



Exploring Personalised Autonomous Vehicles to Influence User Trust

Xu Sun¹ · Jingpeng Li² · Pinyan Tang¹ · Siyuan Zhou¹ · Xiangjun Peng¹ · Hao Nan Li³ · Qingfeng Wang⁴

Received: 15 January 2020 / Accepted: 23 July 2020 / Published online: 1 September 2020

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Abstract

Trust is a major determinant of acceptance of an autonomous vehicle (AV), and a lack of appropriate trust could prevent drivers and society in general from taking advantage of such technology. This paper makes a new attempt to explore the effects of personalised AVs as a novel approach to the cognitive underpinnings of drivers' trust in AVs. The personalised AV system is able to identify the driving behaviours of users and thus adapt the driving style of the AV accordingly. A prototype of a personalised AV was designed and evaluated in a lab-based experimental study of 36 human drivers, which investigated the impact of the personalised AV on user trust when compared with manual human driving and non-personalised AVs. The findings show that a personalised AV appears to be significantly more reliable through accepting and understanding each driver's behaviour, which could thereby increase a user's willingness to trust the system. Furthermore, a personalised AV brings a sense of familiarity by making the system more recognisable and easier for users to estimate the quality of the automated system. Personalisation parameters were also explored and discussed to support the design of AV systems to be more socially acceptable and trustworthy.

Keywords Autonomous vehicle · Driving characteristics · Driving style · Personalisation · Trust · User experience · User study · Human factors

Introduction

Autonomous vehicles (AVs), which can sense their surroundings and navigate without human intervention, are expected to account for 75% of vehicles on the road by 2040 [67]. AVs are changing the way we drive and how we experience driving. They assist drivers in demanding tasks and improve road safety, but they also enhance mobility for users of all generations, especially for ageing populations [31]. Even with the rapid pace of technological advancement in AV, any autonomy remains a staged process which takes place over a period of time [53]. The Society of Automotive Engineering (SAE)

categorised six levels of autonomy in a vehicle, whereby the human driver monitors the driving environment from L0 to L2, while the automated driving system monitors the driving environment from L3 to L5 [54].

Many research articles have been published describing the technological advancement of AVs [11], and while considerable effort has been placed on developing such technology, there is a lack of knowledge on the societal impact of this technology [17]. In particular, the trustworthiness of AVs has to be examined before they can be widely adopted on the road [67]. According to a few national and local surveys, most consumers are not ready to buy an AV [34]. Employing autonomous features in vehicle design means surrendering personal control of the vehicle and trusting technology to drive safely. The underlying rationale is the changing role of the driver, shifting from that of an active controller to a more passive supervisor, such that problems may arise related to reduced levels of perceived trust [47].

The importance of trust has been shown in different studies, especially in the adoption of new technologies (e.g. [29, 56]). In studies into automation, it has also been highlighted that trust is a major determinant of acceptance of any such automation (e.g. [19, 36]). Trust is able to mediate the relationship between people and automation [20]. It plays a significant role in eliciting people's willingness to use or interact

✉ Jingpeng Li
Jingpeng.Li@stir.ac.uk

¹ Faculty of Science and Engineering, The University of Nottingham Ningbo China, Ningbo, China

² Division of Computing Science and Mathematics, University of Stirling, Stirling, UK

³ School of Aerospace, The University of Nottingham Ningbo China, Ningbo, China

⁴ Nottingham University Business School China, The University of Nottingham Ningbo China, Ningbo, China

with such technology in situations where the perception of risk ought to be overcome [27]. Although the importance of human trust in automation has been stated in much of the research, it has yet to be systematically studied in the domain of AVs [31]. Furthermore, prior research suggests that few drivers trust automated driving systems [5, 34], and this lack of trust restricts the potential of drivers to fully utilise the benefits of an AV. To date, little has been done to consider the human trust factor into the design of AV systems [52].

Personalisation has been suggested as a potential strategy with which to enhance user trust [9] by providing a suitable and safe driving experience in close connection with the driver, understanding their requirements and behaviours, but also acting autonomously. Personalisation of systems and services has gained considerable interest from various disciplines over the last 20 years [60]. It is a means through which to make new technologies both more acceptable and more useful for people. This is especially important in the area of AVs, the goal of which is not only to improve driving safety and to prevent accidents caused by human errors but also to improve the driving experience [21]. Since the benefits of AV can only take effect when people use them, AVs must gain the trust of human drivers, matching their expectations concerning driving characteristics [37]. Drivers' expectations differ from driver to driver, as well as for individual drivers, depending on their driving style and driving scenarios [57]. Hence, the design of AVs should cater for any such different requirements and needs through personalisation. The more an AV considers human characteristics, the more people are expected to trust such vehicles [67].

This research hypothesises that a personalised AV driving system, adapting the driving style to match that of the driver, may make the driver feel that the AV system is trustworthy. Driving style refers to how the driving process is conducted [13] and depends on a driver's individual driving habits (such as driving speed). Inevitably, different drivers have different driving styles [15], and studies into driving styles in AVs have only begun recently [30]. A small number of these studies have indicated that the driving style of an AV could be important for users' perceptions and understanding of the AV. It indicated that passengers are not comfortable with current AVs because of the unnatural driving style, which differs from that of the average human driver. Hence, users require tailored solutions to explain what can be improved in the driving style and how this may be achieved [40]. Ekman et al. [15] recently emphasised the importance of driving style for user acceptance in the field of autonomous driving.

This paper presents an empirical study which aims to understand whether a personalised AV system which adapts to a driver's driving style can influence the cognitive underpinnings of drivers' trust in AVs. In prior research, trust in AVs was measured in ways in which the subjects were given very limited exposure to, and interaction with, the target AVs,

owing to methodological challenges. For example, in Verberne et al.'s [66] research, the trust in the automation system was measured by presenting the participants with descriptions of three different systems. Weinstock et al. [68] tested the effect of system aesthetics on trust, using the graphs of three map styles for car navigation systems. There is also research in the form of a survey to investigate trust on a broader level, rather than focused on specific autonomous features. This is a new attempt to examine a novel approach to facilitating trust in AVs, with the participants experiencing the AV in person and in tailored conditions. Little, if any, similar research has been conducted in the same way. This paper also seeks to contribute to the design of AV systems, grounded in an understanding of users by exploring the parameters for the personalisation of driving styles together with drivers. A personalised AV system should be constructed in a process that considers and involves a driver's needs and expectations from the outset and during the whole design and development cycle.

Literature Review

Cognitive Underpinnings of Trust in AVs

Trust has been defined as “the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability” [36]. It is a multidimensional concept which has three aspects in common. First, trust is given by a trustee; second, it corresponds to an expectation of something or someone; and third, trust may be bound to one or multiple characteristics of its object. The trustee must always have an incentive to believe; for example, trust may be based on the intended functionality of the system [29]. The importance of trust has been explored in several studies on system automation (e.g. [29, 56]), and these studies have identified trust as a major determinant of the acceptance of automation ([19, 36]). Inappropriate calibration of trust in an automated system can lead to both the misuse and disuse of automation and thereby result in decreased performance and less adoption [45, 49]. Lee and See [36] suggested that cognition and emotion are essential for building trust. Once trust is built, it is not necessarily stable, and may be prone to changes depending on experiences [29, 36]. Although the importance of the concept of trust between humans and machines has been stated in much of the research, it has yet to be systematically studied in the domain of AVs [31].

