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Designing user interfaces for partially automated Vehicles: Effects of information and modality on trust and acceptance

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ABSTRACT

Trust and perceived safety are pivotal in the acceptance of automated vehicles and can be enhanced by providing users with automation information on the (safe) operation of the vehicle. This study aims to identify how user interfaces (UI) can enhance drivers' trust and acceptance and reduce perceived risk in partially automated vehicles. Four interfaces were designed with different levels of complexity. These levels were achieved by combining automation information (surrounding information vs surrounding and manoeuvre information) and modality (visual vs visual and auditory). These interfaces were evaluated in a driving simulator in which a partially automated vehicle reacted to an event of a merging and braking vehicle in its front. The criticality of the events was manipulated by the factors merging gap (in meters) and deceleration (m/s^2) of the vehicle in front. The reaction of the automation was either to brake or to change lanes. The results show that an optimal combination of automation information and modality enhances drivers' trust and acceptance. More specifically, the most advanced UI, which provided surrounding and manoeuvre information via the visual and auditory modalities, was associated with the highest trust and acceptance ranking and the lowest perceived risk. Manoeuvre information delivered through the auditory modality was particularly effective in enhancing trust and acceptance. The benefits of the UIs were consistent over events. However, in the most critical events, drivers did not feel entirely safe and did not trust the automation completely. This study suggests that the design of UIs for partially automated vehicles shall include automation information via visual and auditory modalities.

1. Introduction

Automated vehicle technology is rapidly developing, promising increased safety and comfort to drivers (Litman, 2017). As technology continues to progress, it is expected to bring disruptive changes to transportation systems and people's lifestyles (Shabanpour et al., 2018). Automated vehicles may enable drivers to engage in non-driving activities, such as working, reading, or resting (Krueger et al., 2016). However, the successful diffusion of automated vehicles depends on the acceptance of the new technology (Nordhoff et al., 2018). Trust is an essential prerequisite for using automation, as it is a key predictor of acceptance and a positive user experience (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Hoff & Bashir, 2015; Parasuraman & Riley, 1997; Wilson et al., 2020). Trust in automation refers to the attitude that the system will help users achieve their goals in a situation characterised by uncertainty

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and vulnerability (Lee & See, 2004). Perceived risk captures the level of risk experienced in driving (Griffin et al., 2020). Li et al. (2019) considered perceived safety as an antecedent of trust, while Nordhoff et al. (2021) found that perceived safety emerges from trust. We consider trust and perceived safety (or risk) to be interacting perceptions which are essential in the interaction between drivers and automated vehicles. Trust and perceived safety primarily derive from the automation performance as perceived by the user and the driving conditions, including the (dangerous) behaviour of other road users. User interfaces can thereby help to calibrate trust and perceived risk as they can inform users of the (safe) operation of the automated vehicle and its capability to deal with other road users (Li et al., 2019). The potential of user interfaces to enhance trust and perceived safety and to foster acceptance of automated driving was demonstrated in our recent study (Kim et al., 2021). However, previous research primarily focused on the overall effect of user interfaces and provided limited insights into the effects of different information types and modalities on driver's trust, perceived risk, and acceptance. In this study, therefore, we design and evaluate user interfaces conveying different types of information in various modalities to investigate their effects on trust, perceived risk, and acceptance in partially automated vehicles.

1.1. *Trust in automated vehicles*

Trust is crucial for the acceptance of vehicle automation (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Ghazizadeh et al., 2012; Hoff & Bashir, 2015; Wilson et al., 2020). It is important to adjust users' trust to an appropriate level depending on the systems' performance (Merritt et al., 2015). To leverage advanced technologies, driver's trust needs to be maintained at an appropriate level (Haspiel et al., 2018) to avoid both under-trust (or distrust) and over-trust (Lee & See, 2004). Over-trust can lead to misuse and unintended use, which can result in various, even fatal accidents (O'Kane, 2020). Conversely, many (potential) users distrust vehicle automation, which may lead to disuse (Pew Research Center, 2017). Transparency is crucial to evoke trust (Lyons et al., 2016). Trust issues may result from a lack of information on the behaviour of a complex system, e.g., a car (Norman, 1990). Transparency, as defined by Endsley et al. (2003), encompasses the clarity and predictability of systems. It enables users to grasp the system's operations, rationale, and anticipated actions (Alonso & de la Puente, 2018). In automated vehicles, a deficiency in transparency, such as the absence of information regarding future actions, may cause inherent distrust (Basantis et al., 2021). Well-designed user interfaces can reduce unnecessary interventions by enhancing the driver's understanding of the vehicle's intentions and capabilities (Carsten and Martens, 2019). Automation system transparency has been shown to enhance trust calibration (Gao & Lee, 2006; Hoff & Bashir, 2015; Lee & See, 2004; Lyons et al., 2017; Mercado et al., 2016; Visser et al., 2014). Nevertheless, the existing studies examine the importance of transparency, with less emphasis on how transparency in user interfaces influences driver's trust. Therefore, we design user interfaces to enhance system transparency and investigate their effects on trust in this study.

1.2. *Surrounding and manoeuvre information*

To foster trust in and acceptance of automated vehicles, it is important to design transparent automated vehicle behaviour supported by a user interface explaining the operation of the automated vehicle. Previous studies have emphasised the necessity of system transparency by providing automation information, which consists of surrounding and manoeuvre information (Chang et al., 2019; Hock et al., 2016; Koo et al., 2015; Ma et al., 2021; Oliveira et al., 2020; Sawitzky et al., 2019). Surrounding information includes other road users detected by the vehicle, and manoeuvre information relates to the decisions made by the automated vehicle. Both information types enable users to anticipate and understand upcoming vehicle behaviour.

Wilson et al. (2020) observed on-road driver behaviour in partially automated vehicles. They confirmed that one obstacle to trusting automated vehicles is a lack of information provided to the driver regarding what the automation "perceives" of the driving environment and how the automation will behave afterwards. When the vehicle detected other vehicles and presented this on the visual interface, drivers were reassured that the vehicle would respond adequately and continued to use the automation. Providing surrounding and manoeuvre information increases trust and convinces drivers to use automation (Hock et al., 2016). Oliveira et al. (2020) and Sawitzky et al. (2019) have shown that augmented reality displays can increase trust by providing different visual aids for displaying driving routes as manoeuvre information. Koo et al. (2015) and Ma et al. (2021) confirmed that information provided using a single modality, auditory and visual, respectively, increased trust, but the impact of different levels of automation information on drivers varied between studies. Koo et al. (2015) compared four different transparency levels of information, with and without surrounding information (the reasons for action) and manoeuvre information (how the car will act), via auditory modality and found that surrounding information increased trust, but the effect of manoeuvre information was not significant. Ma et al. (2021) investigated three transparency levels of information (1. none; 2. surrounding information; 3. surrounding and manoeuvre information) via visual modality and showed that a combination of surrounding and manoeuvre information increased trust more than surrounding-only information. Basantis et al. (2021) compared four different interfaces (1. No feedback; 2. Vehicle path on the visual display; 3. Manoeuvre notification sound 4. Mix of 2 and 3) in the rear seat. The results show enhanced trust and perceived safety with the auditory manoeuvre notification compared to only visual automation information. Although these studies highlight the benefits of providing surrounding and manoeuvre information, they typically examined the impact of these information types in isolation or did not systematically evaluate the combined effects of different modalities (visual and auditory) on trust and perceived safety.

