defensive vs Aggressive	1.167	0.631	0.064	3.211
	150to200	144	Defensive vs Turner	2.191	0.380	0.000*	8.948	144	Defensive vs Turner	1.396	0.410	0.001*	4.038
			Defensive vs Aggressive	1.649	0.440	0.000*	5.204		Defensive vs Aggressive	1.021	0.377	0.007*	2.776
			Aggressive vs Turner	0.542	0.372	0.145	1.719		Aggressive vs Turner	0.375	0.537	0.485	1.455
	less150	144	Defensive vs Turner	2.962	0.431	0.000*	19.336	144	Defensive vs Turner	3.042	0.531	0.000*	20.940
			Defensive vs Aggressive	2.943	0.529	0.000*	18.974		Defensive vs Aggressive	2.438	0.726	0.001*	11.444
			Aggressive vs Turner	0.238	0.303	0.432	1.268		Aggressive vs Turner	0.604	0.790	0.444	1.830

366 *Note.* * $p < .05$. Orders of comparison are based on odds ratios. ^{a b c} 1 observation was missing. ^d GEE with the linear link function was used for naturalness (see Appendix 2).

367 3.3. The influence of personality traits on subjective evaluation

368 Following data collection, participants were divided into two sub-samples, based on their average
 369 scores to the 20 AISS items. Evaluation of the controllers by the two sub-samples, providing the
 370 lowest (mean = 48.54, N = 13), and highest sensation seeking score (mean = 59.45, N = 11), was then
 371 assessed.

372 Table 6 and Figure 9 show that the Defensive driving style was regarded as the most comfortable, for
 373 both the high and low sensation seekers. Interesting results were observed regarding the evaluation
 374 of naturalness. Low sensation seekers evaluated the Defensive as much more natural than the other
 375 two controllers, whereas high sensation seekers rated the Aggressive and Defensive driving styles
 376 about the same, in terms of naturalness. This finding also explains the bimodal pattern of evaluations
 377 on naturalness, shown in Figure 5 (right).

378 **Table 6** - The GEE model parameter estimates and odds ratios regarding comfort and naturalness for
 379 low and high sensation seekers

Comfort							
	N	Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Low sensation seekers	934 ^a	Defensive vs Turner	1.809	0.346	27.305	0.000*	6.102
		Defensive vs Aggressive	1.356	0.378	12.875	0.000*	3.881
		Aggressive vs Turner	0.452	0.436	1.075	0.300	1.572
High sensation seekers	791 ^b	Defensive vs Turner	2.153	0.296	53.039	0.000*	8.607
		Defensive vs Aggressive	1.507	0.281	28.865	0.000*	4.515
		Aggressive vs Turner	0.645	0.348	3.438	0.064	1.906
Naturalness							
	N	Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Low sensation seekers	936	Defensive vs Turner	1.593	0.262	37.061	0.000*	4.919
		Defensive vs Aggressive	0.949	0.368	6.666	0.010*	2.583
		Aggressive vs Turner	0.644	0.463	1.933	0.164	1.904
High sensation seekers	789 ^c	Defensive vs Turner	1.652	0.379	18.98	0.000*	5.217
		Aggressive vs Turner	1.258	0.370	11.584	0.001*	3.518
		Defensive vs Aggressive	0.394	0.334	1.390	0.238	1.483

380 *Note.* * p < .05. ^{abc} observations were missing, with the number of 2, 1, and 3, respectively.

381

382 *Figure 9. Overall comfort (left) and naturalness (right) evaluation of the driving styles from different*
 383 *sensation seekers.*

384 4. Discussion

385 This driving simulator study examined users' subjective evaluation of the driving style of three AV
 386 controllers, in terms of comfort and naturalness, when negotiating a range of rural and village
 387 sections of a UK road. The link between participants' sensation seeking scores and their evaluation
 388 of these controllers was also investigated.