Studies investigating what factors affect driver trust, specifically in AVs, have focused predominantly on how information content affects a driver's trust in the vehicle. For example, Helldin et al. [26] investigated how “uncertainty

information” about the vehicle’s ability to drive by itself, affected the drivers’ trust in the AV system. They found that the group of drivers provided with the uncertainty information trusted the AV system less than the control group, which did not receive any uncertainty information. Korber et al. [35] suggested that providing an explanation for a take-over request in an AV system did not have an impact on the participants’ trust or acceptance, but rather increased their understanding of the AV. Another stream of research has focused on the way user trust is affected by how the content is communicated. Forster et al. [18] developed an in-vehicle information application incorporating anthropomorphic features in an AV. They found that adding human speech to an audio-visual system had positive impacts on drivers’ attitudes towards, and trust in, automated systems. Other studies have presented more elaborate questionnaires to discover the underlying factors influencing trust in terms of specific aspects such as security and reliability (e.g. [32]). Nevertheless, it has been proposed that to fully understand a user’s level of trust in automation, it is important to consider the underlying cognitive processes by which trust is embraced [36].

Personalisation

Personalisation is about tailoring system performance and services to better fit the user. Personalisation can be achieved by focusing on users’ needs, preferences, interests, and characteristics [60]. Various studies have already shown some positive psychological and somatic benefits resulting from personalisation (e.g. Blom et al. 2003; [60, 61]). From a marketing perspective, the advantage of personalisation is user satisfaction. Blom et al. (2003) described how personalisation brings a sense of ownership and identity, and the desire to express personality in public forums. Sun et al. [60] described how personalisation creates a more engaging user experience by designing information and images that they find useful or pleasing. However, there is still a lack of understanding of whether or not personalisation can influence the cognitive underpinning of user trust.

The current development in advanced driving systems is focused mainly on designing a system for the average driver. This approach ignores the fact that drivers differ in their characteristics and preferences. There are considerable interpersonal and intra-personal differences in drivers and their preferences, while any such preferences of one driver will depend on his/her emotional state, and the driving style may change over time and with experience. The importance of personalisation to the driver in an advanced driving system was realised early in the development process [28], but has become feasible only recently owing to progress in sensor systems and increasing levels of computational power in modern vehicles.

Personalisation of vehicle transportation systems is a relatively recent trend in vehicle design and development. There are two main application areas for personalisation in current vehicle design, including the personalisation of the user interface of any in-vehicle information systems (e.g. [24]), and the personalisation of driver assistance systems (e.g. [25]). A personalised in-vehicle information system provides traffic information which is tailored according to a driver’s preference and situational awareness. For example, McGinty and Smyth [39] developed a personalised driving route information system which generates travel routes with the input of the drivers’ preferences and then refined this model through real-time interaction with the driver. Arnason et al. [2] developed a system which recommends personalised audio content and uses sensors to determine when to present this information to minimise distraction from any driving tasks. A personalised driver assistance system drives the vehicle according to the road conditions and situation. An example of automated driving developed by Hasenjager and Wersing [25] dynamically adapted the level of automation according to the driving scenario (e.g. road conditions and lane geometry) and determined the different levels of automation, including partial automation, conditional automation, and high automation.

Driving Style

Driving style refers to how the act of driving is conducted, and includes decisions regarding driving properties, such as driving speed and the rate of acceleration [13]. It is a critical human factor that relates to road traffic safety and control [65]. Recent studies have shown that trust may be affected by an AV’s driving style [9], and Hartwich et al. [25] found that uncomfortable styles of acceleration and deceleration led users in an experiment to change back from automated to manual driving. Dikmen and Burns [12] found that perceived “incompetent” lane positioning of an AV lowers the users’ level of trust. In another study, Bellem et al. [4] investigated whether and how user trust was affected by lateral steering and found that the participants placed more trust in the AV when it maintained a more central position in the lane. Ekman et al. (2017) investigated how a vehicle’s driving style affected the users’ trust in the AV by conducting an experiment using a Wizard of Oz setup to simulate two different driving styles, namely “aggressive” (tending to drive at or above the speed limit and enjoying rapid acceleration) and “defensive” (a less risky driving style in manual driving). They found that the driving style had an impact on trust in the AV, and the defensive driving style was considered to be more trustworthy.

The specific driving style properties of a driver could be important for a user’s perception of an AV’s capability (Lai and Carsten 2003). Yusof et al. [70] focused on differences between defensive drivers and aggressive drivers. They simulated automated driving with a Wizard of Oz approach in real

Table 1 Event-specific behaviours in each scenario

The vehicle was on a two-way and four-lane road with a speed limit of 50 km/h

Event-specific behaviours	Scenario 1: approaching traffic light (only 9 s remaining before the change from a green to an amber light at the intersection)	Scenario 2: overtaking (when another vehicle behind is about to overtake)	Scenario 3: following a vehicle (a truck ahead was gradually slowing down to approximately 30 km/h)
Assertive style	Accelerate or maintain the maximum speed with the intention of passing the traffic light	Accelerate or maintain the maximum speed with the intention of avoiding being overtaken by the following vehicle	Accelerate or maintain the maximum speed with the intention of overtaking the truck
Defensive style	Decelerate with the intention of stopping at the traffic light	Decelerate with the intention of allowing the following vehicle to overtake	Decelerate with the intention of following the truck

road conditions in which the participants sat in the back seats. They found that both the assertive and the defensive driver groups preferred a defensive automated driving style. Basu et al. [3] conducted a similar study in a driving simulator without motion feedback and found drivers typically prefer a more defensive driving style when they are passengers. Hart et al. (2017) investigated the relationship between manual driving styles and automated driving preferences in a simulator study with both older and younger drivers. They found that younger drivers tend to prefer their driving style over other styles, while older drivers perceive their driving style to be less comfortable and less enjoyable than other driving styles when applied to an AV.

There have been several cases of research into investigating driving styles as a source of trust information (e.g. [15]); however, there is no previous study exploring the effects of a personalised AV approach, which adapts to a driver's driving style, on drivers' trust. This study presents a new approach of a personalised AV, which is able to identify user driving behaviours and thereby adapt its driving style accordingly. It also investigates systematically the trust levels of users under various conditions of non-personalised and personalised AV modes.

Development of a Personalised AV

To properly investigate the effects of personalised AVs on perceived trust, a personalised AV prototype was developed for this experimental research. The personalised AV was designed by constructing driver models from the observation of manual driver styles and designing vehicle controllers that can be parameterised to be personalised to specific driving styles using these models.

The driver model which was built was capable of determining how a human would drive. It was designed based on users' actual driving behaviour in a series of typical traffic scenarios. The user model stored three main kinds of information, including driving speed, rate of acceleration, and event-specific

behaviours. The driving speed was the average speed collected in each driving scenario, while the acceleration rate was set to the change in the rate of speed captured in each driving scenario. Table 1 depicts event-specific behaviours in each scenario, based on an early interview study with police officers.

On the basis that the majority of research into driving behaviours has been conducted in very specific traffic scenarios, such as crossing intersections [16] and changing lanes and following other cars [44, 69], we prepared three detailed traffic scenarios through which to explore the possible specific driving styles of drivers in each domain.

The personalisation observes the user driving behaviour and derives a driver model based on these data. Such a model was used to develop a personalised AV that moves and reacts in relation to a human driving style. Based on the driver model and corresponding scenarios, a vehicle controller was developed which defined the speed, the acceleration, and event-specific behaviours to generate human reference manoeuvre parameters for a personalised AV.

The personalised prototype was built to simulate the automated driving procedures, monitor key categories of data streams, and adapt the personalised driving styles through a comprehensive hardware-software co-design. For the software stack, a modified version of OpenDS Driving Simulator [22] was used in this study. For the hardware stack, we integrated pressure sensors for the throttle and brake, and ported steering wheel to obtain spatial changes and event-specific behaviours from drivers during the whole period. To achieve the personalisation during the driving simulation, the simulator produces log files from the OpenDS and pressure sensors of a participant's manual driving performance at run time. Based on the logs, the mean deviation of the steering wheel and the distribution of standard deviation of the mean of speed and acceleration were computed and fed into the performances of the personalised AV. The personalised functions were implemented into the driving simulator, with a focus on three scenarios: approaching traffic lights, following a vehicle, and changing lanes.

