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User comfort and naturalness of automated driving: The effect of vehicle kinematic and proxemic factors on subjective response

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ABSTRACT

User comfort in higher-level Automated Vehicles (AVs, SAE Level 4+) is crucial for public acceptance. AV driving styles, characterised by vehicle kinematic and proxemic factors, affect user comfort, with "human-like" driving styles expected to provide natural feelings. We investigated a) how the kinematic and proxemic factors of an AV's driving style affect users' evaluation of comfort and naturalness, and b) how the similarities between automated and users' manual driving styles affect user evaluation.

Using a motion-based driving simulator, participants experienced three Level 4 automated driving styles: two human-like (defensive, aggressive) and one machine-like. They also manually drove the same route. Participants rated their comfort and naturalness of each automated controller, across twenty-four varied UK road sections. We calculated maximum absolute values of the kinematic and proxemic factors affecting the AV's driving styles in longitudinal, lateral, and vertical directions, for each road section, to characterise the automated driving styles. The Euclidean distance between AV and manual driving styles, in terms of kinematic and proxemic factors, was calculated to characterise the human-like driving style of the AV.

We used mixed-effects models to examine a) the effect of AV's kinematic and proxemic factors on the evaluation of comfort and naturalness, and b) how similarities between manual and automated driving styles affected the evaluation. Results showed significant effects of lateral and rotational kinematic factors on comfort and naturalness, with longitudinal kinematic factors having a less prominent effect. Similarities in vehicle metrics, such as speed, longitudinal jerk, lateral offset, and yaw, between manual and automated driving styles, enhanced user comfort and naturalness.

This research facilitates an understanding of how control features of AVs affect user experience, contributing to the design of user-centred controllers and better acceptance of higher-level AVs.

1. Introduction

The Society of Automotive Engineers (SAE) defines five levels for automated vehicles (AVs), ranging from Level 0 (no driving automation) to Level 5 (full driving automation, SAE, 2021). For SAE Level 4 and above, the automated system operates the vehicle without requiring user intervention, under certain (Level 4) or all (Level 5) driving conditions. For these SAE Level 4+ vehicles, users primarily act as passengers or riders, rather than drivers, even if seated in the driver's seat. However, due to imperfect controllers, for some road geometries and AV manoeuvres, the user experience can be unpleasant or uncomfortable, sometimes resulting in motion sickness (Carsten and Martens, 2018; Diels and Bos, 2015). Accordingly, the concept of user comfort has captured researchers' interest in recent years. Used broadly as a subjective concept, this term is associated with numerous positive experiences and definitions. A range of terms have been used to describe comfort, including: "*a subjective, pleasant state of relaxation given by confidence and an apparently safe vehicle operation*" (Hartwich et al., 2018). It is argued that ensuring user comfort is important for enhancing the public acceptance and uptake of AVs (Dichabeng et al., 2021; Nordhoff et al., 2021a, 2021b).

Considering that users of Level 4+ AVs will lose active control of the vehicle, and experience a range of system-generated motions, understanding how an AV's driving style influences user comfort is a key factor for improving the user experience, as the AV negotiates a range of road geometries. An AV's driving style is influenced by its kinematic factors, such as acceleration and braking behaviour, and proxemic factors, such as the distance maintained from other road users and objects. It also includes vehicle manoeuvres influenced by road surface and geometry, such as how it negotiates road curves and how smooth the ride is (Peng et al., 2024). Kinematic and proxemic factors of vehicle driving styles form the fundamental focus of research investigating comfort and enjoyment, and ultimately the acceptance, of AVs (e.g., Kuderer et al., 2015; Lee et al., 2019).

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One of the factors thought to affect the comfort of AVs is the "naturalness" of its driving style, which is the extent to which the vehicle's handling of the driving task feels familiar and similar to a user's own driving style and habits (Hartwich et al., 2018; Kamaraj et al., 2023; Peng et al., 2022). Naturalness is also linked to terms such as human-like or personalised driving (Gu and Dolan, 2014; Li et al., 2022; Wei et al., 2019). The use of such human-like or personalised driving styles is intended to enhance the familiarity of the drive for users, helping them predict the AV's upcoming manoeuvres (Elbanhawi et al., 2015), perhaps based on past experience. However, it is currently not clear if these concepts actually contribute to user comfort in AVs, with research showing mixed results (Basu et al., 2017; Hartwich et al., 2018; Peng et al., 2022).

In order to create a more concrete link between the vehicle's lateral and longitudinal movements during different driving scenarios, and users' evaluation of the ride experience, it is useful to link subjective responses about the comfort and naturalness of manoeuvres, with the AV's kinematic and proxemic factors. In terms of comfort, the International Organisation for Standardisation (ISO) has suggested several operational limits for the speed, acceleration and jerk of vehicles with Adaptive Cruise Control (ACC) functionalities (ISO 15622, 2018). However, such quantifications for lower-level AVs may not be relevant to higher-level AVs, due to the differences in user control between the two. With a focus on the effect of peak acceleration (0.4–2 m/s^2) and peak jerk (0.5–15 m/s^3) on discomfort, De Winkel et al. (2023) found that larger acceleration levels increased discomfort, while higher jerks with a shorter duration generated by sinusoidal pulses were more comfortable than jerks with a longer duration generated by triangular pulses. The authors also emphasised the role of the direction of motion, with forward motion reported as more comfortable than backward, and lateral motion as the least comfortable. However, since the focus of this study was on vehicle motions, participants were instructed to keep their eyes closed, which is obviously different from real driving environments.

The importance of considering proxemic factors for comfort is based on Summala (2007), who suggests that sufficient distance in space and time between the user's vehicle and other objects on the road constitutes a safety margin, within which users feel safe and comfortable. In the context of SAE Level 2 automated driving – which requires continuous monitoring by the driver - He et al. (2022) investigated users' perceived risk and trust during certain manoeuvres, such as when an adjacent vehicle merges or a lead vehicle brakes hard. The authors found that both spatial distance (e.g., minimum gap) and temporal distance (e.g., time to collision) significantly affect users' perceived risk and trust. However, the effect of these distances on comfort may differ from their impact on perceived risk and trust, due to differences in these concepts (Nordhoff et al., 2021; Paddeu et al., 2020; Peng et al., 2024).

