Effects of various in-vehicle human–machine interfaces on drivers' takeover performance and gaze pattern in conditionally automated vehicles

Jinlei Shi[a], Chunlei Chai[a], Ruiyi Cai[a], Haoran Wei[a],
Youcheng Zhou[a], Hao Fan[a], Wei Zhang[b], Natasha Merat[c]

[a] Modern Industrial Design Institute, Zhejiang University, Hangzhou, China

[b] Department of Industrial Engineering, Tsinghua University, Beijing, China

[c] Institute for Transport Studies, University of Leeds, United Kingdom

Corresponding author: Ruiyi Cai, cairuiyi@zju.edu.cn, Modern Industrial Design Institute, Zhejiang University, Hangzhou, China

Abstract

With the era of automated driving approaching, designing an effective and suitable human–machine interface (HMI) to present takeover requests (TORs) is critical to ensure driving safety. The present study conducted a simulated driving experiment to explore the effects of three HMIs (instrument panel, head-up display [HUD], and peripheral HMI) on takeover performance, simultaneously considering the TOR type (informative and generic TORs). Drivers' eye movement data were also collected to investigate how drivers distribute their attention between the HMI and surrounding environment during the takeover process. The results showed that using the peripheral HMI to present TORs can shorten takeover time, and drivers rated this HMI as more useful and satisfactory than conventional HMIs (instrument panel and HUD). Eye movement analysis revealed that the peripheral HMI encourages drivers to spend more time gazing at the road ahead and less time gazing at the TOR information than the instrument panel and HUD, indicating a better gaze pattern for traffic safety. The HUD seemed to have a risk of capturing drivers' attention, which resulted in an 'attention tunnel,' compared to the instrument panel. In addition, informative TORs were associated with better takeover performance and prompted drivers to spend less time gazing at rear-view mirrors than generic TORs. The findings of the present study can provide insights into the design and implementation of in-vehicle HMIs to improve the driving safety of automated vehicles.

Keywords: Conditional automated driving, human-machine interface, takeover request, takeover performance, gaze behavior

1. Introduction

The automated driving era is approaching rapidly, and automated vehicles are considered valuable since they can release traffic congestion, enhance road safety, and improve drivers' travel experiences (Hussain & Zeadally, 2019). SAE International (2021) classified driving automation into six levels (L0–L5). Partially automated vehicles (L2), such as the Tesla, have entered the consumer market, and conditionally automated vehicles (L3) are expected to be commercialised on a large scale in the near future. In L3 automated vehicles, the automation will fully control the vehicle for extended periods of time, during which the driver can engage in non-driving-related tasks (NDRTs), such as playing games and watching movies. However, when the automated vehicle encounters a performance-relevant failure or a situation that exceeds its operational design domain (ODD), drivers must be receptive to the system's takeover request (TOR) and respond in a timely manner. Therefore, designing an effective human–machine interface (HMI) to present TORs to drivers is critical to ensure driving safety.

In a manually driven vehicle, driving-related information, such as speed, revolutions per minute, low fuel warnings, etc., is primarily presented on the instrument panel. Therefore, the instrument panel is a common place to present TORs in automated vehicles, and most previous studies have presented visual TOR warnings on the instrument panel (e.g., Albert et al., 2015; Feldhütter et al., 2019; Forster et al., 2019; see Bengler et al., 2020, for a review). Although drivers are highly familiar with this location, TORs occurring here would lead to interference for drivers when they are observing the real takeover scenarios ahead. Once drivers are notified to resume control of the vehicle, looking at information displayed on the instrument panel would delay their redirection of attention back to the road. This issue was revealed in a recent study by Gonçalves et al. (2022), which utilised eye-tracking technology and found that drivers gaze at the instrument panel with supportive information longer just before performing takeover decisions, at the expense of glances to the road environment.