Research Experiment

Methods

Studies into user trust are mainly undertaken by asking participants to indicate their agreement using a single-survey approach [42]. Nevertheless, it has been proposed that to fully understand a user's level of trust in automation, it is important to consider the underlying cognitive processes by which trust is developed [36]. This experimental research integrated the methods of simulator study [47] and user enactment [43] to set the context for future AVs, in addition to making the driving experience more concrete for participants to enable an exploration of human trust in the system. In addition, user driving behaviours were captured and adopted to generate personalised driving styles in different scenarios to expose the participants to the target experience in the simulator. Such a method enabled the testing of typical scenarios that would not have been possible during on-road evaluations. Before the experiment, ethical approval for this study was obtained from Research Ethics Sub-Committee of the University of Nottingham, Ningbo.

Participants

A total of 36 drivers (24 males and 12 females) were recruited to take part in the study. The drivers were screened for their experience of driving, with the criterion that they could demonstrate at least 1-year driving experience, while the driving frequency criterion was at least three times per week. Their average age was 36.4 years ($SD = 9$ years). Their average driving experience was 7.08 years ($SD = 4.74$ years). The participants were from different professional backgrounds, including education, finance, marketing, and freelancing. No professional drivers were involved.

Driving Scenarios

The driving scenario simulation focused on three typical driving scenarios, based on the majority of cases of research conducted into driving behaviours (e.g. [69]). In the full scenario, the vehicle drives on a two-way, four-lane road (from point A) with a speed limit of 50 km/h to a parking place (at point B), but with three different specific events to deal with, as follows: (1) when there were only a few seconds left before the traffic lights changed from a green to an amber light at an intersection; (2) when another car behind was about to overtake; and (3) when a truck on the road ahead was moving slowly at approximately 30 km/h. The driving scenarios were designed using the driving simulation software OpenDS (<https://opens.dfk.de/>) to cover a range of typical scenarios and contexts. A navigation map from point A to point B was provided during the study.

The performance indicators (e.g. driving speed, acceleration) when driving the personalised AV were compared with those when driving the non-personalised AV, and with those when driving manually; hence, the participants drove along the same scenario route once without any automation, once with the standardised automation, and once with the adaptive automation activated.

Apparatus

The user evaluation was conducted in an Innovative Design Laboratory. The laboratory is equipped with a driving simulator, four projectors and projection screens, and a data collection platform to capture audio and video data from both outside and inside the simulator. The driving simulator is composed of a car body, a car seat, a steering wheel, a horn button, a throttle, and brake pedals which allow participants to control the vehicle (i.e. to steer, accelerate, and brake). During the experiment, the participants were invited to sit in the simulator and were introduced to the available controls. The simulated driving trip was run on laboratory computers and projected onto four roof-mounted projection screens (1920×1080 px each) so that the driver had a 360° field of view (see Fig. 1). The rear-view and wing mirrors and dashboard were also projected onto the screen.

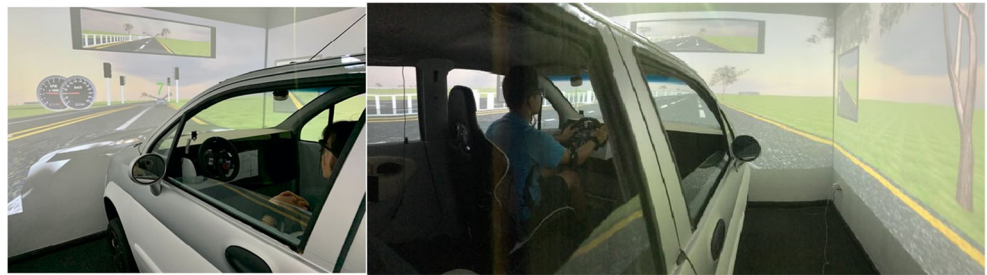
Experimental Conditions and Experiment Design

The study employed a within-subject design, with the independent variables of driving condition having three levels, i.e. a manual driving mode and two AV conditions, including standard AV driving and personalised AV driving. Each participant performed under the three driving conditions in the simulated study. The participants' driving performance was recorded in the OpenDS, while they were also given questionnaires in which to rate the cognitive aspects of their experience.

For the baseline drive, driving began in the manual mode. Under the manual driving condition, participants were entirely responsible for the manipulation of the standard longitudinal (accelerator and brake pedals) and lateral (steering wheel) controls.

The standard AV was designed based on an expert interview study with 10 professional traffic police officers in Ningbo, China. The traffic police were asked to define a standard AV driving style according to their professional experience and expertise in manual driving. The details have been reported in another paper [64]. A standard AV driving style was defined by the demonstration of anticipatory and consistent driving, maintaining a safe distance from the vehicle in front, leaving a safe distance from a vehicle being overtaken before returning to the original lane, fewer overtaking manoeuvres in general, and little change in lateral or longitudinal

Fig. 1 The driving simulator with a 360° visual field of view



acceleration. The longitudinal controller was set with a default driving speed of 40 kph. The system was modelled in the simulator according to the specifications outlined by the traffic police and was constrained to a maximum acceleration rate of 0.1g and deceleration rate of 0.2g.

In the personalised AV condition, the driver model captured data input from the manual driving in the simulated environments and was calculated in the vehicle controller to determine a personalised speed, rate of acceleration, and event-specific behaviour, which operated and reacted in a style similar to that of a human driver.

Procedure

At the beginning of the study, a participant information sheet, which explains the purpose of the research project, was issued to all participants. Next, they were informed that they were free to withdraw from the research project at any stage and their personal results would remain confidential. In addition, they were informed that the data collected would be stored in accordance with data protection laws. Finally, a written consent form was obtained from all participants. Participants were then allowed 5 min to sit in the simulator by themselves to adapt to the environment, and were screened by questionnaire to ensure that they were at low risk of motion sickness while experiencing the driving simulation. After the introduction, participants were given a trial drive. The experiment began when participants understood the briefing and were comfortable with the simulator. It included the three driving conditions, as explained above. Each participant began with the baseline manual mode, with drivers in control of the vehicle operations, following which they undertook the two AV experimental drives (standard AV and personalised AV) which were completed in a counterbalanced order. During the experiment, driving data was logged. After each driving session, the participants were asked to fill out a questionnaire about the cognitive aspects of their experience, including an assessment of perceived trust, comfort, and situational awareness. The study lasted approximately 1 h for each participant. Finally, a post-interview was conducted to discuss further any perceived levels of trust under the various conditions, and to

investigate parameters for the personalisation of driving styles. Refer to the flow chart of the experiment in Appendix 1.

Data Collection and Analysis

To examine the effect of personalisation of an AV on user trust, the performance of the automated driving with and without personalised functions were first compared with the human driving performance. The driving performance data for velocity and acceleration rates were captured in the OpenDS, following which an analysis was undertaken of the underlying cognitive experience (i.e. feelings of comfort, situational awareness, and user trust) under the various conditions.

Trust was measured using the automation trust scale from Bisantz and Seong [6], which was developed from a theoretical framework of describing potential factors affecting automation trust. It is a questionnaire with 12 statements, for each of which the participants needed to assign numbers from 1 to 7 to indicate their level of agreement (1—totally distrust, 7—totally trust). Comfort is an essential aspect of the driving experience, and a close relationship was observed between comfort and trust in an AV [58]. The feeling of comfort was measured on a 6-point scale ranging from 1 “not comfortable” to 6 “very comfortable” [24]. Situational awareness is a significant determinant of trust in an AV [46]. Trust is facilitated when there is a match between an agent’s ability and a given situation [51]. Participants’ situational awareness was evaluated immediately following the task performance, using a subjective rating of the 3D SART on three dimensions that included attentional demands (*D*), attentional supply (*S*), and understanding (*U*). The ratings for each of the three dimensions were combined into a single SART value according to the formula (Selcon et al. 1992): Situational awareness = $U - (D - S)$. See detailed scales in Appendix 2 Table 2 and 3.