While Mackay et al. (2020) and Chang et al. (2019) suggested that more information does not always lead to increased trust, the nuances of how different levels of information interact with modality to influence trust and acceptance in partially automated vehicles have not been fully explored. Examination of how auditory information, when synchronised with visual cues, can maintain driver attention without causing distraction or irritation is still needed, as highlighted by Liu (2001) and Edworthy (1998).

Thus, further research is essential to address the current gap in understanding the interaction of modality and information and how the combination of information types and modality affects trust, perceived safety and acceptance in the specific context of partially automated vehicles. Existing studies have not fully explored the systematic effects of auditory and visual information, indicating a pressing need for further research to systematically examine the impact, guiding the design of effective user interfaces that provide the necessary information to establish an appropriate trust level in partially automated vehicles.

1.3. The current study

This study systematically investigates how different information types and modalities of user interfaces in driving automation information affect drivers' trust, perceived safety, and acceptance during partially automated driving. We hypothesised that user interfaces providing surrounding information, manoeuvre information, or both enhance drivers' trust, perceived safety and acceptance in driving automation. We expected that user interfaces that provide more information enhance trust and perceived safety. As a result, we also expected a reduced frequency of drivers' interventions (e.g., braking) during driving automation. We evaluated visual and auditory UI to compare their effectiveness and user acceptance. For the challenge of maintaining the driver's attention, we expect that visual displays impact the driver's eye gaze distribution, which is significantly correlated with the driver's trust and perceived risk levels.

To validate our hypothesis, we designed four user interfaces using four combinations of information (surrounding information vs surrounding and manoeuvre information) and modalities (visual modality vs visual and auditory modality). The interfaces were intended to support drivers in understanding the reactions of automated vehicles to other vehicles merging in front, where the automated vehicles could react by either braking or changing lanes.

2. Method

We designed four user interfaces (UI) providing automation information via visual and auditory modalities and evaluated the interfaces in a driving simulator, adding No UI as a baseline condition in a partially automated vehicle (Table 1). Effects of UI were assessed objectively through brake behaviour and eye-gaze behaviour, as well as subjectively through perceived risk, trust and acceptance. In a preliminary experiment (see Appendix), participants evaluated one type of UI among these five UI conditions (between-subject experiment design). The results showed significant benefits for all four UIs compared to the No UI condition, but differences between the four UIs were not significant, presumably due to large individual differences. To further investigate the effects of UI information type and modality, the main experiment was performed using a within-subject design, which is less sensitive to individual differences.

2.1. Participants

Twenty-two drivers participated in the experiment. All had driving licenses for more than a year. The average age of the participants was 28.3 years (SD = 13.1). Thirteen were male, and nine were female. Eleven had experience with adaptive cruise control (ACC), seven with lane-keeping assist (LKA), and four with both ACC and LKA. Eight drove a few times per year, ten drove a few times per month, and four drove a few times per week.

2.2. Apparatus

Participants experienced the scenarios in the DAVSi driving simulator with a Toyota Yaris cockpit (Fig. 1) at Delft University of Technology. It used three high-quality projectors to display the environment on a cylindrical 180-degree screen. Two 7-inch tablets were used as side mirrors. The automation UI presented visual information on a 10.1-inch tablet at the centre console, while an in-vehicle embedded speaker presented the auditory information. A 5.8-inch tablet was placed on the left side of the steering for a questionnaire. The instrument panel showed vehicle speed and engine revolutions per minute. A fixed four-camera Smart Eye Pro tracked the participant's eye gaze and was used to classify the region of interest.

Fig. 1. Exterior and interior of the DAVSi simulator, with visual UI right of the steering wheel and tablet for the questionnaire left of the steering wheel.

Table 1
User Interface Conditions.

Modality	Information	
	Surrounding	Surrounding & Manoeuvre
Visual	*S-V UI*	*SM-V UI*
Visual & Auditory	*S-VA UI*	*SM-VA UI*

* baseline is *No UI*.

2.3. Experimental conditions

The experiment evaluated the effects of two information types (i.e., surrounding and manoeuvre) and two modalities (i.e., visual and auditory). The visual modality was used to provide continuous information, and event-based information was presented using visual or auditory cues. We always included surrounding information in four UIs, which was shown beneficial in a range of studies as outlined above, and explored the benefits of adding manoeuvre information. Table 1 shows the five UI conditions: 1) Baseline (*No UI)*, with no additional (automation) information provided, 2) Surrounding information via the visual modality (*S-V UI*), 3) Surrounding and manoeuvre information via the visual modality (*SM-V UI*), 4) Surrounding information via the visual and auditory modality (*S-VA UI*), 5) Surrounding and manoeuvre information via the visual and auditory modality (*SM-VA UI*). Each participant executed all five UI conditions in randomised order.

2.4. Scenario design

This experiment selected highway driving scenarios with other vehicles merging into the driving lane of the ego-vehicle. Participants drove partially automated vehicles where they monitored the driving environment and kept their hands on the steering wheel. An adjacent vehicle (the yellow car in Fig. 2) entered the highway and approached to merge into the right lane where the ego-vehicle (the blue car in Fig. 2) was driving. Participants could see the adjacent vehicle approaching their lane. After detecting the merging vehicle, the ego-vehicle braked (Fig. 2 left) or steered to the left lane (Fig. 2 right). The velocity of the ego-vehicle and the traffic vehicles was set to 100 km/h. In the braking manoeuvres, the braking lasted until the merging vehicle velocity decreased to 60 km/h, followed by acceleration back to 100 km/h. In the lane change manoeuvres, the ego-vehicle steered into the left lane, overtook the merging vehicle and returned to the original lane. No accidents or automation failures were designed.

Six merging events were studied (Table 2), varying in terms of *merging gap* (5 m and 25 m) and *automation action* (-2 m/s^2 or -8 m/s^2 deceleration, or lane change). The slowing-down manoeuvre and lane change manoeuvre contained four and two merging events with different criticalities (*automation action*) respectively. To integrate these into a single drive, a series of onramps were designed along the road with one-minute intervals between merging locations. In total, merging events occurred in eight of the ten ramps. The order of events was randomised for every drive.