To diminish the visual competition between the instrument panel and the road ahead, several researchers have proposed using head-up displays (HUDs) (e.g., Li et al., 2021; Feierle et al., 2021; Roche et al., 2019). HUDs can project driving-related information on the windshield or another location in the driver's field of view. In this way, drivers do not need to look away from the road ahead to obtain information from the HUD. HUDs have proven capable of improving driving performance and decreasing drivers' workload in manually driven vehicles (Liu, 2003; Liu & Wen, 2004). Additionally, it was revealed in a simulated driving study that HUDs can encourage drivers to gaze at the takeover event sooner following a TOR (Xu et al., 2023). Nevertheless, HUDs are also likely to capture drivers' attention, resulting in an 'attention tunnel' (Dowell et al., 2002), though there is a demand for drivers to return their attention to the road quickly and gain situational awareness to support the takeover manoeuvre when TORs are issued (Lu et al., 2019). As quick attentional shifts play a critical role in the resumption of situational awareness in drivers, it is essential to prevent HUDs from capturing attention.

Peripheral HMIs have great application potential for presenting takeover information in automated vehicles. Peripheral HMIs are interfaces outside of drivers' primary focal area of attention (Kunze et al., 2019). The visual field of drivers covers approximately 180° horizontally and 70° vertically (Traquair, 1927). Central vision (approximately 5° of the visual field) is reliant on the fovea of the retina, which has the highest photoreceptor density and maps to the largest part of the visual cortex in the brain (approximately half of the early visual cortex; Tootell et al., 1982). The remaining area of the retina is responsible for peripheral vision, and photoreceptor density rapidly decreases with incremental increases in the distance from the retina's fovea. Although peripheral vision has a lower resolution than central vision due to anatomical differences, it is sensitive to motion and ensemble perception. Peripheral vision also plays an important role in environmental perception during manual driving (see Wolfe et al., 2017, for a review). Moreover, the field of view of peripheral vision (the remaining part of the field of view excluding the 5° for central vision) is much broader, which may be beneficial in automated vehicles. Specifically, drivers can engage in NDRTs during automated driving, so their eyes are oriented toward the NDRT. When TORs are presented on the HMI based on drivers' central vision (i.e., HUD and instrument panel), drivers may not detect and process the TOR in time, leading to a delay in takeover actions and a threat to driving safety. Contrastingly, drivers can easily detect TORs on the peripheral HMI when their central vision is focused on an NDRT. Furthermore, according to multiple resources theory (Wickens, 2002), the cognitive resources required for central and peripheral vision are independent, so drivers can process information in their central and peripheral vision concurrently without mutual competition for resources. Hence, drivers can simultaneously use their central vision to get event-related information about the road ahead and their peripheral vision to process takeover messages displayed on the peripheral HMI. This pattern would facilitate drivers' recovery of situational awareness and improve driving safety. Therefore, peripheral HMIs, theoretically, have great potential to enhance takeover performance in automated vehicles.

Several studies have proposed using the peripheral HMI to convey automated vehicle-related information to drivers (Borojeni et al., 2016; Hecht et al., 2022; Kunze et al., 2019; Yang et al., 2018; Gonçalves et al., 2023). For example, Yang et al. (2018) and Hecht et al. (2022) developed peripheral HMIs using LED strips to convey the status and intentions of automated vehicles during automated driving. Their results showed that peripheral HMIs can significantly improve drivers' subjective experience and are beneficial to gaze behaviour during automated driving. Borojeni et al. (2016) also used the peripheral HMI to convey TORs and explored the effects of two patterns (static versus moving). They found no noticeable difference in takeover performance between these two patterns. However, despite the great potential of peripheral HMIs presenting TORs, no study has systematically explored its effectiveness compared with the instrument panel and HUD, which have frequently been used in previous studies (see Bengler et al., 2020, for a review). Therefore, it is essential to fill this research gap to provide some empirical evidence for relevant practitioners when designing HMIs for presenting TORs.