In terms of the link between vehicle kinematic and proxemic factors and naturalness of the driving experience, Kamaraj et al. (2023) explored whether participants' subjective evaluation of the similarity between manual and automated driving styles corresponds to objective similarities, characterised by Euclidean distance. The authors suggest that the differences in the speed profiles of the manual and automated driving styles served as an objective predictor of the subjectively evaluated similarity of manual-automated driving styles by participants. The study by Kamaraj et al. (2023) established a connection between vehicle kinematic factors and naturalness (termed as "similarity" in their study). However, it only considered longitudinal speed, leaving unanswered questions about whether other kinematic and/or proxemic factors play a role in users' evaluation of naturalness.

1.1. Research gap

Although an AV's driving style is considered a critical factor in determining user comfort and naturalness, knowledge about how its kinematic and proxemic factors affect user experience and evaluation remains limited. Previous studies have primarily focused on vehicle acceleration and jerk. However, it is important to consider both kinematic and proxemic factors to comprehensively understand the effect of individual vehicle metrics on subjective evaluation. Furthermore, exploring whether these kinematic and proxemic factors play a different role in comfort versus naturalness could further enrich our understanding of the relationship between these two closely connected concepts.

1.2. The current study

This research aims to investigate the effect of vehicle kinematic and proxemic factors, as two concepts characterising automated driving styles, on user comfort and naturalness, using data collected by the UK-funded HumanDrive project (TS /P012035/1). Participants evaluated two human-like and one machine-like AV driving style, in terms of their comfort and naturalness, in a moving-based high-fidelity driving simulator study (Peng et al., 2022). We investigated the effect of a range of kinematic and proxemic factors of the AV, on subjective evaluation of its driving style. Moreover, we examined how user evaluation was affected by the objective similarities between the automated driving styles and participants' own manual driving, characterised by the Euclidean distance for a range of kinematic and proxemic factors (Kamaraj et al., 2023).

The research objectives of the study were to.

1) Investigate the role of different vehicle kinematic and proxemic factors in shaping subjective evaluation of the AV ride, in terms of both comfort and naturalness.
2) Explore how similarities between an individual's manual driving style, and that of an automated vehicle affect their subjective response, in terms of comfort and naturalness.
3) Examine whether evaluation of comfort and naturalness are associated with the same vehicle kinematic and proxemic factors.

2. Method

This study used a motion-based driving simulator to capture participants' manual driving styles, assessing their comfort and naturalness evaluation of three automated driving styles, across 24 road sections. While in a previous experiment we focused on evaluating comfort and naturalness of three driving styles (Peng et al., 2022), the present study focused on understanding the association between the kinematic and proxemic factors of these three driving styles and subjective evaluation. This involved assessing how subjective evaluation of each controller was influenced by its speed, lateral offset, acceleration etc. Therefore, we conducted a post hoc analysis of the data, to calculate indicators characterising the kinematic and proxemic factors of the three automated driving styles, for each road section. The maximum absolute values of each factor (for each road section) were used to characterise the automated driving style. For each factor, the Euclidean distance between automated and manual driving styles (for each road section) was also used to characterise the similarity between the two driving styles. These indicators were then modelled to associate with subjective evaluation.

2.1. Participants

Twenty-four participants (12 female and 12 male); aged between 20 and 49 years (M = 35.7, SD = 7.1) were recruited for this study. We used the University of Leeds Driving Simulator database to recruit participants, who were required to hold a valid UK driving licence for at least 2 years and be in good health (e.g., not suffering from claustrophobia and severe motion sickness). All participants provided informed consent to attend the study and were compensated £30 for their time. The study was approved by the University of Leeds Ethics Committee (LTTRAN-086).

2.2. Apparatus

The experiment was conducted in the University of Leeds Driving Simulator (UoLDS), a high-fidelity, motion-based simulator. This includes a 2006 Jaguar S-type vehicle cab, housed within a spherical projection dome (4 m diameter). Within the dome, eight visual channels render at 60 frames/s, at a resolution of 1920×1200 pixels. This provides a horizontal forward field of view of 270°. The simulator has an eight degree-of-freedom motion system, which provides acceleration within ± 5.0 m/s^2 (Jamson et al., 2007).

2.3. Experimental design

This study used a 3 (AV driving styles: Defensive, Aggressive, and machine-learning-based) × 24 (road sections) within-participant experimental design. Participants provided subjective evaluation of the three automated driving styles for each of the 24 road sections, which differed in terms of geometry, roadside environment, and speed limit. This resulted in 72 sets of kinematic and proxemic factors in total, for evaluation. There were six automated drives in total, with three rated in terms of comfort, and the other three rated in terms of naturalness.

2.4. The three driving styles

Among the three driving styles, the machine-learning (ML)-based controller was trained using driving data from 10 participants who drove freely on the same simulated road in a previous experiment (Solernou et al., 2020). These participants were different from the 24 participants involved in the current study. While the ML-based controller was developed to imitate human driving behaviour by adapting yaw rate and speed to upcoming changes in driving demand, such as curves and roadside furniture, we considered it a more machine-like driving style for two reasons. First, the controller mostly stayed close to the lane centre, differing from the participants' curve-cutting behaviour observed in the training data. Second, it only looked 1 s ahead, potentially resulting in a somewhat jerky perception and frequent speed changes.