389 In terms of human- vs machine-like controllers, results showed that users preferred the two human-
 390 like AV controllers, in terms of both comfort and naturalness. Contrasting our findings with similar
 391 studies is challenging, as, at the time of writing, there are very few studies which have explicitly
 392 compared participant preferences for human-like and machine-like automated vehicle controllers.
 393 One exception is a study by Oliveira et al. (2019), who measured users' trust towards a highly

394 automated pod, which showed either human- or machine-like driving behaviours, when crossing a T-
395 junction. In this study, human-like behaviour was produced by demonstrating a cautious “peeking”
396 behaviour by the pod, before it crossed the junction, while machine-like behaviour was produced by
397 an assertive crossing, as if the road conditions were known to the automated pod. Oliveira et al.
398 (2019) showed no difference in trust ratings for the two behaviours of the pod. There are two reasons
399 why our study results are in contrast to those of Oliveira et al. (2019). One may be due to a difference
400 in the concept used between our two studies: trust versus comfort and naturalness. The other may
401 be because of the lower operating speed of the AV used in an urban road, by Oliveira et al, compared
402 to the higher travelling speeds of our vehicle, travelling in rural road sections. This contrast in results
403 illustrates the importance of considering the scenarios used to evaluate AV driving styles in such
404 studies, since they vary across different road environments, based on both geometry and posted
405 speed limit, which clearly influences any subjective assessment and evaluation (Hajiseyedjavadi et al.,
406 submitted). Further work on the influence of different scenarios on subjective appraisals of human-
407 vs machine-like AV driving styles, should clarify this.

408 Overall, participants rated the Defensive controller more comfortable than the other two controllers,
409 while both the Defensive and Aggressive controllers were assessed as more natural than the Turner.
410 This suggests that there may be a distinction between what human evaluators consider a comfortable
411 versus natural driving style, which is perhaps in contrast to the suggestion made by Elbanhawi et al.
412 (2015), who regarded natural, or familiar, driving manoeuvres as one contributor to driving comfort.
413 Our results suggest that comfort and naturalness of a controller should not be used interchangeably
414 in such research, and that while human-like driving styles can be considered as equally more natural
415 than a ML-based controller, they are not necessarily as equally comfortable. Therefore, factors which

416 contribute to the comfort of a controller are not the same as those that determine its naturalness.

417 Regarding how road geometries and vehicle kinematics affected subjective ratings, our results show
418 that variations in speed potentially had a greater influence on evaluation of comfort and naturalness
419 of the controllers, when compared to differences in lateral offset. This was especially the case for the
420 rural sections, which contained roads of tighter curvature, and higher speed. These results are in line
421 with the work of Hajiseyedjavadi et al. (submitted), who found that their model-based human-like
422 AV driving controllers were assessed as less pleasant when negotiating narrower curves. These
423 authors also found that a more rigid controller, which always followed the centre of the lane, received
424 better evaluations. Together, these results suggest the influence of vehicle kinematics and road
425 geometry on subjective evaluation of AV controllers. Moreover, our results showed little difference
426 in lateral kinematic features of the three controllers, which was also reflected in the evaluations.
427 Therefore, future studies need to examine the effect of more pronounced lateral offset on subjective
428 evaluation, especially since maintaining sufficient and safe distance to road edges is thought to
429 enhance driving comfort (Summala, 2007).

430 We found an interesting interaction between personality trait and evaluation of the controllers, with
431 high sensation seekers rating the Aggressive driving style (which was a recording of another
432 representative high sensation seeker) as natural, which was not the case for low sensation seekers.
433 As naturalness in this study was defined as a driving style that is *"closest to your own driving"*, it is
434 interesting to see this strong influence of personality traits on driving style and preference. The
435 distinction between comfort and naturalness as concepts is also highlighted here, because there was
436 no difference in the two groups, when evaluating the comfort of the Aggressive driving style. In other
437 words, while the high sensation seekers thought the Aggressive driving style was natural, they did

438 not find it comfortable. These results highlight the value of personalisation of automated controllers,
439 to benefit the range of preferences by consumers with varying personality traits, notwithstanding
440 their safety considerations.

441 4.1. Limitations

442 One limitation of the present study is the motion-planning performance of the Turner controller,
443 which was developed using a small number of participants. Moreover, although the motion planner's
444 output consists of a series of aim speeds and positions, we only used simple controllers that were
445 manually calibrated for the automated vehicle to drive, using this data flow. Thus, a future study
446 could use more data to train the motion planner and consider a better approach for implementing
447 the controllers.