Eye-tracking technology is a great tool for probing drivers' visual attention. Longer gaze times toward a particular visual area indicate that the driver is devoting more information processing resources to that area (Ahlström et al., 2021; Grüner & Ansorge, 2017). Sullivan et al. (2012) revealed that drivers gaze longer at locations with valuable information (e.g., instrument panel) in order to support their tasks when they are in situations of uncertainty. A systematic review conducted by Orquin et al. (2013) argued that attention plays an active role in decision-making, suggesting that drivers gaze more frequently at an area with useful information to support their decision-making. Several researchers have explored drivers' gaze behaviour during an automated driving takeover process. Louw et al. (2019) conducted a simulated driving experiment to investigate how drivers distribute their visual attention across various areas of interest (AOIs) during the transition of control. They found that drivers prioritise gazing at and processing information from the HMI (placed on the instrument panel) over the road ahead during the takeover process, no matter whether there is an NDRT or not. Gonçalves et al. (2022) also found that drivers look more frequently and for longer at the HMI (placed on the instrument panel) and less often at the road ahead when the HMI presents automated vehicle-related information before a vehicle takeover. These studies highlighted the importance of designing an appropriate and effective HMI to guarantee driving safety, as drivers intuitively gaze more often and for longer at HMIs before taking over (Louw et al., 2019). Additionally, drivers heavily depend on their visual modality to observe their surrounding environment, recover their situational awareness, and support their takeover actions (Scharfe-Scherf et al., 2022). A reasonable gaze pattern plays an important role for drivers returning to the control loop. Therefore, it is significant to examine and understand drivers' gaze patterns during the takeover process with the use of various HMIs. However, few studies have done so.

Apart from the HMI, the presented TOR information is of great importance for takeover performance and safety. There have generally been two types of TOR information used in previous studies, namely a generic TOR and an informative TOR. A generic TOR refers to a simple warning that informs drivers to take over but provides no other information, such as a simple visual TOR icon (Yoon et al., 2019), an auditory beep (Petermeijer et al., 2017), or a purely tactile alert (Wan et al., 2018). However, some researchers have argued that TORs should not be pure warnings; they should be informative TORs that contain some supportive information to help drivers recover their situational awareness and complete the takeover manoeuvre (see Kim et al., 2021, for a review). Shi et al. (2023) found that informative TORs that tell drivers where they should steer or where the hazard is can shorten takeover time and improve takeover quality compared with generic TORs. Heo et al. (2022) also determined that informative TORs (a potential trajectory for driving) can alleviate the detrimental impact of low-vision environments (e.g., foggy and rainy weather) and improve takeover performance. However, as described previously, drivers' peripheral vision has a much lower resolution than their central vision due to anatomical differences (Wolfe et al., 2017), so drivers struggle to identify semantic information (such as text or icons) in their peripheral vision (Wolfe et al., 2017). Therefore, the effectiveness of generic and informative TORs presented on the peripheral HMI may be different from those presented on the instrument panel or HUD. Although the peripheral HMI can aid drivers in detecting TORs quickly, an informative TOR presented on the peripheral HMI may be an interference factor for drivers to observe the traffic environment ahead because they may have to use their central vision to gaze at informative TORs to understand them. Hence, the question arises whether it is possible to convey an informative and supportive TOR to drivers via peripheral HMIs, and if it is, what its effect is on takeover performance compared to conventional HMIs. Moreover, though previous studies (Shi et al., 2023; Heo et al., 2022; Eriksson et al., 2018) have validated the effectiveness of informative TORs, they have mainly drawn conclusions based on takeover behaviour or subjective ratings. Few studies have investigated the impact of informative TORs on drivers' gaze patterns compared to generic TORs, a topic that is also of great value in enhancing our ability to design more effective TORs.

1.1 Aims of the present study

Using an appropriate and effective HMI to convey TORs to drivers is highly critical to ensure the driving safety of automated vehicles. Most previous studies have used instrument panels or HUDs as HMIs to present TORs. Although several studies have proposed presenting TORs on a peripheral HMI due to its potential, few studies have empirically explored the effectiveness thereof compared to conventional HMIs. Therefore, we conducted a simulated driving experiment to investigate the effects of various HMIs while considering the impact of the TOR type. Moreover, apart from driving performance and subjective ratings, we also collected drivers' eye movement data to examine the influence of various HMIs on gaze patterns during the takeover process since drivers' gaze patterns play an important role during the transition of control of automated vehicles. The present study aimed to answer the following questions:

1. Can the peripheral HMI improve takeover performance compared with conventional HMIs (instrument panels or HUDs) when presenting TORs?
2. What differences in gaze patterns do drivers exhibit during the takeover process when using various HMIs?
3. Does the TOR type (informative versus generic) influence the effects of the

various HMIs, and how does the TOR type affect drivers' gaze patterns during the takeover process?