Each participant tested the three driving conditions, resulting in a total of 108 sessions. Person correlations were performed to analyse the relationships between data. Friedman tests (Gibbons 1992) for the three dependent samples were conducted using quantitative data to analyse the differences between the three conditions. When the test showed significance, values were corrected, and all multiple dependent samples paired comparisons were corrected. An affinity diagram technique was

used to analyse the qualitative data to synthesise the key themes, and then identify patterns in the data.

Results

Driving Performance

Person correlations were computed among the three driving modes in terms of driving speed and acceleration during the experiments. There was a significantly strong correlation in driving speed between manual driving and adaptive driving ($r(0.667) = , p < 0.001$), while there was no significant correlation between manual driving and standard driving ($p > 0.05$) nor between personal driving and standard driving ($p > 0.05$). There was also a significantly strong correlation in acceleration between manual driving and adaptive driving ($r(0.385) = , p < 0.05$), while there was no significant correlation between manual driving and standard driving ($p > 0.05$) nor between personal driving and standard driving ($p > 0.05$). Person correlations further showed no significant relationships between age and driving speed ($p > 0.05$) nor between age and acceleration rates ($p > 0.05$) (Figs. 2 and 3).

To observe individual differences, Person correlation has further showed no significant correlations between age and cognitive factors of user trust, comfort, and situational awareness in the manual driving mode (trust $p = 0.75$, comfort $p = 0.92$, situational awareness $p = 0.76$), in the standard AV mode (trust $p = 0.93$, comfort $p = 0.67$, situational awareness $p = 0.97$), and in the personalised AV mode (trust $p = 0.29$, comfort $p = 0.06$, situational awareness $p = 0.083$). It also showed no significant correlations between driving behaviour (in terms of speed) and perceived user trust ($p = 0.23$), comfort ($p = 0.24$), and situational awareness ($p = 0.28$) in the manual driving mode.

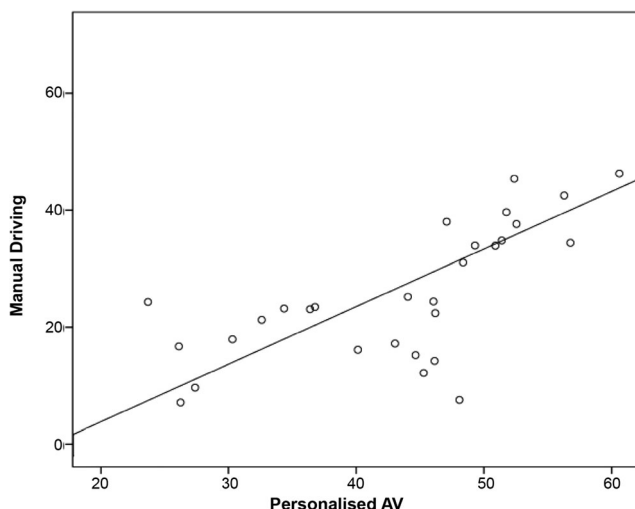


Fig. 2 Correlation of driving speed between manual driving and a personalised AV

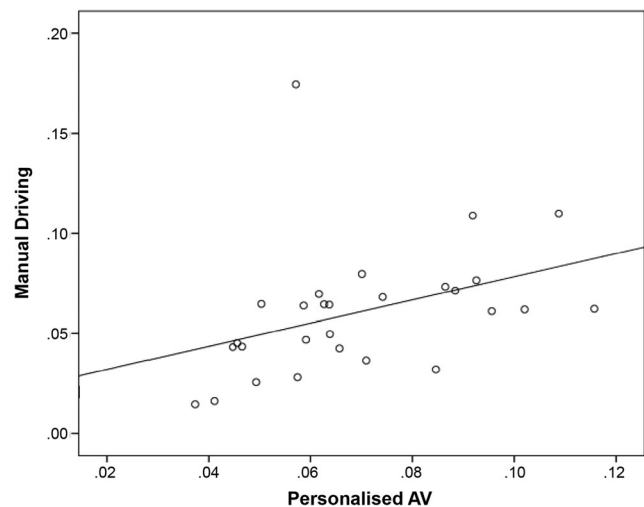


Fig. 3 Correlation of acceleration between manual driving and a personalised AV

The driving performance measurement data of all subjects showed differences between the conditions in the driving speed and rates of acceleration. In the first scenario, there were different speeds approaching the traffic lights. In the manual driving condition, participants with an assertive driving style typically accelerated 9 s (reading from a visible countdown indicator) before the traffic light changed from green to amber. Similar trends of behaviour were also observed in the personalised AV condition. For participants with a defensive driving style, there were decelerations in the manual driving 50 m before the traffic light. Decelerations were also recorded when approaching the traffic lights in the personalised AV condition. The standard AV maintained a more even pace when passing through the traffic lights. Subtle changes varied depending on the participants (Fig. 4).

In the second scenario, typically, participants with an assertive driving style tried to prevent the vehicle behind from overtaking, while those with a defensive style decelerated to allow the vehicle behind to overtake. Similar trends of driving in terms of speed and lateral accelerations were observed in the personalised AV and manual driving. Uncomfortable overtaking manoeuvres with high lateral accelerations did not occur under the standard AV condition (Fig. 5).

In the third scenario, when the truck ahead was moving slowly at approximately 30 km/h, the participants with an assertive driving style typically changed lane and overtook the truck. Similarly, the personalised AV for the assertive participants also overtook the truck. Participants with a defensive driving style decelerated and followed the vehicle in front. Some participants with a defensive driving style also decelerated and overtook the truck slowly. The personalised AV for defensive