The other two driving styles were recordings of representative drives from a different group of participants. The selection process of driving styles used two approaches to ensure the two driving styles were representative and distinct from each other, including i) cluster analysis of driving behaviours and ii) individuals' sensation seeking characteristics. The latter was based on previous findings that an individual's sensation seeking propensities are associated with their driving styles, with higher sensation seekers generally driving faster (Louw et al., 2019; Zuckerman and Neeb, 1980). First, using data from a previous study in the project, we clustered 14 drivers into three categories: aggressive, moderate, and defensive, using k-means cluster analysis. Second, we collected the sensation seeking scores of these 14 drivers, and found a moderate correlation between their sensation seeking scores and their clustering membership. However, probably due to the small sample size, this correlation was not significant. Once this clustering was done, we contacted the drivers with high sensation seeking scores from the aggressive cluster ($N = 4$) and those with low sensation seeking scores from the defensive cluster ($N = 4$), and asked them to return to the lab for further data collection. Each driver then manually drove the same route again three times. Following this manual drive, another cluster analysis was conducted to confirm that the driving behaviours of our sample still fell into the previously identified defensive and aggressive groups. We then used data from two drivers (one high, one low sensation seeker) whose data was closest to the median of the defensive and aggressive clusters, as the representative human-like driving styles to create an Aggressive and Defensive controller, respectively. More details about the selection of the two driving styles are provided in the Appendix.

2.5. Road environment

The simulated road was approximately six miles long and replicated a real UK road, to reflect the real-world driving environment (Figs. 1 and 2). It contained diverse road widths and geometries, to enrich the driving styles, in terms of vehicle kinematic factors, such as acceleration/deceleration and curve negotiation, and proxemic factors, such as the distance of the vehicle from roadside furniture and objects.

As the road environment (e.g., rural versus village areas) and geometry (i.e., curve radii) were likely to influence subjective ratings of a driving style (Peng et al., 2022), we further classified these road sections into four categories, according to the posted speed limit (high and low) and curvature of the road section (sharp and gentle) (Table 1). Road sections with a high-speed limit (60 mph) were primarily rural areas, where roadside furniture consisted mostly of vegetation. Road sections with a low-speed limit (30/40 mph) predominantly represented village and university areas, characterised by more buildings, pavements, and parked cars along the road. As a result, the kinematic and proxemic features of the drive were expected to vary.

2.6. The procedure of the experiment

A two-day schedule was allocated for each participant to complete the experiment, to mitigate the potential influence of fatigue on results. Data collection lasted approximately 1.5 h, for each day.

For the first visit, upon arrival, participants received written information about the study, including definitions of comfort and naturalness. A comfortable driving style was defined as "*a driving style that does not cause any feeling of uneasiness or discomfort*", while a natural driving style was defined as "*a driving style that is closest to your own driving*". Instructions were also provided on how to evaluate each controller using 11-point Likert scales, ranging from -5 (Extremely Uncomfortable/Unnatural) to $+5$ (Extremely Comfortable/Natural). Participants were instructed to provide ratings verbally for each road section during the ride when they heard an auditory prompt, and also in writing after completing each drive. After reading the information, participants provided their written informed consent to take part in the experiment. After being introduced to the driving simulator and its controls, participants first completed two practice drives, including a practice manual drive and then a practice automated ride, in the presence of the experimenter, after which the experimenter exited the simulator dome. Participants then experienced the three automated driving styles in a counterbalanced order, evaluating each controller in terms of its comfort or naturalness. During their second visit, participants experienced the three automated driving styles again, evaluating them for the concept not previously assessed (i.e., if they evaluated comfort first, they then evaluated naturalness, and vice versa) (Fig. 3). For the evaluation, participants were cued via an auditory beep and a voice reminder saying "rate now" as the controller negotiated each road section (24 times in total), and also provided an overall rating of the controller, at the end of each drive. Each automated ride took approximately 15 min to complete. There was an additional manual driving task. For half of the participants, this task was completed before all automated drives, while for the other half, it was conducted after all automated drives. The order accounted for the potential influences of familiarity with the environment and exposure to automated driving on an individual's manual driving. After all drives participants completed a set of questionnaires, which included questions on demographics and a range of personality traits, the latter are not reported in this study.

2.7. Vehicle kinematic and proxemic factors of driving styles

The kinematic and proxemic factors of each AV controller and manual drive changed continuously in response to various road geometries and posted speed limits, while participants only provided evaluation for the AV controller once for each road section. Therefore, it is

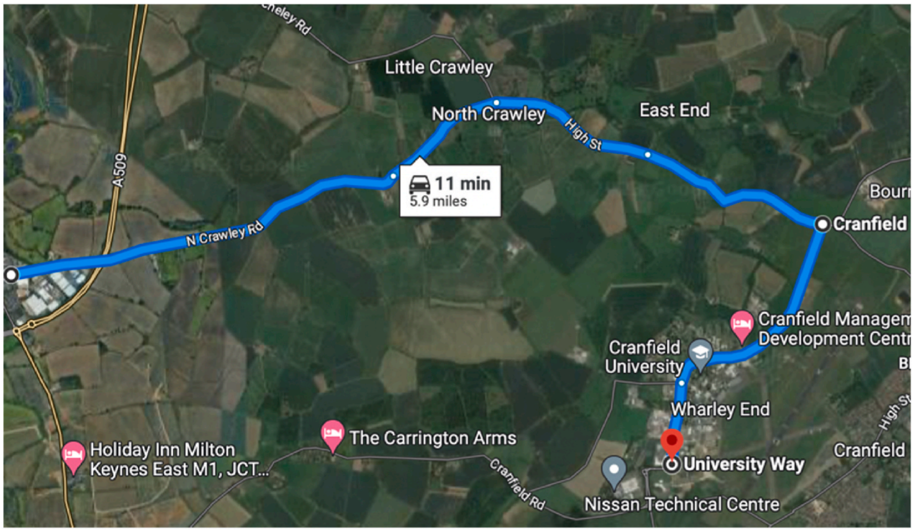

Fig. 1. The stretch of a real UK road that was used to simulate the experimental driving route.

Fig. 2. Examples of the simulated roads, showing road geometries such as different curves and on-road and roadside objects such as buildings, parked cars, and vegetation.

Table 1
Categorisation of road sections based on the posted speed limit and curve radius.