2. Methods

2.1 Participants

A total of 30 participants (15 men and 15 women) were recruited for the experiment. All of them were undergraduate or graduate students. Their ages ranged from 19 to 23 years, with an average of 20.5 years. Their driving years ranged from one to three years, with an average of 1.56 years. They all held valid Chinese driving licences. All participants had normal or corrected-to-normal vision and reported that they did not suffer from any driving-affecting diseases.

2.2 Apparatus

The driving simulator included driving software (STISIMDRIVE, M1000R), an operation system (Logitech G29, including a steering wheel, brake pedals, and accelerator), an adjustable seat, two desktops (Nvidia GeForce RTX 3080 [10GB], Intel Core i7-10700K), a 55-inch monitor (3840 × 2160 pixel resolution), and a camera.

A head-mounted eye-tracking system (Tobii Pro Glasses 3) was used to measure participants' gaze behaviour. The sampling frequency was set at 50 Hz. The eye movement data were analysed using ErgoLAB software on a laptop.

A 10.2-inch iPad was placed behind the steering wheel and functioned as the instrument panel. Its resolution was 2160 × 1620 pixels. It was connected with the STISIM software to present driving-related information in real time. The HUD was set up per the instructions mentioned in the study of Park and Jung (2014). We used a projector to present information on the windshield.

The peripheral HMI consisted of three LED strips (WS2812B) fixed on one frame (see Figure 1). The LED strips were wrapped in white semi-transparent piping to prevent dazing. Each LED strip included 144 LED light beads. An Arduino module controlled the three LED strips.

Figure 1. The experimental setup

2.3 Driving scenario

The driving scenarios were built using STISIM software. The road was a three-lane straight highway with each lane measuring 5 meters in width and no curves along the road. The automated driving system drove the vehicle in the middle lane at 90 km/h. The lead time of TORs was set at 7 s (Eriksson et al., 2017). The takeover scenarios were adopted from the studies of Eriksson et al. (2018) and Huang et al. (2022). When the vehicle approached a vehicle broken down in the middle lane, drivers were alerted to take over. Meanwhile, two fleets of vehicles were travelling alongside the ego vehicle in the left and right lanes at a speed of 130 km/h. The distance between the ego vehicle and each fleet of vehicles was either 50 m or 160 m. When the distance was 50 m, the first vehicle would pass in approximately 4.5 s, so the driver could not turn the ego vehicle toward this fleet when taking over. When the distance was 160 m, the first vehicle would pass in approximately 14.4 s, so the driver had enough time to turn the ego vehicle toward this fleet and overtake the broken-down vehicle ahead. With these locations for the two fleets of vehicles, there were two scenario types, namely, the lane change scenario and the braking scenario (see Figure 2). The lane change scenarios included left and right lane change scenarios, which were symmetrical.