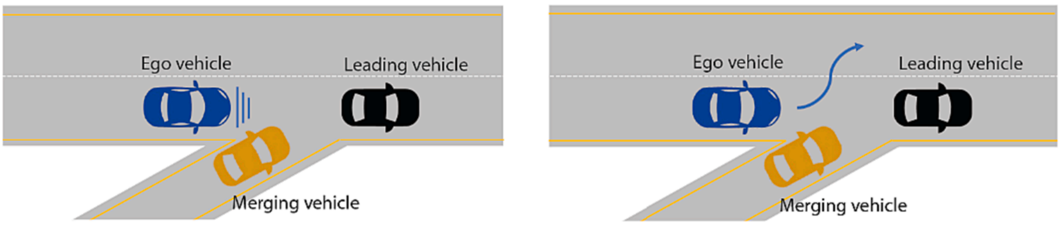

Fig. 2. Merging scenario (Blue: ego-vehicle, Black: leading vehicle, Yellow: merging vehicle), slowing down manoeuvre (Left) and lane change manoeuvre (Right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Events types.

Manoeuvre	Event elements	
	Merging gap (m)	Automation action
Slowing down	5	-2 m/s^2 deceleration
		-8 m/s^2 deceleration
	25	-2 m/s^2 deceleration
		-8 m/s^2 deceleration
Lane change	5 *	Lane change
	25 *	Lane change

* Lane change events were repeated twice.

Fig. 3. Visual UI with surrounding and manoeuvre information. Bird-eye view with pop-up message of surrounding information (Left) and pop-up messages for manoeuvre information (Right).

2.5. UI design

2.5.1. Visual interface

A bird-eye view with pop-up messages provided visual surrounding information (Fig. 3 left). The bird-eye view was visible the entire time while driving. It showed the driving environment 60 m forward and 10 m backwards, including two adjacent lanes. The colour of the ego-vehicle was red to ensure that participants easily recognised their car, while the colour of other vehicles was grey. A pop-up message displayed safety-related surrounding information (i.e., *merging vehicle detected*). In *SM-V UI* and *SM-VA UI* conditions, manoeuvre information was also provided as a pop-up message with text and an icon after the surrounding information pop-up message in the same location (Fig. 3 right) and was presented just before the ego-vehicle performed a manoeuvre (i.e., when the ego-vehicle is slowing down or changing lane).

2.5.2. Auditory interface

A combination of abstract sounds and language-based explanations was used. An abstract sound of a low alarm level was provided to draw attention to prevent participants from being surprised by the language-based explanations. A wood and xylophone sound with a fundamental frequency of 625 Hz was two times repeated and lasted a total of 1.24 s. It was chosen because it can provide a feeling of simplicity (Özcan & Egmond, 2012). Comprehension-level perception information was provided (Avetisyan et al., 2022) as surrounding information. Explanations were generated using a female voice to be more likeable and comfortable (Dong et al., 2021) on the Google text-to-speech engine. The surrounding information was provided as: 'm*erging vehicle detected' of* 1.4 s. Manoeuvre information used a first-person pronoun (i.e., 'we') as an anthropomorphism to increase trust (Waytz et al., 2014). Manoeuvre information was provided as: 'we *are slowing down' of* 1.0 s or 'we *are changing lane' of* 1.1 s. These sounds can be found in the digital appendix.

2.5.3. Timing

The provision of automation information prior to the action of the automated vehicle has been found to improve trust, as demonstrated in previous studies (Du et al., 2021; Haspiel et al., 2018). Therefore, the information was provided before the vehicle took action in the experiment. To determine the optimal timing for information provision, we conducted a pilot test using an online survey to compare *on-time* and *early-timing* conditions. The *on-time* condition provided surrounding and manoeuvre information as soon as the merging vehicle changed direction to the ego-vehicle lane. The *early-timing* condition provided the information four seconds before the *on-time* condition. Twenty-four participants watched videos with different information provision timing and answered the trust comparison question. The manoeuvre was when a merging vehicle approached with a 5 m merging gap with $-5 m/s^2$ deceleration. As a result, fifteen participants answered that they trusted automation more with *early timing.* One participant trusted more *on time*, and eight had no preference. Therefore, we decided to provide the information four seconds before the merging started. Hereby, we assumed the AV to timely detect the merging intention from the directional indicator or V2V communication.

2.6. Measurement

During the simulation, brake pedal signals, eye gaze behaviours, trust, and perceived risk were collected. The brake pedal signal was recorded by the driving simulator automatically as braking is an effective indicator of distrust and perceived risk during automated driving (He et al., 2022; Li et al., 2020; Tenhundfeld et al., 2020). We deactivated the option for participants to take over control by steering to ensure a controlled study environment because different traffic conditions in the left lane influence the driver's steering behaviour, which would introduce additional factors into the analysis. Eye gaze behaviour, an indicator of the driver's attention and situation awareness, is impacted by user interfaces as they can change the driver's eye gaze distribution (Goncalves et al., 2022). The redistribution of eye gaze is particularly important as it is indicative of the driver's engagement with the driving environment and the automated system. Eye gaze behaviour was recorded at 60 Hz using a smart-eye system with four infrared cameras mounted in the vehicle cockpit. It was measured to evaluate the eye gaze fixation time ratio on the display and the road and the eye gaze transition numbers between the display and the road. Participants were requested to report the level of trust and perceived risk after each merging event on the tablet on the left side of the steering wheel (He et al., 2022). After each merging event, the experimenter verbally asked two 10-point Likert scale questions: "*how much do you trust the driving automation according to the previous performance of the system?*" and "*how risky do you perceive the previous event*". After each UI condition, participants answered three questions related to communication and acceptance on a 7-point Likert scale. Communication with automation measured whether drivers understood the system operation through the interface. We measured perceived usefulness and perceived ease of use to evaluate acceptance based on the Technology Acceptance Model (TAM) (Davis, 1989). Perceived usefulness measures the degree to which the technology is useful and enhances driving performance. Perceived ease of use measures the degree to which the technology is easy to use and understandable. After participants experienced five UI conditions, they were asked to rank the five UIs on communication with automation, perceived usefulness, and perceived ease of use. In addition, the preferred modality (visual vs auditory vs both) of given the type of information was evaluated using a 7-point Likert scale.

2.7. Procedure

Participants were welcomed and introduced to the experiment. They were asked to read the experiment information and sign an informed consent form before they filled out a demographic questionnaire, including age, gender, and vehicle automation experience. After finishing the questionnaire, they moved into the driving simulator. Participants adjusted the sitting position according to their individual preferences, and an experimenter calibrated the eye-tracking system. Participants were informed that they would be driving a partially automated vehicle, with the vehicle performing lateral and longitudinal motion control while they monitored the driving automation and kept their hands on the steering wheel. They were instructed that they could intervene in the automation by braking whenever they felt it was necessary, and partially automated driving would automatically reactivate right after their intervention. In the training session, participants drove partially automated driving on the highway to familiarise themselves with the simulator and learn how to answer the trust and perceived risk questions in the tablet when they were asked. This training lasted until participants could handle all tasks well. Then, the simulator experiment started. For each UI condition, participants experienced eight merging events in randomised order. Participants were informed they could stop if they felt uncomfortable or experienced motion sickness. During driving, participants rated their level of trust and perceived risk using a 10-point Likert scale questionnaire on the tablet located on the left side of the steering wheel after each event. Each UI condition took around ten minutes. After each UI condition, participants answered the questionnaire about communication with automation and acceptance. This was repeated five times to experience five UI conditions. The order of five UI conditions was randomised. Participants had a break between the third and the fourth UI conditions. After five UI conditions, they answered the ranking questionnaire on preferred information and modalities. The entire procedure took around two hours.