Speed limit	Curvature	Road context examples
Low	Sharp	Kerb, grass, parked cars, village
	Gentle	Kerb, grass, hedge, fence, village, bushes, pavement
High	Sharp	Kerb, grass, hedge, trees
	Gentle	Kerb, grass, hedge, bushes, fence

Note. The low speed limit was 30 or 40 mph, while the high speed limit was 60 mph. Sharp curves were with r≤200, while gentle curves were with r > 200.

necessary to use indicators to characterise a driving style for each road section, in order to associate it with subjective evaluation.

The acceleration of the three automated driving styles and manual driving was firstly filtered to reduce noise. The filtering was necessitated by the discrepancy between the motion planner - particularly the longitudinal performance of the ML-based controller - and the capabilities of the driving simulator. This was, due to factors such as the relatively small training dataset and the usage of AI toolbox (Peng et al., 2022). For example, accelerations with very large magnitudes (e.g., -10 m/s^2) exceeded the capabilities of the simulator and could not be perceived by participants. Then, indicator calculations were based on the filtered data.

Regarding the indicator calculation, vehicle data for the road section with a roundabout was excluded, because the road geometry of a roundabout largely differed from the other road sections, resulting in kinematic and proxemic factors that were not comparable with the other road sections.

Participants' manual driving data were included in the analysis, with the exception of two missing recordings from two participants. Longitudinal and lateral acceleration were also filtered.

2.7.1. Acceleration data filtering

The longitudinal and lateral acceleration data was filtered to remove noise (Fig. 4), using the *hampel* function in MATLAB 2019a. The filter calculates the median of a window containing the sample point and a specified number of surrounding points, as well as the standard deviation of the window. If the difference between the sample point and the median exceeds the specified number of standard deviations, the sample point is replaced with the median.

2.7.2. Indicators for characterising driving styles

2.7.2.1. Indicators of a driving style. Previous studies have used a range of vehicle kinematic and proxemic factors to classify driving styles. For example, Hartwich et al. (2018) used the cumulative absolute speed

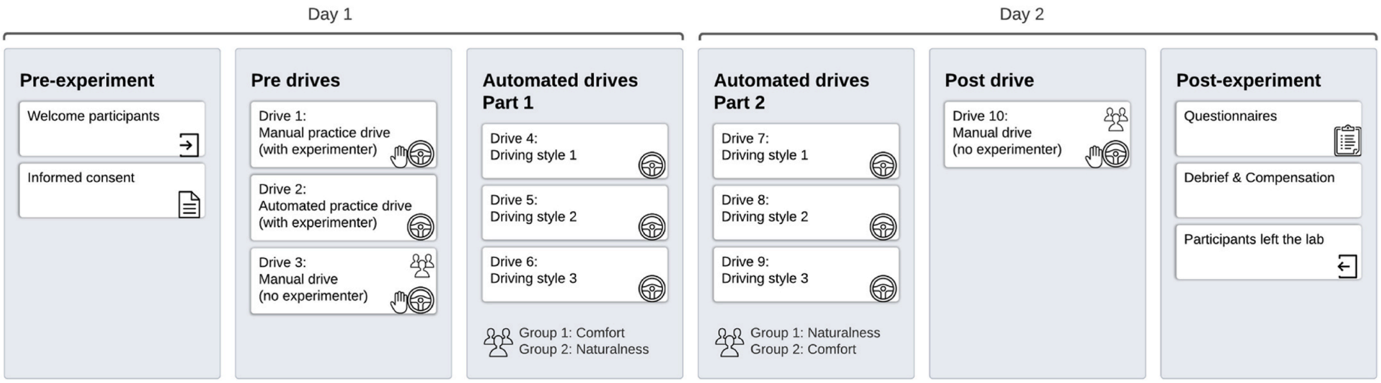

Fig. 3. Experimental procedure. Half of the participants had Drive 3, and the other half had Drive 10 as the manual drive.