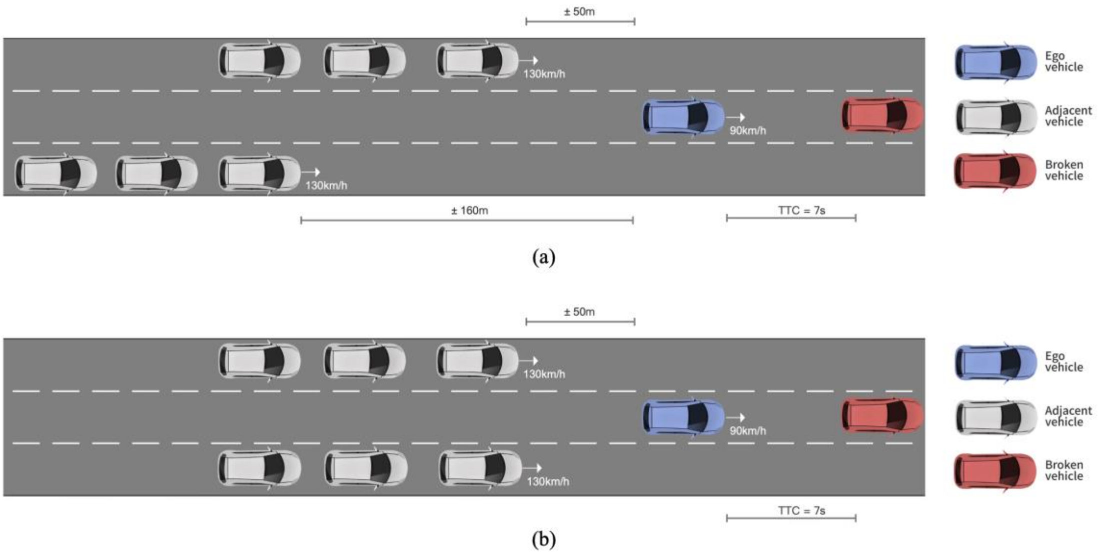

Figure 2. Takeover scenarios: (a) lane change scenario, (b) braking scenario

2.4 Human–machine interface design

Previous studies have shown that multimodal TORs can improve takeover performance (see Zhang et al., 2019, for a review). Therefore, we used a bimodal interface (visual and auditory) to present TORs. The auditory stimulus was a pair of 240 ms beeps (2700 Hz) with an interval of 100 ms (Petermeijer et al., 2017). The visual interface was designed as follows.

2.4.1 Visual interface design displayed on the instrument panel and head-up display

For the instrument panel and HUD, icons were presented on an iPad (as the instrument panel) and the windshield (as the HUD), respectively (see Figure 1). The visual interface design was adopted from that in studies of Xu et al. (2023) and Eriksson et al. (2018). During automated driving, a blue steering wheel icon, indicating that the vehicle was in automated mode, was presented in the centre of the instrument panel or HUD (see Table 1, a). When drivers were required to take over, the generic takeover information icon was shown, designed as two hands on a red steering wheel (see Table 1, b), for both the lane change and braking scenarios. The informative takeover icon is also shown in Table 1 (c, d, e). The red line denoted that drivers could not turn the ego vehicle toward the lane on the side on which it was displayed due to potential hazards, whereas the green line denoted that the lane on the side on which it was shown was safe to turn toward (Eriksson et al., 2018). If red lines were shown on both sides, drivers had to brake to decrease the ego vehicle's speed.

2.4.2 Visual interface design displayed on the peripheral human–machine interface

The peripheral HMI consisted of three LED strips placed at the frame's left, right, and undersides, as shown in Figure 1. When the ego vehicle was in automated mode, the three LED strips were lit blue (see Table 1, f). The generic TOR was presented by lighting the three LED strips in red for both the lane change and braking scenarios. The informative TOR was similar to the icon presented on the instrument panel and HUD. The left or right LED strip lit in red indicated that that side had potential hazards and drivers could not turn the ego vehicle into that lane. If it was lit in green, drivers could safely turn the vehicle into the lane on that side. In addition, if the left and right LED strips were both lit in red, drivers had to brake to decrease their speed.

Table 1. The visual icons presented on the instrument panel, head-up display, and peripheral human–machine interface

Type	Visual interface for the instrument panel and head-up display	Visual interface for the peripheral human–machine interface
Automated mode	 (a)	 (f)

Generic takeover request		 (b)	 (g)
Informative takeover request	Lane change to the left	 (c)	 (h)
	Lane change to the right	 (d)	 (i)
	Brake	 (e)	 (j)

2.5 Non-driving-related tasks

During automated driving, participants were required to engage in the game of Tetris on a smartphone, which has frequently been used as an NDRT in previous studies (e.g., Shi and Bengler, 2022; Ma et al., 2020; Zhang et al., 2021). The main reason we chose the Tetris game as the NDRT was that it is a relatively engaging task for drivers, allowing them to achieve a good level of immersion. The fall speed of the pieces was set at 1.6 squares per second, based on Ma et al. (2020), to ensure the game presented a moderate level of difficulty—neither too easy nor too challenging. Participants were instructed to fully immerse themselves in the game during automated driving. Additionally, when TORs were issued, participants were required to prioritize driving safety over game performance.

2.6 Experimental design

The present study adopted a 3 (HMI type) × 2 (TOR type) mixed design. The HMI type was treated as the within-subject variable and the TOR type as the between-subject variable. There were three HMI types: the instrument panel, HUD, and peripheral HMI. There were two TOR types: the generic TOR and the informative TOR. Participants were randomly assigned to the generic and informative TOR groups. They were required to complete three driving blocks corresponding to the three HMI types. The sequence of blocks was balanced using a Latin square. Each block contained four trials. Two trials were with the lane change scenario, and another two were with the braking scenario. The sequence of the four scenarios was random.