2.8. Data analysis

Statistical analysis was conducted using IBM SPSS ver.27. A two-way repeated-measure ANOVA was used to analyse the effects of *UI* and *Event* type on trust, perceived risk and eye gaze behaviour. The data were analysed using a separate repeated-measures analysis for each dependent variable (trust, perceived risk and eye gaze behaviour) with independent factors UI (5 levels) and Event type (6 levels) as within-subject variables. To analyse the effects of UI on communication with automation, perceived ease of use, and perceived usefulness, a one-way ANOVA was used. Effects were declared statistically significant if $\alpha < 0.05$. Post-hoc analysis was conducted with a Bonferroni test where the α value was adjusted by dividing it by the number of comparisons. Therefore, 0.005 and 0.003 were used as α for post-hoc analysis on the effects of UI and event type, respectively.

3. Results

All twenty-two participants completed the experiment, and no motion sickness was reported. Eye gaze signals were successfully collected in 106 simulations (22 participants × 5 UIs with four UI conditions missing eye gaze data). 880 answers (22 participants × 5 UIs × 8 events) about trust and perceived risk and 110 answers (22 participants × 5 UIs) about communication with automation and acceptance, and 22 answers (22 participants) about information and modality preference were collected from questionnaires and analysed.

3.1. Trust and perceived risk

Fig. 4 shows the mean score for *trust* (Left) and *perceived risk* (Right) over all events for each user interface. The *SM-VA UI* received the highest *trust*. The effect of user interface on *trust* was significant ($F(4, 84) = 5.30$, $p < .001$, $\eta^2 = 0.20$). The *SM-VA UI* received significantly higher trust compared to the *S-V UI* ($p = .029$) and the *S-VA UI* ($p = .025$) (Fig. 4 left). As expected, *perceived risk* showed an

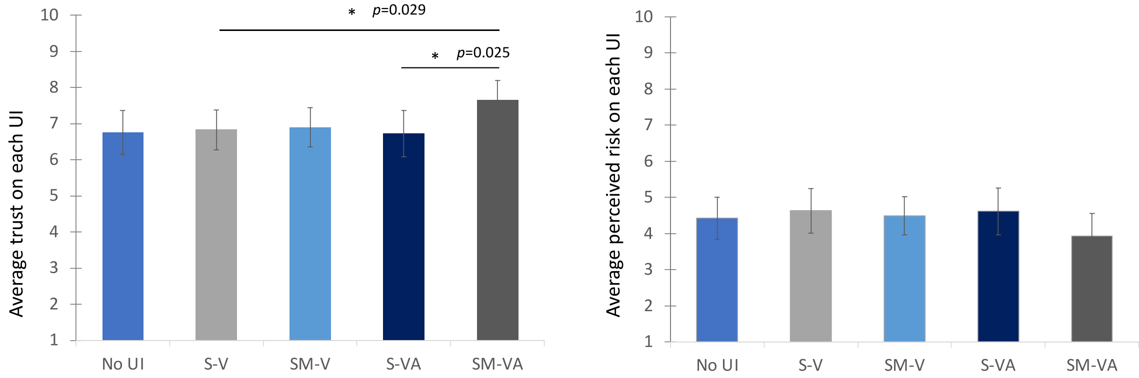

Fig. 4. Drivers' Trust (Left) and Perceived risk (Right) on each user interface over all events, means and standard error over 22 participants (* p < 0.05).

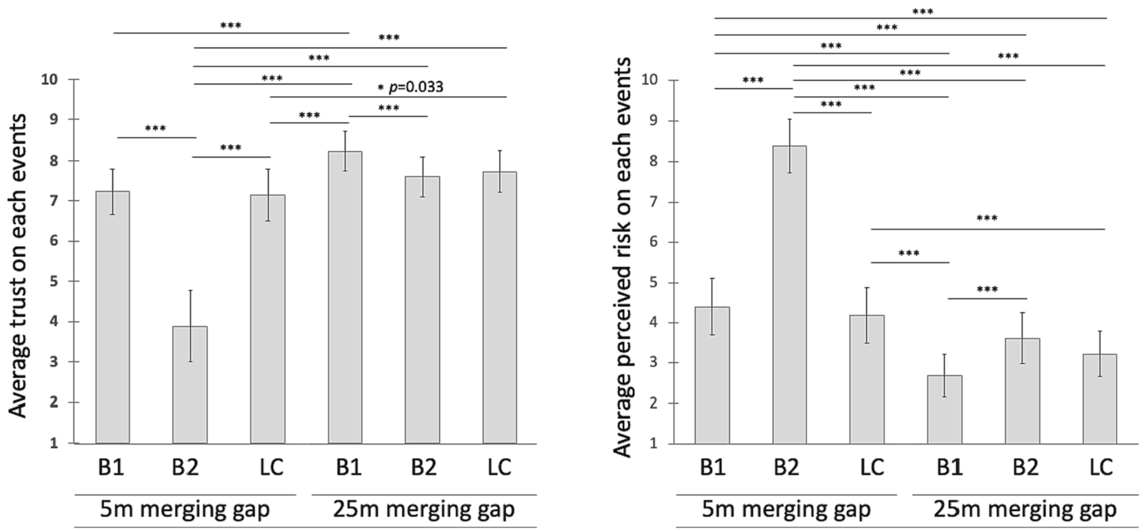

Fig. 5. Drivers' trust (Left) and perceived risk (Right) as a function of automation action and merging gap (* p < 0.05, *** p < 0.001). B1: -2 m/s^2braking intensity; B2: -8 m/s^2 braking intensity; LC: Lane change.

opposite trend as *trust,* where the lowest risk was perceived with the *SM-VA UI* (Fig. 4 right). However, the effect of UI conditions on *perceived risk* was just not significant ($F(4, 84) = 2.48$, $p = .050$, $\eta^2 = 0.11$).