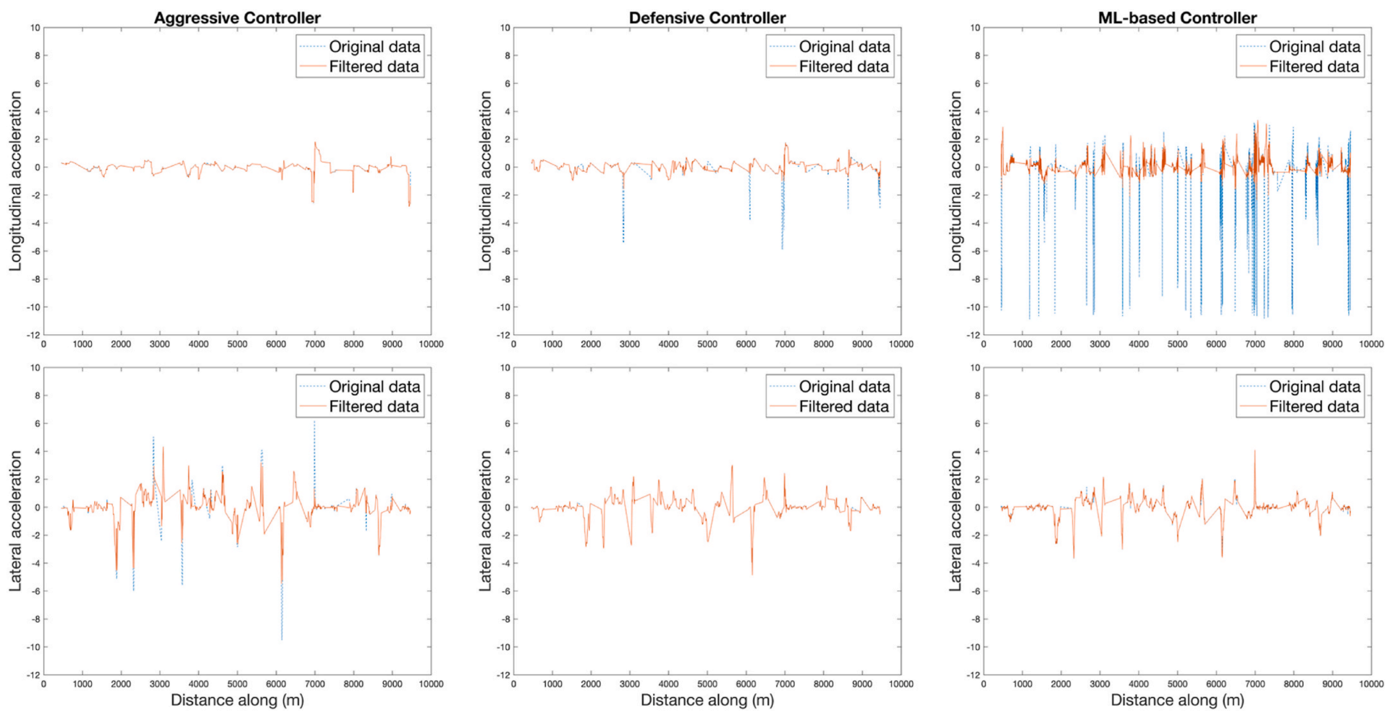

Fig. 4. The original and filtered longitudinal and lateral acceleration values of the three controllers.

difference to identify similarities between automated driving and an individual's manual driving style. Murphey et al. (2009) used the standard deviation and the typical jerk during negotiation of a particular road type, to classify different manual driving styles, and Feng et al. (2017) suggest that a large negative jerk (i.e., a value that is smaller than the 99.9th percentile of the jerk distribution) can be used to identify aggressive drivers. Haghzare et al. (2021) used the average and maximum speed, the positive and negative peaks of acceleration, and the positive and negative peaks of jerk to characterise both manual and automated driving styles. Moreover, although rotational movements are regarded as important for ride comfort in the control engineering domain (e.g., Lee et al., 2014), the importance of rotational metrics has rarely been examined in human factors studies. Therefore, to add value, we used vehicle kinematic and proxemic factors for all three directions of the vehicle: longitudinal, lateral, and vertical/rotational, to characterise automated driving styles for each road section (Fig. 5 and Table 2).

In this study, we adopted a method similar to that of Haghzare et al. (2021) to calculate indicators of a driving style. Specifically, we computed the maximum absolute value for each factor, rather than using average values. This approach was chosen because maximum values are more likely to be more noticeable to users and impact their ratings of the automated driving experience. Apart from speed, which is always positive, we focused on the absolute values of other metrics, disregarding their directional components. All values were standardised

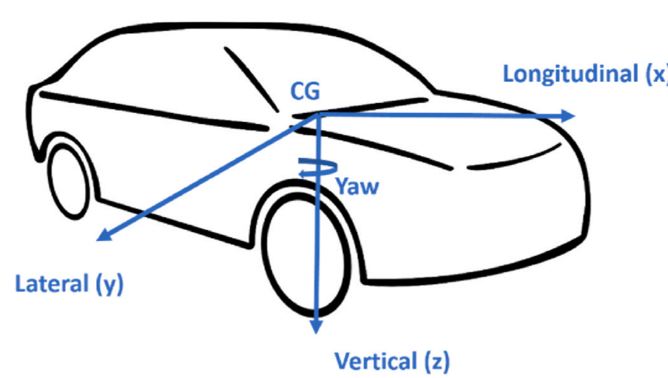

Fig. 5. The coordinate system of a vehicle. CG is the centre of gravity.

Table 2
A summary of the vehicle kinematics and proxemics that are included in the present study.

Directions	Vehicle metrics
Longitudinal	Vehicle speed (m/s). Longitudinal acceleration (m/s^2). Longitudinal jerk[a]: the rate of change of the longitudinal acceleration (m/s^3). Calculated using $j_x = \dot{u} - \dot{v}r - v\dot{r}$, where $\dot{u}$ is the rate of change of longitudinal acceleration, $\dot{v}$ is lateral acceleration, r is yaw rate, v is lateral speed, and $\dot{r}$ is yaw acceleration (m/s^3).[b]
Lateral	Lateral offset: vehicle position CG with regards to road centre (m) (negative values refer to the left of centre line). Lateral acceleration (m/s^2). Lateral jerk[a]: the rate of change of the lateral acceleration (m/s^3). Calculated using $j_y = \ddot{v} + \dot{u}r + u\dot{r}$, where $\ddot{v}$ is the rate of change of lateral acceleration, $\dot{u}$ is longitudinal acceleration, u is longitudinal speed, r is yaw rate, and $\dot{r}$ is yaw acceleration (m/s^3).[b]
Vertical/ Rotational	Yaw: the rotation of the vehicle around the vertical axis (rad). Yaw rate: the rotational speed of the vehicle about the vertical axis (rad/s). It determines how quickly the vehicle is turning. Yaw acceleration: the rate of change of velocity in the yaw axis (rad/s^2).

Note.
[a] Longitudinal and lateral jerk were calculated based on the Vehicle Dynamics Model (Abe and with Manning, 2009), rather than directly using the derivative of acceleration, to avoid noise from discrete sampling.
[b] For the calculation of longitudinal jerk, the third term $v\dot{r}$ was omitted, as it is too small. For the calculation of the first term $\ddot{u}$, longitudinal acceleration was first linear-interpolated and then differentiated. Data pre-processing was conducted using MATLAB R2019a. For lateral jerk, the first term $\ddot{v}$ was omitted, as it is primarily affected by lateral tyre deformation, lateral disturbance, and lateral slip.

to account for the wide range of scales among these metrics.