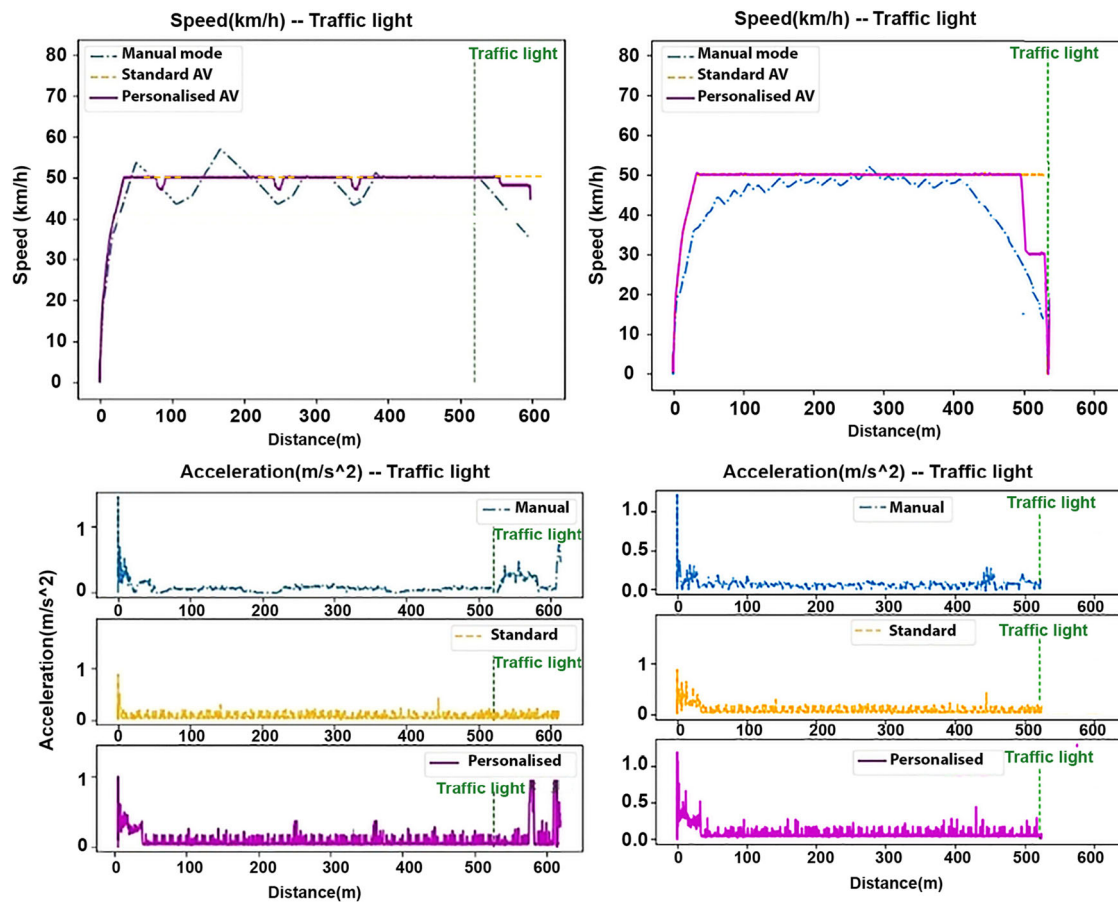


Fig. 4 An example of an assertive driving style (left) and a defensive driving style (right) in the first scenario

participants decelerated when the truck ahead was slowing down, then adjusted its speed according to the manual driving speed and overtook the truck. The standard AV maintained an estimated safe speed and overtook the truck (Fig. 6).

Feelings of Comfort

On average, participants rated the feeling of comfort as 3.63 (SD = 1.84) in the manual driving mode, 4.6 (SD = 1.60) in the standard AV mode, and 5 (SD = 1.24) in the personalised AV mode. Statistically significant differences in the overall levels of comfort were shown in the Friedman test for three dependent samples ($N = 36$, $\chi^2(2) = 7.52$, $p < 0.05$). The multiple dependent samples paired comparison showed that participants in both the standard AV mode ($p = 0.004$) and the personalised AV mode ($p = 0.011$) rated significantly higher than they did for the manual driving mode, while there was no significant difference between driving in the standard mode and the personalised AV mode ($p > 0.05$) (Fig. 7).

Situational Awareness

The average level of situational awareness for participants when driving was 55.5 (SD = 11.9) in the manual driving condition, 53.7 (SD = 11.1) in the standard AV condition, and 51.4 (SD = 9.7) in the standard and personalised AV conditions. The analysis of the participants' responses in respect of situational awareness showed that, on average, participants had a higher level of situational awareness during manual driving, compared with those in the other two conditions.

A Friedman test showed no significant differences in the cognitive aspect of situational awareness ($P > 0.05$) across the three experimental conditions. There was no significant difference in situational awareness between the conditions of the standard AV mode and manual driving ($p > 0.05$), between the personalised mode and manual driving ($p > 0.05$), nor between the standard AV and personalised AV modes ($p > 0.05$) (Fig. 8).

User Trust

The average level of perceived trust of participants in the manual driving condition was 3.82 (SD = 1.21), 3.88 (SD =

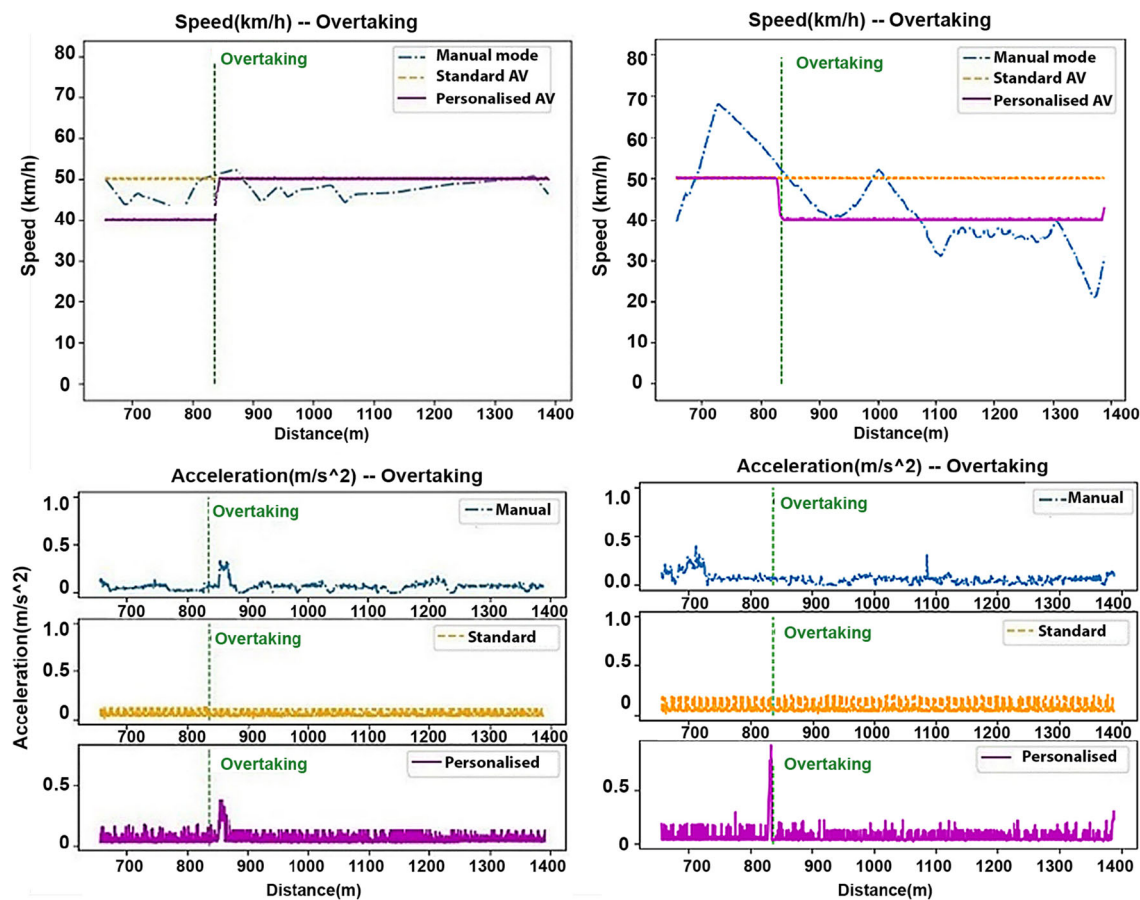


Fig. 5 An example of an assertive driving style (left) and a defensive driving style (right) in the second scenario

1.32) for the standard AV mode and 4.32 (SD = 1.05) for the personalised AV mode. An analysis of the participants' responses in respect of trust showed that, on average, participants had a higher level of trust in the personalised AV mode, compared with those in the other two conditions.

Quantitatively, a Friedman test for three dependent samples showed significant differences in the overall levels of perceived user trust, according to whether they drove in the standard mode, the personalised mode, or the manual mode ($N = 36$, $\chi^2(2) = 31.3$, $p < 0.05$). The multiple dependent samples comparison further showed that perceived user trust in the personalised AV mode was higher than that in the standard mode ($p = 0.045$), and was also higher than the manual driving mode ($p = 0.033$). There was no significant difference between the standard AV mode and the manual driving mode ($p > 0.05$) (Fig. 9).

Personalisation Parameters

During the post-interviews, the study further examined the main personalisation parameters which could define and distinguish the driving styles, and would influence how personalised AVs should be incorporated into the design of AVs from the perspectives of end-users.

More than 70% of participants mentioned that the parameters of driving speed, rate of acceleration, pulse rate, real-time location, use of a mobile phone, and eye movement could define and distinguish their driving styles. Following the above ranking, physical activities were mentioned by 67% of all participants, brainwaves (the electrical signals detected by electroencephalography) by 66%, braking by 61%, real-time driving routes by 61%, personality by 50%, and facial expression by 43%.