Fig. 5 shows the mean score for *trust (Left) and perceived risk (Right)* over all user interfaces for each event type. Here, no significant effects of the order were found between these events, so lane change results were averaged over the two equivalent events tested. The most critical event (Slowing down with a 5 m merging gap and $-8m/s^2$ deceleration) received the lowest *trust* and the highest *perceived risk*. The least critical event (Slowing down with a 25 m merging gap and $-2m/s^2$ deceleration) received the highest *trust* and the lowest *perceived risk*. As shown in Table 2, the effect of each event element (merging gap and automation action) on *trust* and *perceived risk* was analysed. The merging gap included 5 m and 25 m, and the automation action included $-2m/s^2$ and $-8m/s^2$ deceleration and lane change. The merging gap significantly affected *trust* ($F(1, 21) = 89.48$, $p < .001$, $\eta^2 = 0.81$) and *perceived risk* ($F(1, 21) = 179.09$, $p < .001$, $\eta^2 = 0.90$). The post-hoc analysis indicated that 25 m merging gap events received higher *trust* and lower *perceived risk* than 5 m merging gap events ($p < 0.001$). The automation action also significantly affected *trust* ($F(1.28, 26.88) = 55.03$, $p < .001$, $\eta^2 = 0.72$) and *perceived risk* ($F(1.64, 34.52) = 76.97$, $p < .001$, $\eta^2 = 0.79$) with a Greenhouse-Geisser adjustment. The post-hoc analysis indicated that $-2m/s^2$ deceleration events received the highest *trust* and the lowest *perceived risk* ($p < .001$), and $-8m/s^2$ deceleration events received the lowest *trust* and the highest *perceived risk* ($p < .001$). There was an interaction effect between the merging gap and automation action on trust ($F(1.44, 30.28) = 45.88$, $p < .001$, $\eta^2 = 0.69$) and perceived risk ($F(1.40, 29.34) = 58.84$, $p < .001$, $\eta^2 = 0.74$) with a Greenhouse-Geisser adjustment. The *trust* and *perceived risk* difference between $-2m/s^2$ deceleration or lane change and $-8m/s^2$ deceleration were much greater when the merging gap was 5 m than 25 m. There was no interaction effect between UIs and elements of events on *trust* and *perceived risk*.

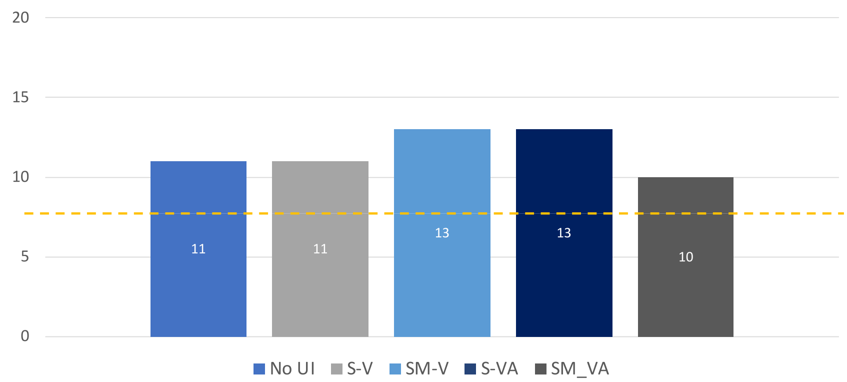

Fig. 6. Number of participants who used the brake pedal in at least one event with each user interface. The yellow dashed line represents the eight participants who braked in all five UI conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. *Braking behaviour*

The use of the brake pedal was detected in 58 out of 110 UI conditions (22 participants × 5 UIs). All instances of braking occurred in the most critical events (slowing down with a 5 m merging gap and -8 m/s^2 deceleration). Eight participants braked in all five UI conditions in at least one event, two participants used the brake pedal in four UI conditions, three participants in three, and one participant in one UI condition, whereas eight participants did not use the brake pedal at all. As shown in Fig. 6, there is almost no brake pedal behaviour difference between the five UI conditions. The eight participants who braked in all UI conditions had lower trust levels ($F(1,14) = 4.96$, $p = .04$) and higher perceived risk levels ($F(1,14) = 4.56$, $p = .05$) than the eight participants who never braked. There was no effect of experiment order on *braking behaviour*.

3.3. *Eye gaze behaviour*

As shown in Fig. 7, eye gaze behaviour (i.e., the eye gaze fixation time on the display and the road and the eye gaze transition number between the road and the display) differs over all four UIs (*S-V, SM-V, S-VA,* and *SM-VA UI*), compared to *No UI*, primarily due to the visual display on the centre console. No significant difference was found between the four UIs. UI presence significantly impacted the *eye gaze fixation time ratio on the display* ($F(4, 72) = 8.56$, $p < .001$, $\eta^2 = 0.32$), the *eye gaze fixation time ratio on the road* ($F(4, 72) = 7.69$, $p < .001$, $\eta^2 = 0.30$), and the *transition number between the road and the display* ($F(4, 72) = 10.38$, $p < .001$, $\eta^2 = 0.37$). The Bonferroni test reveals that the *eye gaze fixation time ratio on display* and the *eye gaze transition number between the road* and *the display* are significantly higher with the four UIs than with *No UI*. Significant differences were also found with the four UIs and with *No UI* except *SM-V UI* regarding the *eye gaze fixation time ratio on the road*. No significant effect of different events on eye gaze behaviour (i.e., the *fixation duration ratio on the road* and *the display* and the *transition number between the road and the display*) was found, as shown in Fig. 8 and Table 3. A marginally significant ($p = .045$) interaction was observed between the merging gap and automation action on eye gaze fixation time ratio on the display.

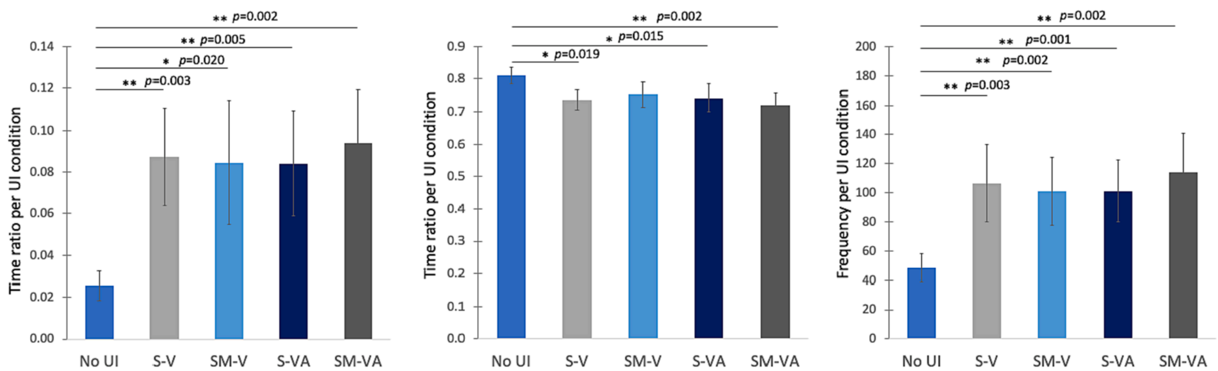

Fig. 7. Eye gaze fixation time ratio on the display per UI (Left); Eye gaze fixation time ratio on the road per UI (Middle); Transition numbers between the road and the display per UI (Right) (* $p < 0.05$, ** $p < 0.01$).