2.7.2.2. The similarity between two driving styles. Based on Kamaraj et al. (2023), we used Euclidean distance to measure how human-like the automated controllers were in relation to participants' own driving style. To be specific, assuming there are two driving styles negotiating a road, they can be represented as two time series, A and B, each consisting of a number of points. Each point includes a range of vehicle factors. The similarity between driving styles A and B was calculated using the equation $d(A,B) = \sqrt{\sum_{i=1}^{n} (A_i - B_i)^2}$, where the distance between the i^{th} point of each series was computed. This equation was applied to each of the vehicle kinematic and proxemic factors listed in Table 2, to represent the similarity between two driving styles in terms of each factor. As the Euclidean distance method requires both time series to be of the same length, we conducted a resampling of the two series in each road section, to ensure two corresponding points from each series were at the same location (i.e., spatial alignment). This process included two steps: a) using spatial coordinates of each road section to locate corresponding sections in the two time series, and b) interpolating the data of each section to the same length.

2.8. Statistical models

Mixed-effects models were used for the statistical analysis in this study. A mixed-effects model is suitable for data with a hierarchical or nested structure and includes both fixed and random effects. Fixed effects represent our primary interest, anticipated to be constant and identical across all groups in a population. In contrast, random effects can vary across different groups and account for variations resulting from the clustered structure of the data, such as multiple responses from the same participant in repeated measures.

By combing fixed and random effects, mixed-effects models are suitable for analysing data in which observations within groups (e.g., evaluation for the same controller, or evaluation from the same participant) may be correlated. The accuracy of estimates of fixed effects is expected to improve by accounting for variability between groups (Gelman, 2005).

All models were fitted using the R package *lme 4* and *lmerTest*. Statistical significance was set at 0.05.

3. Results

We investigated the effect of kinematic and proxemic factors of automated driving styles on users' evaluation of comfort and naturalness of the AV ride. By comparing individual's manual driving styles with the automated driving styles, we also examined how such similarities in driving styles were associated with their evaluation of the AV ride, in terms of comfort and naturalness.

3.1. The effect of kinematic and proxemic factors of automated driving on evaluation of comfort and naturalness

We first examined the impact of AV kinematic and proxemic factors, using indicators of driving styles (see 2.7.2), on comfort and naturalness. We used two linear mixed-effects models, with comfort and naturalness ratings as the dependent variable, respectively. For the fixed-effects part of independent variables, we considered eight variables, including maximum absolute values of speed, longitudinal acceleration, longitudinal jerk, lateral offset, lateral acceleration, yaw, yaw rate, and yaw acceleration in both models. Since our experiments involved repeated measurements over participants and AV controllers, it is important to capture the similarities between observations for the same participant and controller. We also expected similarities between observations for similar road environments (e.g., posted speed limit and road curvature). However, the inclusion of the two random effects (i.e., posted speed limit and road curvature) did not significantly improve the model fit, based on the Bayesian Information Criterion (BIC). Therefore, only participants and controllers were added to the models as random effects. Due to its high correlation with yaw acceleration ($r = 0.92$, $p < .01$), lateral jerk was not included as an independent variable. We examined potential multi-collinearities using the variance inflation factors (VIF) and found the VIFs for all predictors in each model were under five, indicating the absence of collinearities. The linear mixed-effects model assumes a normal distribution of residuals of the data; such an assumption was also verified by the examination of the Quantile-Quantile plot (QQ Plot).

3.1.1. Model results

For the fixed-effects analysis of the established models (Table 3), the maximum absolute values of longitudinal jerk were positively associated with comfort ratings ($p < .001$), while there was no significant association between this value and naturalness. For lateral metrics, both comfort and naturalness ratings were negatively associated with lateral acceleration ($p < .001$). Regarding the vertical/rotational direction, evaluation of both comfort and naturalness were negatively associated with yaw acceleration, but positively associated with yaw and yaw rate of the AV ($p < .001$). Overall, lateral acceleration appeared to be the most influential metric, as one unit increase in maximum lateral acceleration was associated with a 0.93 and 0.81 decrease in comfort and naturalness ratings, respectively.

For the random-effects (Table 3), the estimated variance of the random intercepts for participants and controllers suggests that there was considerable variability between participants in terms of their evaluation of comfort and naturalness for AV controllers, which are not explained by the predictor variables. Compared with the lower marginal R^2, the higher conditional R^2 values indicate that incorporating random effects into the models improved the overall fit and accounted for more

Table 3
Results of linear mixed-effects models for comfort and naturalness ratings by AV kinematics and proxemics. ICC is the Intra-class Coefficient, reflecting how strongly the observations in the same group are similar to each other. Marginal R^2 indicates variance explained by fixed effects only, whereas conditional R^2 indicates variance explained by both fixed and random effects.

	Comfort			Naturalness		
Fixed effects						
	Estimate	SE	p	Estimate	SE	P
(Intercept)	2.10	0.68	0.06	2.00	0.54	0.04*
Speed	0.08	0.06	0.15	0.02	0.06	0.81
Longitudinal acceleration	−0.08	0.09	0.40	−0.08	0.10	0.41
Longitudinal jerk	0.34	0.09	0.00***	0.13	0.10	0.19
Lateral offset	−0.07	0.06	0.20	−0.11	0.06	0.08
Lateral acceleration	−0.93	0.09	0.00***	−0.81	0.10	0.00***
Yaw	0.19	0.06	0.00***	0.28	0.06	0.00***
Yaw rate	0.37	0.08	0.00***	0.40	0.09	0.00***
Yaw acceleration	−0.57	0.09	0.00***	−0.47	0.10	0.00***
Random effects						
	Variance (SD)	ICC		Variance (SD)	ICC	
Participant	1.43 (1.20)	0.18		0.86 (0.93)	0.11	
Controller	1.19 (1.09)	0.22		0.75 (0.86)	0.17	
Marginal/ Conditional R^2	0.11/0.47			0.10/0.32		

Note: '***' $p < .001$, '**' $p < .01$, '*' $p < .05$. All vehicle metrics were calculated as absolute maximum values and were standardised. ICC values were calculated based on intercept-only models.

of the variability in comfort and naturalness of the AV controllers.