448 As with all controlled driving simulator studies, there are caveats regarding the relevance and
449 generalisability of these findings, and their implications with respect to real-world AV controllers.
450 Creating very realistic controllers was possible in this driving simulator study, due to its advanced
451 motion-controller capabilities. However, future studies would benefit from evaluating these sorts of
452 controllers in more real-world settings, also assessing how such evaluation is affected by other real-
453 world factors, such as different road surfaces, or presence of other roadside objects and road users.

454 4.2. Conclusions

455 Participants rated the two human-like driving styles as more natural, compared with the less human-
456 like, ML-based, controller. Most participants also rated the Defensive driving style (gentler speed
457 profiles) as more comfortable than the Aggressive controller (higher accelerations and more sudden

458 braking profiles). This study shows, for the first time, that participants are able to distinguish between
459 the natural driving manoeuvres of humans and the more machine-like negotiations of an artificial
460 controller. In addition, we illustrate that there is a more complex relationship between concepts such
461 as comfort and naturalness when evaluating automated vehicle controllers.

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467 simulator scenarios.

468 Key points

- 469 • Human-like driving features were rated as more comfortable and natural than the ML-based,
470 less-human-like, driving style, under most road contexts for users with different sensation
471 seeking traits.
- 472 • Between the two human-like driving controllers, the slower, milder and more conservative
473 controller (Defensive) was preferred, in terms of comfort and naturalness.
- 474 • When exposed to more complicated road environments (e.g., sharper curves, higher speed
475 limits, potentially hazardous roadside objects), the Defensive driving controller was preferred.
- 476 • A natural driving style was not necessarily perceived as comfortable, especially by high
477 sensation seekers.

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628 Appendices

629 **Appendix 1 - Cluster analysis for categorising driving behaviour**

630 From a previous study of the project, driving behaviours were collected from a sharp curve (radius <
631 150m), a zone with parked cars (length = 162.68m), and the entire drive. The variables used as
632 behavioural indicators for clustering were: root mean square of speed, standard deviation of
633 longitudinal acceleration, and standard deviation of yaw rate. The k-means clustering analysis was
634 conducted.

635 **Appendix 2 - Configuration of the GEE model**

636 The working correlation matrix was specified as *exchangeable*, which characterises the correlation
637 structure of multiple observations within a participant as the same. As the comfort and naturalness
638 were rated using an ordinal Eleven-point Likert scale, the distribution of the dependent variable was
639 specified as a *multinomial* distribution. A link function is used to characterise the relationship
640 between the mean of the response (i.e., subjective ratings) and the linear predictor (i.e., controllers).
641 The *ordered logit regression* was specified as the link function.

642 However, in some Village road segments, including the Straight road sections, the 200-300 Radius
643 sections, and the 150-200 Radius sections, the statistical model did not provide valid results, because
644 the participants' responses to the three controllers in these sections showed very similar patterns,
645 which resulted in collinearity. For example, in the Curve Radius 150-200 section, most responses
646 clustered between 2 to 5 for all three driving styles. Therefore, we treated the data as continuous in
647 these road sections, to allow statistical comparisons. The distribution was specified as normal in the

648 GEE.

649 **Appendix 3 - Vehicle kinematics inspection for the two village road sections with unexpected**
650 **assessments**

651 Inspection of the vehicle-based metrics for these two particular road sections (Figure 10) showed
652 that the Aggressive controller's speed was markedly higher than that of the two other controllers in
653 the 300-800 Radius section, and higher than the designated speed limit of 30 mph. A sudden
654 fluctuation of speed for the Turner controller was also seen in the 200-300 Radius section, although
655 it was within the speed limit of 40 mph. Further inspection of the simulated scene did not show the
656 presence of any unusually placed road furniture, such as parked cars. A possible explanation here is
657 that the Turner controller did not look far enough ahead to smooth out the speed changes, and was
658 also inadequately sensitive to roadside furniture. Regardless, these results show that the effect of
659 these kinematic changes were clearly felt by our users, which can possibly explain their evaluation of
660 the controllers for these two sections.

661

662 *Figure 10. Vehicle speed of three controllers in the two village road curves*