Incorporating these parameters in vehicle design requires a collection of personal data which raises privacy concerns. We further asked users' willingness to disclose their personal information regarding their parameters. More than 70% of participants were willing to enable the AV system to collect their real-time driving information, namely driving speed, acceleration, braking, and driving routes. In excess of 50% of participants agreed that the system could collect their biological information, including pulse rate, eye movement, brainwaves, and facial expressions. The same percentage is applied to real-time location, physical activities, and personalisation. Fewer participants (40%) would allow the system to collect their historical records relating to the use of mobile phones.

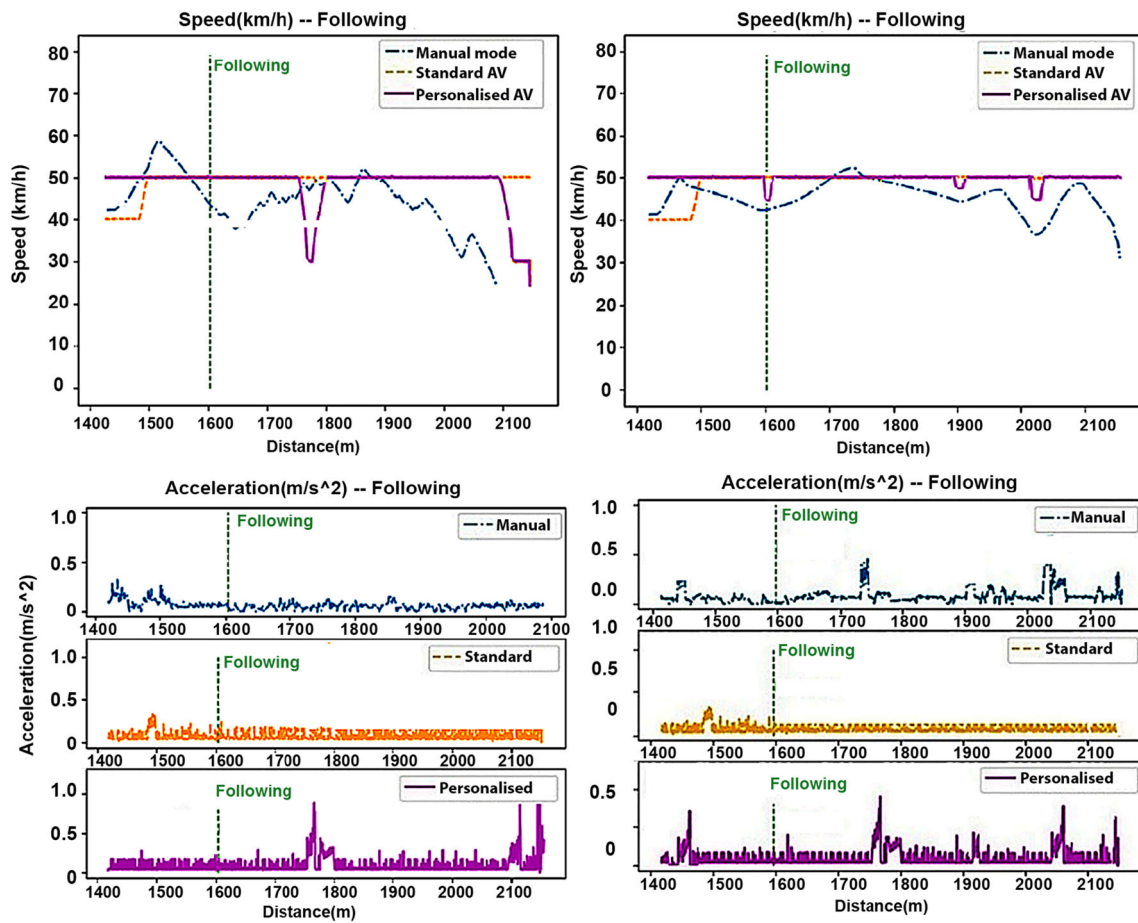


Fig. 6 An example of an assertive driving style (left) and a defensive driving style (right) in the third scenario

Comparison of the Different Driving Modes

During the post-interviews, the participants were also questioned about the differences in user trust under the different driving modes.

When comparing manual driving with the AV, the majority of participants (95%) preferred the AV modes, which provided a sense of experiencing a high-technology system and which was welcomed by users as a future trend. Participants felt more comfortable in the AV modes, and there was more

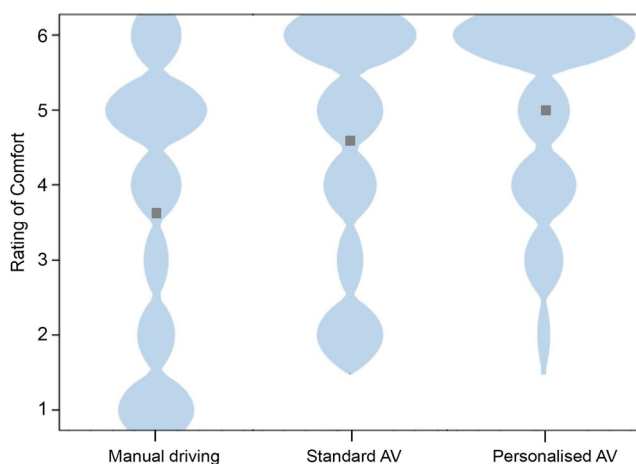


Fig. 7 Feelings of comfort under the different experiment conditions

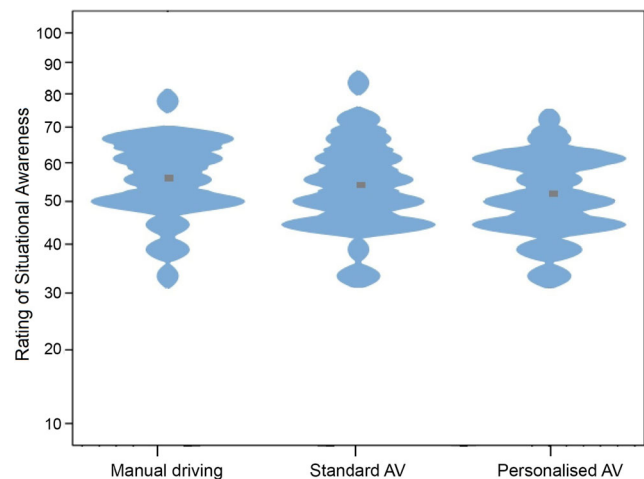


Fig. 8 Situational awareness under the different experiment conditions

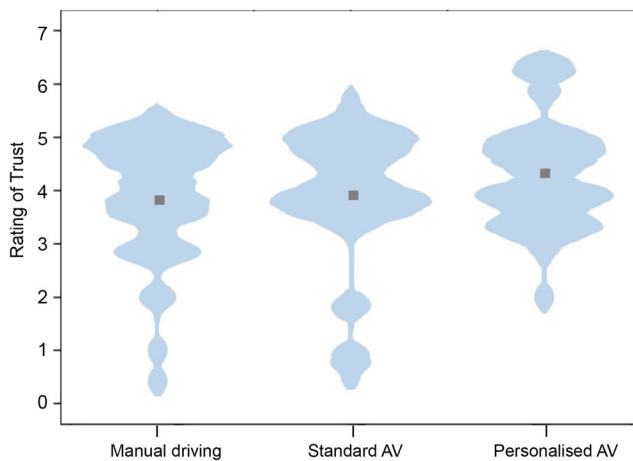


Fig. 9 User trust under the different experiment conditions

freedom for them to perform different tasks when driving. Also, the AV appeared to follow the traffic rules more correctly, thereby gaining more user trust. In comparison, the manual driving mode was mentally demanding, which required a higher level of attention. Participants were more cautious when driving in this condition and felt tired afterwards.