3.2. The effect of similarities in manual and automated driving on evaluation of comfort and naturalness

We investigated the effect of similarities between an individual's manual driving, and that of the different automated driving styles, using the Euclidean distance of a range of vehicle metrics, on the evaluation of comfort and naturalness of the AV controllers. A mixed-effects model was applied to comfort and naturalness ratings, respectively. For both models, independent variables included Euclidean distance in speed, longitudinal jerk, lateral offset, lateral acceleration, lateral jerk, and yaw, between manual and automated driving.

For both models, we included participants, AV controller type, road curvature, and the posted speed limit as random effects. The choice of random effects was supported by the lower BICvalues, which indicate a better model fit, compared to models with fewer random effects.

Strong correlations were observed between the Euclidean distance of certain vehicle metrics, with all correlations being significant ($p < .001$) (Table 4). Therefore, longitudinal acceleration, yaw rate, and yaw acceleration were not included in the models, to avoid multi-collinearities, as verified with VIFs. Between longitudinal acceleration and longitudinal jerk, we excluded the former due to stronger correlations between comfort and naturalness with longitudinal jerk ($r = -0.29$, $r = -3.10$, respectively) than with longitudinal acceleration ($r = -0.26$, $r = -2.82$, respectively).

Table 4
Correlations between Euclidean distance of certain vehicle metrics.

	Long. Acc.	Long. Jerk	Lateral jerk	Yaw rate	Yaw acc.
Long. Acc.	1				
Long. Jerk	0.93	1			
Lateral jerk	–	–	1		
Yaw rate	–	–	0.79	1	
Yaw acc.	0.52	0.55	0.95	0.70	1

Note. This table only shows strong correlations. All significant at $p < .001$.

3.2.1. Model results

The fixed-effects analysis (Table 5) shows that Euclidean distance in speed and longitudinal jerk was negatively associated with both subjective evaluation ($p < .001$, $p < .01$, respectively). On the other hand, lateral jerk had a positive association ($p < .01$), and yaw showed a negative association with both evaluation ($p < .001$). The similarity in lateral jerk had the most significant impact on comfort, while naturalness was primarily influenced by speed, as indicated by the absolute estimate coefficients.

Regarding the random-effects part, the higher conditional R^2 values suggest that the inclusion of random effects in the two models improved the model fit and accounted for more variability in subjective evaluation of the AV driving styles.

4. Discussion

The present study investigated the relationship between subjective evaluation of three AV controllers, in terms of their perceived comfort and naturalness, and the AV's kinematic and proxemic factors. We also examined how the similarities between an individual's manual driving style and the automated driving style experienced, affect participants' evaluation of AV controllers.

For the first research objective, examining the effect of AV controllers' kinematic and proxemic factors on subjective evaluation, we found

Table 5
Model results for the effect of similarities in manual-automated driving on comfort and naturalness ratings. ICC is the Intra-class Coefficient, reflecting how strongly the observations in the same group are similar to each other. Marginal R^2 indicates variance explained by fixed effects only, whereas conditional R^2 indicates variance explained by both fixed and random effects.

	Comfort			Naturalness		
Fixed effects						
	Estimate	SE	Pr (>|t|)	Estimate	SE	Pr (>|t|)
(Intercept)	1.88	0.94	0.12	1.88	0.68	0.05*
Speed	−0.46	0.10	0.00***	−0.75	0.10	0.00***
Longitudinal jerk	−0.36	0.14	0.01*	−0.46	0.15	0.00**
Lateral offset	−0.14	0.09	0.12	−0.10	0.09	0.30
Lateral acceleration	0.12	0.11	0.27	0.20	0.12	0.08
Lateral jerk	0.56	0.12	0.00***	0.40	0.13	0.00**
Yaw	−0.46	0.10	0.00***	−0.37	0.10	0.00***
Random effects						
	Variance (SD)	ICC		Variance (SD)	ICC	
Participant	1.32 (1.15)	0.17		0.92 (0.96)	0.11	
Controller	1.61 (1.27)	0.22		0.62 (0.79)	0.16	
Curvature	0.49 (0.70)	0.07		0.29 (0.54)	0.05	
Speed Limit	0.09 (0.30)	0.01		0.13 (0.36)	0.01	
Marginal/ Conditional R^2	0.04/0.46			0.10/0.34		

Note: '***' $p < .001$, '**' $p < .01$, '*' $p < .05$. All vehicle metrics are calculated as the Euclidean distance between manual and automated driving. ICC values were calculated based on intercept-only models.

that most lateral and rotational kinematics have a role to play in influencing both comfort and naturalness. A notable example is that the yaw of the AV, regardless of the driving direction, had a positive effect on both user comfort and naturalness. This effect might be attributed to users' preference for AV exhibiting human-like behaviour when negotiating curves. In manual driving, drivers tend to cut curves (Mulder et al., 2012; Wei et al., 2019). When drivers become passive passengers in AVs, they appear to maintain this preference for curve cutting. However, there was less of an effect from longitudinal kinematics on subjective evaluation, when compared to lateral kinematics. In particular, no effect of longitudinal acceleration was seen on subjective evaluation. This lack of an effect of longitudinal acceleration on the evaluation of comfort is in contrast to previous studies (Bae et al., 2019; de Winkel et al., 2023). This may be explained by the geometry of the simulated road used in this study, with the curved road sections necessitating many lateral and rotational manoeuvres. On the other hand, there were no particular events that elicited strong changes in longitudinal kinematics, such as sudden brakes, which means most longitudinal kinematic factors may have consistently remained comfortable for users. Our findings highlight the importance of taking the road environment, including road geometries, into account when designing AV driving styles, which is in line with the findings of Hajiseyedjavadi et al. (2022). Despite the insignificance of most longitudinal metrics studied, we found that longitudinal jerk significantly affected comfort evaluation, which supports results from previous studies (Bellem et al., 2018; Martin and Litwhiler, 2008). Furthermore, the association between longitudinal jerk and comfort was found to be positive. This contrasts with the general idea of minimising jerk for comfort (Bae et al., 2019; Bellem et al., 2018; Eriksson and Svensson, 2015), but aligns with the results of de Winkel et al. (2023). The latter found a similarly "counterintuitive" positive relationship between jerk and comfort, and explained that a higher jerk usually has a shorter duration, which has a negligible effect on comfort. Taken together, these findings suggest that higher jerk can be comfortable when of a shorter duration but can become uncomfortable when the duration exceeds a certain level. However, this conjecture requires further investigation to quantify the relationship between jerk, such as its amplitude and duration, and comfort evaluation.