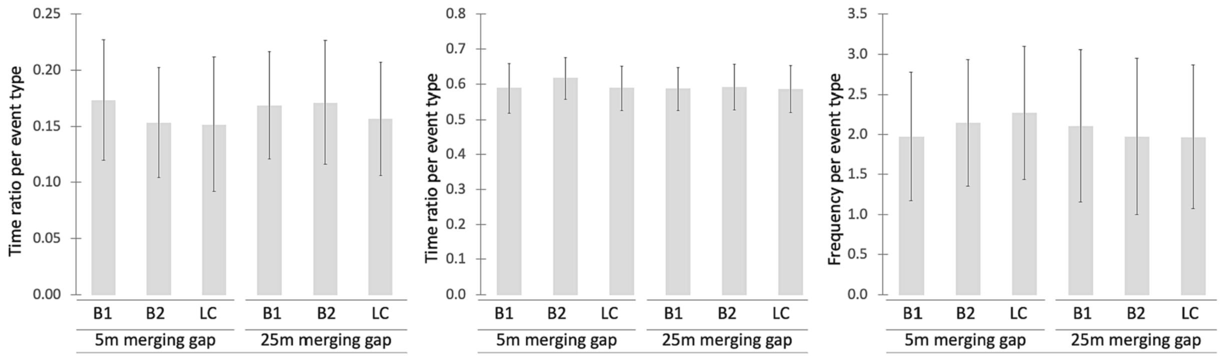

Fig. 8. Eye gaze fixation duration ratio on the display per event (Left); Eye gaze fixation duration ratio on the road per event (Middle); Transition numbers between the road and the display per event (Right). B1: −2 m/s^2braking intensity; B2: −8 m/s^2 braking intensity; LC: Lane change.

Table 3
Statistics of the event's effect of merging gap and automation action on eye gaze behaviours.

Eye-gaze measurement	*Event elements*	*F*	*Sig.*	*Effect size* (η^2)
Eye gaze fixation time ratio on the display	Merging gap	F(1.00, 15.00) = 2.04	0.112	0.15
	Automation action	F(1.05, 15.73) = 0.08	0.860	0.01
Eye gaze fixation time ratio on the road	Merging gap	F(1.00, 16.00) = 3.33	0.087	0.17
	Automation action	F(1.26, 20.20) = 0.62	0.478	0.04
Eye gaze transition numbers between the road and the display	Merging gap	F(1.00, 16.00) = 1.52	0.236	0.09
	Automation action	F(2.00, 32.00) = 0.10	0.908	0.01

The results showed insignificant effects of user interface on the eye gaze distribution (except UI versus *No UI)*. However, there was a notable individual difference in the average eye gaze distribution on the display. Cronbach's analysis showed the high reliability between each participant's *fixation duration ratio on the display* of four interfaces, excluding the *No UI* (Cronbach's $\alpha = 0.86$). There was no correlation between the *fixation duration ratio on the display* of each participant and their *trust* and *perceived risk*. The eye gaze behaviour results indicate that participants indeed checked the visual display during driving but kept the same eye gaze behaviour regardless of different event types and UI.

3.4. Communication with Automation, perceived ease of use and perceived usefulness

As shown in Fig. 9, the *SM-VA UI* received the highest score on all attributes. The main effects of UI were significant for *communication with automation* ($F(4, 84) = 5.08$, $p < .001$, $\eta^2 = 0.26$), *perceived ease of use* ($F(4,84) = 4.54$, $p < .001$, $\eta^2 = 0.62$) and *perceived usefulness* ($F(4, 84) = 3.99$, $p < .001$, $\eta^2 = 0.42$). The post-hoc analysis indicated that participants preferred the *SM-VA UI* to the *No UI,* and *S-V UI* on all attributes ($p < .001$).

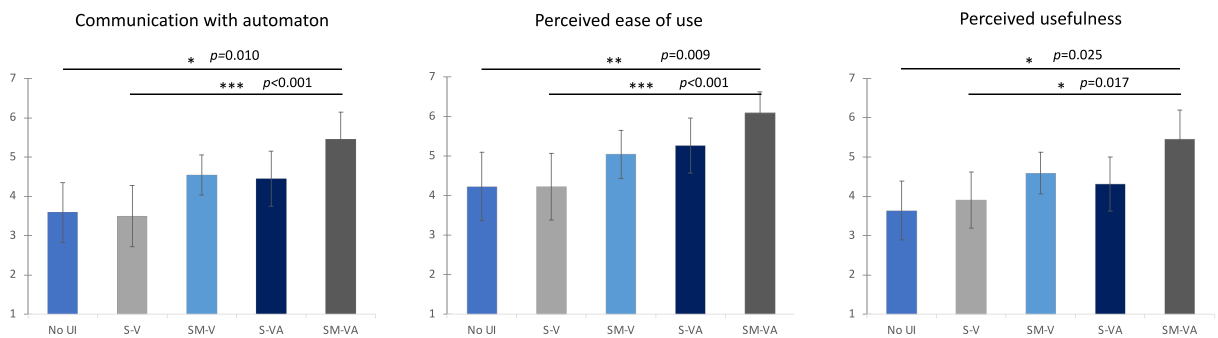

Fig. 9. Drivers' communication with automation (Left), perceived ease of use (Middle) and perceived usefulness (Right) scores on each User interface (*p <.05, **p <.01, ***p <.001).

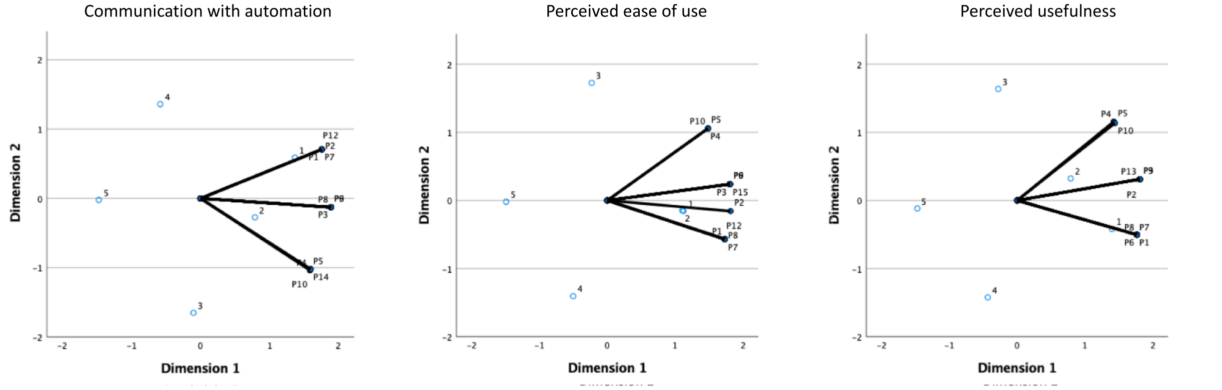

Fig. 10. UI ranking, CATPCA results of communication with automation (Left), perceived ease of use (Middle) and perceived usefulness (Right).

Concerning the UI ranking, (ordinal) data were analysed using categorical principal component analysis (CATPCA). Answers from two participants were shown to contain outliers, according to CATPCA, and therefore, we excluded all answers from these two participants.