When discussing the differences in user trust under the various conditions of the AV modes, most participants (65%) thought that the system performed competently. The personalised AV affected driving positively in several ways. First, the personalised AV was perceived to be intelligent, as it could accelerate smoothly and choose an appropriate speed according to the speed limit and traffic conditions. As one participant explained, “It [the personalised AV] is very smart. It chose the most effective and appropriate way of driving, which made me feel delightfully surprised”. Second, it appeared to be reliable as there were also fewer errors in following the traffic rules when compared with manual driving, and it seemed to drive according to the users’ expectations. Lastly, it echoed the participants’ driving styles and created a sense of understanding and familiarity, and one driver stated “I like it [the personalised AV] because it drives like me. I understand its behaviour”.

For the standard AV, on the positive side, correct driving with regard to maintaining a standard safe distance from the vehicle ahead, and maintaining a uniform speed, led to a reduction in velocity compared with human driving, which enhanced the feeling of comfort. On the negative side, participants pointed out how the AV without personalisation behaved recklessly and senselessly. For example, it did not react to other road users who wanted to make a lane change. It was felt that the standard system was less flexible, and could have driven at a higher velocity, such as in some situations where a higher rate of acceleration would have been advantageous.

In the case of manual driving, negative effects of this mode were observed, revealing that human drivers made errors (including errors in keeping an appropriate distance from the vehicle in front, and exceeding the speed limit). As a consequence of these issues, some participants experienced high levels of stress and cognitive load.

Discussion and Design Implications

Personalisation in AVs

In this study, the personalisation of AVs has been introduced. It allows personalisation of an autonomous driving style. By analysing the individual driving style of a human when they are driving a vehicle manually, it is possible to identify certain driving behaviours and thereby adapt the driving style of the AV accordingly. The quantitative and qualitative data both highlight the advantages of personalised AVs. Driving performance was perceived to be trustworthy because it selected an appropriate speed and accelerated smoothly. User ratings, both of trust and feelings of comfort, indicated a significant superiority of the personalised AV system in selected typical traffic situations during the experiments.

The underlying reasons of this perceived higher level of trust include the acknowledgement that a personalised AV appeared to be more intelligent for successful actions which they performed with apparent foresight and planning [10] compared with actions they performed on a standard basis [1]. The driving style in a personalised AV was considered more efficient, by selecting an appropriate speed and applying smooth acceleration, both of which improved the driving experience. By adapting the systems to the individual style of the driver, the personalised AV seemed to have human-like capabilities, so that the vehicle occupants could trust it to perform its intended functions competently [48]. Thus, personalisation of an AV system would increase psychological measures of trust in the vehicle’s ability to drive effectively [31].

The personalised AV was found to be reliable because the interaction between the driver and vehicle could personalise the AV to the drivers’ driving style and thereby meet their expectations. Sun et al. [61] indicated that the path to personalisation is an important aspect to be considered to meet users’ expectations. Beller et al. [5] pointed out that the interaction between a human and an intelligent system could enable the user and the system to work together in a mutually beneficial way, during which trust could be improved based upon good collaboration between the user and the system. As Lee and See [36] also highlighted, trust in automation is not simply an

engineering issue since it involves both interpersonal and interactional perspectives.

This experiment also suggested that participants felt they could understand a personalised AV, which brought a sense of familiarity by making the system more , as suggested by Sun et al. [60]. This consideration is also relevant to recent research into trust, which stated that the quality of an automated system could not be estimated as easily by users [52]. However, it is simpler when personalising the system to a human driver because it is easier to presume what a human driver can handle and what the driver can use for reference purposes [18]. The personalisation made the AV feel more personal to a user by accepting and understanding their behaviours, which could thereby increase their willingness to trust the system [7]. This finding provides further support for the theoretical connection between personalisation and the perception of trust. Attributing a characteristic of an automated system is particularly important because it could create a machine to which users might entrust their lives [67].

However, during the experiment, there were still some clear advantages observed in the standard AV and manual driving. Some participants appreciated the uniform speed in the standard AV, which resulted in a reduction of the rate of acceleration and a more comfortable ride compared with human driving during the experiments. This was experienced by Hartwich et al. [24], who identified that the rate of acceleration is a key variable for occupants with regard to their experience of in-vehicle comfort. Such findings also suggest some implications of automation in convoy operations, which have also been investigated by different researchers, especially in a military setting (e.g. [41]). AVs have proved successful in convoy situations and have demonstrated the ability to improve the maintenance of a consistent safe distance and emergency stopping distances compared with non-automated systems. Specifically, simulator research in Lyons and Stokes [38] indicated that human drivers tended to rely more on automation systems over human assistance during high-risk decisions. It is therefore reasonable to presume that in convoy operations, there could be a negative correlation between personalisation and the complexity of driving tasks. Further research could be undertaken to test this further.

Participants rated highest for situational awareness in the condition of manual driving, where drivers had to remain focused at all times. This is reflected in a study which found the high situational awareness of manual driving leading to a higher level of measured situational awareness [46]. Although there were no significant differences in situational awareness between manual driving and the AV modes, this study observed that when drivers were no longer required to fully engage in driving, and thus performed non-driving activities in the AV modes, this led to a decline in the situational awareness of a driver. Robert [50] suggested driver assistance systems

in AVs to support situational awareness through which the driver can be warned of potential problems and take control before any such events occur.

L3 to L5 automations are evolving from conditional automation, to high-level automation, and finally full automation, and this transition is expected to be taken in stages. Personalisation of AVs is presumed to be a long-term measure rather than a transitional solution. The detailed content of personalisation will evolve together with AVs to enhance users' perceptions of trustworthiness and acceptability, as well as improving user experience from the aspects of in-vehicle comfort and situational awareness.

Design Implications

The positive effects of personalised AVs may affect the implementation of AVs to facilitate user trust and, hence, production and market penetration. The goal of a personalised AV design should be providing a system with the ability to personalise to each individual driver and to gain the trust of such drivers. This study has presented an example by incorporating a driver's driving behaviour and adjusting the control system accordingly. Our experiment showed how the driving style model could be implemented in the system to affect a user's trust in an AV, which is consistent with the findings of Ekman et al. [14], in which they further found that a defensive driving style was perceived to be more trustworthy. If the match between the AV and the human driver is inappropriate, the driving experience could be affected, and the driver may feel uncomfortable before reverting from automated to manual driving [25]. Adapting AV driving styles to individual styles requires an accurate definition of an individual's driving style [63]. Most studies of driving styles have been based on subjective measures through self-reported questionnaires ([42]). In spite of the fact that the reliability and usefulness of such self-reported measures of driving behaviours have been demonstrated by multiple recent studies (e.g. [8, 64]), such studies may still retain some potential weaknesses, such as recall bias and self-serving bias [33], which to some extent make the reports of an individual's personal driving patterns less trustworthy. This study has attempted to address this issue by inviting participants to drive the simulator, and by performing context-based interviews to gain new and in-depth insights of those parameters which can be used to define driving styles and which should be incorporated into a personalised AV system. It is important to identify these parameters for system designs and setups that can lead to better human acceptance of AVs.

The personalisation parameters can be considered the inputs or triggers for the personalised AV system, which influence the output presented to the user [59]. We have summarised the personalisation parameters from the end-users in two main categories of vehicle/user dynamics (i.e. real-time driving relevant data and real-time user physiological data), and static driver characteristics (i.e. personality and historical mobile usage behaviour). Personalisation requires that the user model takes the vehicle and user dynamics into account, including the vehicle states and user status. This implies the integration of a dynamic control approach into a static control approach, in which the dynamic control approach directly learns from both the human driver and the vehicle to gain dynamic information that can be used in the controller. In this way, the controller can act more like a human driver and adjust the autonomous driving in real-time. On the other hand, the static control approach collects users' historical behaviour, and this is analysed to infer driver characteristics which are then applied into the personalised AV design. The analysis of the personalised parameters helps to specify, in a systemic way, the preferences of users. This can provide a better understanding of the situations in which personalised AVs will be used, and help to identify users.