For research objective two, which examined how human-like automated driving styles affected users' perceived comfort and naturalness of the AV controllers, we calculated Euclidean distances in multiple kinematic and proxemic factors to characterise the objective similarities between manual and automated driving styles. We found that objective similarities in several vehicle metrics had a positive effect on user comfort and/or naturalness. Specifically, similarity in vehicle speed was found to improve users' perceived naturalness of the driving styles. This aligns with the results of Kamaraj et al. (2023), while we have extended this finding by confirming that similarity in speed was also associated with higher comfort ratings. In addition to speed, we discovered that similarities in longitudinal jerk and yaw positively influenced user evaluation of both comfort and naturalness. Apart from positive effects, we found that the effect of similarity in lateral jerk on evaluation was negative. Previous research investigating the effects of natural driving styles on comfort has yielded mixed results, which might be explained that naturalness of these driving styles was characterised by different vehicle factors (Basu et al., 2017; Hartwich et al., 2018; Peng et al., 2022; Yusof et al., 2016).

For research objective three, we examined whether evaluation of the two concepts - comfort and naturalness - were associated with the same kinematic and proxemic factors. We did not always find this to be the case. While most factors showed similar patterns in their effects on both concepts, longitudinal jerk affected only comfort and not naturalness. Regarding similarities between kinematic and proxemic factors in automated and manual driving styles, all factors showed the same direction of effect (i.e., either positive or negative), but the strength of the effect varied. For example, lateral jerk was most influential for comfort, while speed was most influential for naturalness. As both concepts contribute to positive user experiences (Hartwich et al., 2018; Ramm et al., 2014), having similar associations with the same kinematic and proxemic factors is reasonable. However, the differences suggest that the associations between objective vehicle metrics and different psychological concepts can vary. This finding provides potential explanations for differences in results from research comparing different concepts in automated driving (e.g., He et al., 2022; Paddeu et al., 2020; Peng et al., 2022). It also highlights the importance of providing clear definitions to assist participants in evaluating AV controllers, thereby enhancing the precision of subjective evaluation for AV controller designs.

4.1. Limitations

One limitation of our study is the driving scenario used in the experiment. While our replication of a real road provided participants with a variety of road geometries and roadside furniture, we did not include interactions with other road users (e.g., pedestrians and other cars). Consequently, we could only incorporate one proxemic factor (i.e., lateral offset) in our analyses, which did not yield any significant results. It is plausible that the scenarios employed in our study were not critical enough to elicit concerns regarding distance from roadside furniture, in comparison with scenarios involving interactions with other road users, such as merging vehicles on a highway (He et al., 2022). Moreover, scenarios that involve more interactions with other road users will bring more spatial or temporal proxemic factors into analyses, such as (time) headway. Therefore, further investigation of scenarios and road environments, which encompass diverse interactions between the AV and different road users, is needed.

4.2. Implications for designs

In terms of implications for future AV designs, the fact that a large longitudinal jerk can be comfortable while it has no significant influence on perceived naturalness suggests that it could be used as a cue to communicate with users both inside and outside the vehicle. For example, Zgonnikov et al. (2023) designed a "nudge" manoeuvre (i.e., brief acceleration or deceleration) of an AV to interact with manually driven cars and they found that the deceleration nudge increased drivers' willingness to pass the AV. Regarding the design of human-like driving styles for AVs, we recommend that system designers consider users' perception of such human-like features in the development of motion planner algorithms (e.g., Bae et al., 2022; Gu and Dolan, 2014), as objective similarities in different metrics can have varying and sometimes opposing effects on user comfort and perceived naturalness. These findings provide guidelines for designing more comfortable and acceptable driving styles for future automated vehicles.

CRediT authorship contribution statement

Chen Peng: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Data curation, Software. **Chongfeng Wei:** Data curation, Investigation, Supervision, Writing – review & editing. **Albert Solernou:** Investigation, Software, Writing – review & editing. **Marjan Hagenzieker:** Investigation, Supervision, Writing – review & editing. **Natasha Merat:** Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing – review & editing.

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.

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Appendix

The selection of representative driving styles

We used two approaches to select the representative drivers from a previous study in the project, before recruiting participants for the recorded driving of this study. In the first study, 14 participants manually drove through the same route as the present study.

1) We conducted a k-means cluster analysis using data from these 14 drivers. Here, we calculated the root mean square of speed, standard deviation of longitudinal acceleration, and standard deviation of yaw rate, for three areas. To include geometric variability, these three areas were: a sharp curve, an area with parked cars, and the entire drive. Using this data, we clustered these 14 drivers into three categories: defensive, moderate, and aggressive, based on research on driving styles (e.g., Basu et al., 2017; Murphey et al., 2009).
2) We also collected the sensation seeking scores of these 14 drivers, and found a moderate correlation between their sensation seeking scores and their cluster membership. However, probably due to the small sample size, this correlation was not significant.

Once this clustering was done, we contacted the drivers with high sensation seeking scores who were from the aggressive cluster (N = 4) and also those with low sensation seeking scores from the defensive cluster (N = 4), and asked them to return to the lab for further data collection. Each driver then manually drove the same route again three times.

To select the final driving data for use in the current study, we conducted another cluster analysis to confirm that the driving behaviours of our sample still fell into the previously identified defensive and aggressive groups. After this confirmation, we selected the manual driving data of two participants, one from each sensation seeking group, after confirming that their data was also closest to the median values of the defensive and aggressive clusters. We also checked for any unexpected or unusual manoeuvres in the data.

With this approach, we assumed that the selected driving styles were representative and distinct from each other and used the driving data from these two participants in the current study.

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