The Friedman test examined the differences in the ranking among UI conditions. Participants ranked the five UI conditions significantly different on *communication with automation* ($\chi^2(4, 20) = 69.80$, $p < .001$), *perceived ease of use* ($\chi^2(4, 20) = 70.77$, $p < .001$), and *perceived usefulness* ($\chi^2(4, 20) = 69.92$, $p < .001$). As the results of CATPCA, biplots of all attributes (*communication with automation, perceived ease of use* and *perceived usefulness*) on the five UIs are shown in Fig. 10. The eigenvalues and percentage of total variance are presented in Table 4. The results of the analysis explained 100 % of the total variance. Dimension 1 accounted for around 90 % of the variance in the ranking of *communication with automation, perceived ease of use* and *perceived usefulness. SM-VA UI* is ranked highest over the three attributes (*communication with automation, perceived ease of use* and *perceived usefulness*), followed by *S-VA UI, SM-V UI, S-V UI*, and *No UI*. The *No UI* and *S-V UI* were least preferred in *perceived ease of use*. When examining the x-coordinate pertaining to Dimension 1 across all three attributes in Fig. 10, participants are consistently positioned on the right side of the graph. This is because participants tended to evaluate the UI with the ranking *SM-VA UI*, *S-VA UI*, *SM-V UI*, *S-V UI*, and *No UI*, which were displayed from left to right in the graph. Dimension 2 accounted for around 10 % of the total variance. It corresponds to the difference in the preferred interface between *S-VA UI* and *SM-V UI*. The results showed differences in preference for *S-VA UI* and *SM-V UI* as the second highest-rank interface, depending on the individual. Considering the y-coordinate reflecting Dimension 2 in Fig. 10, the *S-VA UI* and *SM-V UI* are positioned on opposite sides, while the remaining UIs congregate around zero. This discrepancy arises from varying participant preferences, particularly regarding the *SM-V UI* ranking. Participants clustered around zero expressed a preference for *SM-V UI* as their third choice. Conversely, participants positioned near the *SM-V UI* reported a lower preference for it compared to other participants. Notably, participants in proximity to the *S-VA UI* indicated a heightened preference for *SM-V UI* compared to their counterparts, resulting in a relatively lower ranking for *S-VA UI*.

3.5. Information type and modality preference

Participants highly appreciated both UI information types, where surrounding information received 6.18 (SD = 1.2) points and manoeuvre information received 6.50 (SD = 0.96) points on a 7-point Likert scale. Fig. 11 shows the preferred modality for surrounding and manoeuvre information. Participants preferred receiving the surrounding information via both visual and audio modalities. Among twenty-two participants, fourteen participants (64 %) preferred surrounding information in both visual and audio, four participants (18 %) chose only audio, and four chose only visual (18 %). The right figure indicates the modality preference for manoeuvre information. Compared to the surrounding information modality preference, more participants preferred to receive the manoeuvre information through audio only. Ten participants (45 %) preferred both visual and audio manoeuvre information. Nine participants (41 %) preferred only audio, and three participants (14 %) preferred only visual.

Table 4
UI ranking, CATPCA eigenvalues and % total variance explained.

	Communication with automation			Perceived ease of use			Perceived usefulness		
Dimension	*Total (Eigenvalue)*	*% of Variance*	*Cronbach's Alpha*	*Total (Eigenvalue)*	*% of Variance*	*Cronbach's Alpha*	*Total (Eigenvalue)*	*% of Variance*	*Cronbach's Alpha*
1	17.80	89.00	0.99	18.06	90.31	0.99	17.86	89.32	0.99
2	2.20	11.00	0.57	1.94	9.69	0.51	2.14	10.68	0.56
Total	20.00	100.00	1.00*	20.00	100.00	1.00*	20.00	100.00	1.00*

* Total Cronbach's alpha is based on the total eigenvalue.

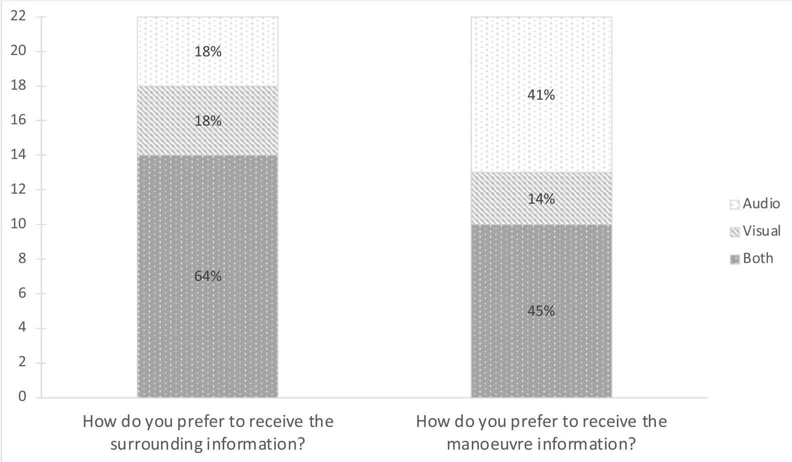

Fig. 11. Ratio of drivers' modality preference on surrounding information (Left) and manoeuvre information (Right).

4. Discussion

This study investigated the effects of user interface (UI) on trust, perceived risk, and acceptance in partially automated highway driving with a simulator experiment. Four interfaces were designed, combining surrounding and manoeuvre information and visual and auditory modalities.

4.1. Effects of UIs on Trust, perceived risk and acceptance

We systematically added information types (surrounding and manoeuvre) and modalities (visual and auditory). The most advanced UI, *SM-VA UI,* providing surrounding and manoeuvre information via both visual and auditory modality, received the highest trust and lowest perceived risk scores and the highest communication with automation and acceptance scores. In addition, ranking showed that participants chose *SM-VA UI* as the best and *No UI* or *S-V UI* as the worst ranking communication with automation, perceived ease of use and perceived usefulness. Effects are highly significant comparing the most advanced *SM-VA* to *No UI* and thereby support our hypothesis that "user interfaces providing surrounding information, manoeuvre information, or both enhance drivers' trust, perceived safety and acceptance in driving automation". Although we did not find the expected "reduced frequency of drivers' interventions (e.g., braking) during driving automation" in the main study, we found some reduction in the preliminary experiment. Adding only manoeuvre information has more effect on reducing drivers' interventions than only adding surrounding information, but this trend is not significant. Regarding modality, manoeuvre information displayed through both visual and auditory modalities demonstrated an increase in trust and acceptance of the information. However, when manoeuvre information was presented solely through visual modality, there was no significant increase in trust and acceptance compared to when no information was provided. Eye gaze behaviour showed that drivers check the UI at the centre console when present. However, at the same time, there was no significant difference in UI gaze time between the four UIs. Presumably, drivers check the driving situation on the road after receiving surrounding information instead of perceiving visual manoeuvre information.

Interestingly, the effects of UIs show more significance in acceptance compared to driving behaviour, trust and perceived risk. Acceptance increases when receiving more information with more modalities. Drivers want to monitor the safe operation of partially automated vehicles (Buckley et al., 2018). Therefore, regardless of the actual use of the interface, the presence of the interface can support the acceptance of automation (Kim et al., 2024).