A personalised AV is likely to process a certain amount of personal data. Participants expressed surprise that a considerable amount of personal information could be gathered from them during the driving process, although they expressed understanding that such data could be collected, processed, and . This understanding raised concerns about privacy and security issues, including concerns about the potential misuse of data by both public and private individuals and . This implies the consent of the driver should be obtained before processing any personal data, and any data collected must be proportionate to the announced purposes and must be processed securely. It is also necessary to have a limit control for users to specify which data can be collected and shared within specific contexts. Making the collection/sharing of personal data and vehicle personalisation transparent to users can ensure that they understand and are willing to accept the risks/rewards of using their data via a personalised AV system.

Conclusion and Limitations

Trust is one of the most important cognitive factors that has been neglected by the existing studies of personalised systems [29], and it has yet to be systematically studied in the domain of AVs [31]. In this paper, we have proposed and examined a new approach of personalisation to make AVs more

trustworthy and thereby gain higher levels of acceptance. It is evident that personalised AVs could advance the performance of automated driving systems. The results of this research contribute to making driving safe and more comfortable. Personalised AVs will react more effectively to the preferences and behaviours of drivers, will be resilient to different types of driving styles, and will adapt dynamically the automation performance according to each driver.

This simulator study has three limitations. First, it is difficult to ensure that drivers in the driving simulator will behave as they would in the real world. Simulator study is frequently used to test design features and also the relevant user behaviour. In the research of future designs, such a method facilitates the users to create a space to imagine and test possible future experiences. Nevertheless, on-road validation will still be necessary to test driving simulation-related effects. Previous research has demonstrated good validity of driving simulator results, although there is still a paucity of on-road research to investigate the influences of individual characteristics on user trust. Future research could be undertaken to validate the results of the current research. Second, there is little knowledge about the long-term effects on drivers' levels of trust of driving an AV, or on user acceptance and behavioural adaption over time. Future research should gather data from controlled field trials. Finally, the influences of age and experience on driving performance and driving styles have been highlighted by recent studies (e.g. [55]). Our data showed no significant relationships between age and cognitive factors in trust, comfort, and situational awareness and between driving behaviour and these factors. The interpretation of the current results could be limited by the relatively young sample (with an average age of 36.4 years). Future studies should recruit a diverse driver population to measure individual factors such as age, driving experience, and their relation to driving behaviours and preferences in an AV driving mode.

Funding Information This study received financial support from the National Natural Science Foundation of China programme () and Ningbo Hefeng Creative Industrial Park.

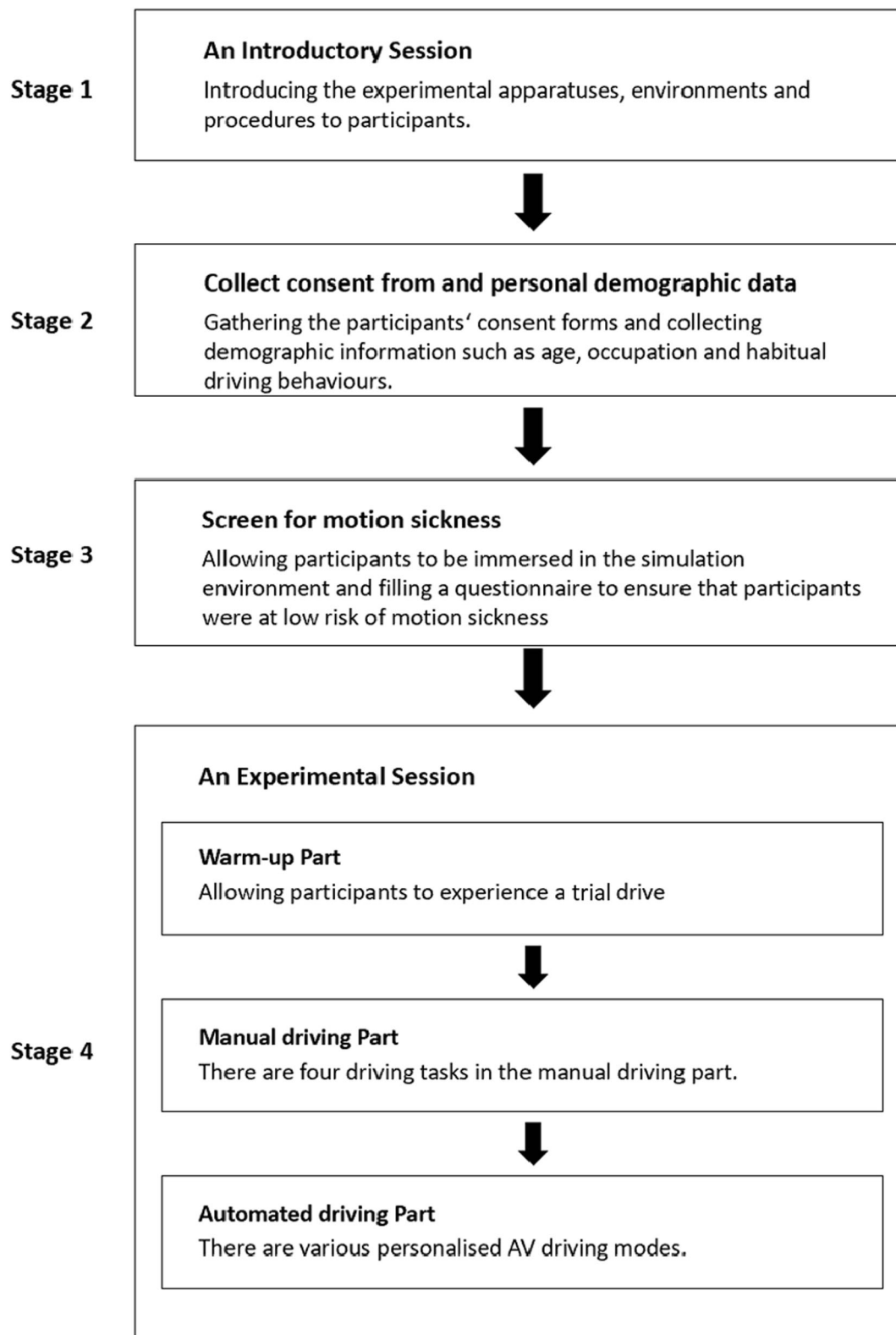
Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Human and Animal Rights All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Appendix 1. Flow chart of the experiment



Appendix 2

Table 2 Automation trust scale [6]

No.	Items	Rating
1	The system is deceptive	1 2 3 4 5 6 7
2	The system behaves in an underhanded manner	1 2 3 4 5 6 7
3	I am suspicious of the system's intent, action, or output	1 2 3 4 5 6 7
4	I am wary of the system	1 2 3 4 5 6 7
5	The system's action will have a harmful or injurious outcome	1 2 3 4 5 6 7
6	I am confident in the system	1 2 3 4 5 6 7
7	The system provides security	1 2 3 4 5 6 7
8	The system has integrity	1 2 3 4 5 6 7
9	The system is dependable	1 2 3 4 5 6 7
10	The system is reliable	1 2 3 4 5 6 7
11	I can trust the system	1 2 3 4 5 6 7
12	I am familiar with the system	1 2 3 4 5 6 7

Table 3 D-SART Scale to measure situation awareness (Selcon, S. J., Taylor, R. M., and Shadrake, R. A., 1992)

No.	Items	Rating
1	Demands on attentional resources: a combination of complexity, variability, and instability of the situation	1 2 3 4 5 6 7
2	Supply of attentional resources: a combination of arousal, focusing of attention, spare mental capacity, and concentration of attention	1 2 3 4 5 6 7
3	Understanding of the situation: a combination of information quantity, information quality, and familiarity of the situation	1 2 3 4 5 6 7

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