Drivers evaluated both the surrounding and manoeuvre information positively. However, the preference for modality differed between participants and between surrounding and manoeuvre information. More than half of the participants preferred that surrounding information be delivered in both visual and audio modalities. When the surrounding information was provided in both visual and auditory modalities, there was no significant difference in the gaze time on the display compared to when it was provided only in the visual modality. Hence, surrounding information via auditory modality can be interpreted as supplementing the visual modality, not replacing it. On the other hand, the participants preferred manoeuvre information to be delivered in only an auditory modality or a combination of visual and auditory modalities. Drivers checked the centre console display when it showed the detected vehicle. After the participants perceived the merging car, their view moved to the road, with no difference in gaze time across the four UIs. Hence, the visual manoeuvre information was presumably not attended to, explaining the lack of benefits of SM-V vs. S-V and SM-VA vs. S-VA.

The preliminary between-subject design experiment presented in the Appendix already indicated that UI could increase trust, compared to no UI, but disclosed no significant differences between the four UIs. The main experiment, using a within-participant design, disclosed significant differences between the four UIs, with the best overall results for the most advanced *SM-VA UI*. A possible explanation is that individual differences obscured the effects of UI in the preliminary between-subject experiment. An alternative explanation is that, being exposed to multiple UIs, participants develop expectations regarding automation behaviour and

UI affecting their behaviour and subjective evaluation. This could include learning and trust calibration with exposure to specific UIs affecting responses with following UIs. However, we found no significant effects of order in the main results, which indicates that such learning has no strong effects. Anyhow, we see benefits in both the within and between-participant experimental design. The within-participant design discloses significant effects with a limited cost-effective sample, whereas the between-participant design better represents real-life exposure where users will presumably use one UI only.

4.2. Effects of criticality of event types and individual differences

Event criticality (Fig. 5) had a much larger effect on trust and perceived safety as compared to UIs (Fig. 4). We additionally compared the effects of UI on trust and perceived risk in the most critical event (slowing down with 5 m gap and $-8 m/s^2$ deceleration) and least critical event (slowing down with 25 m gap and $-2 m/s^2$ deceleration). In both events, the effect of UIs on perceived risk was not significant. The effect of UIs on trust was just not significant in the most critical event ($F(4, 84) = 2.43$, $p = .054$), but the effect was significant in the less critical event ($F(4, 84) = 3.06$, $p = .021$). Apparently, the effects of UI on trust and perceived risk are insufficient to make participants feel entirely safe and trust automation in the most critical events. This may be explained by Hoff and Bashir (2015), who described three layers of variability in human-automation trust: dispositional trust, situational trust, and learned trust. Situational trust depends on the context of interaction, while learned trust represents users' evaluations of systems drawn from previous experience or the current interaction. The surrounding and manoeuvre information through the interface affects the learned trust, at the same time, situational trust is affected by the driving situation, such as different events. This study evaluated three automation manoeuvres: strong braking (-8 m/s^2), mild braking (-2 m/s^2) and lane changing. The latter two manoeuvres were tested with identical behaviours of the merging vehicle and resulted in similar trust and perceived safety, where the UIs provided similar benefits with positive effects of manoeuvre information.

The relationship between UI and braking behaviour appears to be moderated by individual driver characteristics. Eight out of twenty-two participants did not brake in any of the five UI conditions, while another eight used pedals in all five UI conditions. Those who used the brake pedal less tended to have higher trust and lower perceived risk, which is consistent with findings by He et al. (2022), where trust of the braking group is lower than that of the non-braking group. It will be interesting to investigate trust calibration and its expected effect on braking in prolonged experiments or observations. The braking behaviour was quite different in the preliminary experiment, where participants braked the most in the *No UI* and the least in the *SM-VA* UI. However, the individual differences in braking behaviour may mask UIs' effect on the braking behaviour in the preliminary experiment (Niels et al., 2019). Regarding the eye gaze behaviour, each participant looked at the display similarly regardless of the interface condition, which supports the notion that it is challenging to evaluate drivers' understanding of information in vehicles as eye gaze behaviours, as noted by Cohen-Lazry et al. (2017). The result is aligned with the preliminary experiment (see Fig. A3 in the Appendix) and confirmed the trend with significant effects between the *No UI* and other UI conditions on drivers' eye gaze behaviour.

4.3. Limitations and perspective

Several limitations must be considered when interpreting our findings. The sample size, while sufficient to identify trends, is relatively small, which could potentially lead to biased effects. The artificial nature of the experimental setting, despite its high control level, may not fully capture the complexity of real-world driving dynamics. In addition, the results of user interface experiments under controlled conditions may vary depending on changes in the user interface (Albers et al., 2021) (i.e., aesthetics and layout) or changes in the environment (i.e., the urgency of the scenario) (Kim et al., 2021). These factors could limit the ecological validity of our findings. For example, the lack of significant variation in eye-tracking measures across UI conditions prompts further investigation into how different designs may influence drivers' visual attention and performance to detect the driving environment. Nevertheless, our results show significant benefits of UIs, enhancing trust and acceptance and reducing perceived risk. We provided a visual interface in the centre console display, which is common in commercial cars. However, a head-up display (HUD) could yield even better results, allowing drivers to keep their eyes on the road. HUD cannot easily present spatial surrounding information but can present event-based information such as pop-up messages. We should also consider that drivers may not perceive the auditory UI correctly when engaged in secondary tasks or may find it annoying if presented too often (Hashimoto et al., 2019). For auditory UI recognition, the volume of other audio systems shall be controlled. It is also necessary to consider irritation or stress when exposed to auditory information for a longer time. Future research will focus on interfaces providing a broader range of manoeuvre information, considering various human factors such as annoyance, workload, as well as trust and acceptance. Additionally, future studies should be extended towards UI enhancing trust and perceived safety in higher automation levels, allowing users to take their eyes off the road.

5. Conclusion

This study confirms that automation UI can enhance drivers' trust and acceptance of partially automated vehicles. Significant benefits were found for both surrounding (perception) and manoeuvre (action) information. Specifically, the most advanced UI (*SM-VA UI*), which displayed surrounding and manoeuvre information via the visual and auditory modalities, received the highest trust and acceptance ranking and the lowest perceived risk among drivers. Manoeuvre information displayed through the auditory modality was particularly effective in enhancing drivers' trust and acceptance. Current partially automated vehicles show the image received by sensors on the display, similar to the UI in our study that displays surrounding information visually (*S-V UI*). Our study shows that the surrounding information displayed via the visual modality draws the driver's attention to the display, but it needs additional auditory communication by the UI to enhance driver's trust and acceptance. Therefore, including manoeuvre information via the auditory modality should be considered for partially automated vehicles. This may make the UI more complex but also more understandable and acceptable. To paraphrase Donald Norman, people hate things to be complicated but like complexity, which this study supports. Furthermore, the study has shown the impact of the user interface in relation to the risk level of the driving situation. When the driving situation poses a high risk, even with UI, drivers do not feel entirely safe and do not trust the automation completely. At the same time, drivers accept driving automation more with UI, regardless of perceiving the information, which was also shown by Kim et al. (2024). This demonstrates both the impact and limitations of UI.

CRediT authorship contribution statement

Soyeon Kim: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiaolin He:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **René van Egmond:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Riender Happee:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2024.02.009.

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