2.7 Dependent variables

There were three types of dependent variables used in the present study, namely takeover performance, eye-tracking metrics, and subjective ratings.

(1) Takeover performance: Previous studies have argued that to get a comprehensive overview of takeover performance, the objective measurement should contain both takeover timing and quality aspects (Cao et al., 2021; Zeeb et al., 2016). Therefore, we used takeover time and maximum resultant acceleration to quantify takeover timing and quality, respectively. Takeover time was defined as the time from the onset of the TOR to the first takeover input (turning the steering wheel to an angle greater than 2° or depressing the brake pedal more than 10 %) (Gold et al., 2013). The maximum resultant acceleration was defined as follows:

$$Maximum\ resultant\ acceleration = maximum\sqrt{{acceleration_{longitudinal}}^2 + {acceleration_{lateral}}^2}$$

The simulator provided real-time outputs of the vehicle's lateral and longitudinal accelerations, which we used to calculate the resultant acceleration during the takeover process and capture the maximum value as the metric. A higher value indicated poorer takeover quality. All takeover performance metrics were collected and calculated between the onset of the TOR and the moment that the ego vehicle overtook the broken-down vehicle.

(2) Eye-tracking metrics: The 7 s segment after the onset of the TOR was utilised for eye-tracking metric analysis (Liang et al., 2021). We defined four AOIs, including the road, rear-view mirrors (left, right, and middle), the broken-down vehicle ahead, and the TOR visual interface displayed on the instrument panel, HUD, or peripheral HMI, as shown in Figure 3. The amount of time (as a percentage) that participants spent gazing at each AOI was then calculated.

Figure 3. Demonstration of various areas of interest.

(3) Subjective ratings: Two questionnaires were used for the experiment. The first questionnaire was the NASA Task Load Index (NASA TLX), measuring participants' workload during the takeover process. The NASA TLX includes six dimensions, namely mental demand, physical demand, temporal demand, performance, effort, and frustration. Each dimension is rated from 0 to 100, with intervals of five points. The overall workload is calculated using the mean scores of the six dimensions (Hart et al., 1988). The second questionnaire was developed by van der Laan et al. (1997) to assess participants' usefulness and satisfaction ratings. Usefulness is measured by five items: (1) useful–useless, (3) bad–good, (5) effective–superfluous, (7) assisting–worthless, and (9) raising alertness–sleep-inducing. Satisfaction is determined by four items: (2) pleasant–unpleasant, (4) nice–annoying, (6) irritating–likeable, and (8) undesirable–desirable. All items range from -2 to +2. The means of the items determine the overall usefulness and satisfaction scores. The digital versions of these two questionnaires were used (made using the Wenjuanxing platform [https://www.wjx.cn/]). Participants were required to complete both on an iPad.

2.8 Procedure

Upon arrival, participants were welcomed and asked to sign an informed consent form. They also had to complete a demographic questionnaire about their gender, age, driving years, and health state. They were then required to adjust the seat until they felt comfortable. Next, the experimenter introduced them about the nature of Level 3 automated driving as defined by SAE (2021). They were informed that during automated driving, they could engage in NDRTs but were required to remain fallback-ready users. The automated driving system was restricted to its ODD, and if a driving situation exceeded this domain, the system would issue a TOR. Upon detecting a TOR, participants were expected to assess the situation and take appropriate takeover actions in a timely manner; otherwise, the automated system would disengage after a certain period, potentially leading to a risk of collision. Following this, the experimenter showed participants demonstrations of the various visual TOR interfaces used in the experiment. The experimenter explained to participants the specific meanings of the visual interfaces for the three HMIs in detail until participants fully understood their meanings. Then, the experiment entered the practice section.

During the practice section, participants first drove a vehicle in manual mode for approximately 2 mins to familiarise themselves with the simulated driving system (e.g., the operation of the steering wheel and depression of pedals). They were then required to complete two practice takeover trials to familiarise themselves with the automated driving system and takeover process. The practice takeover scenarios were similar to the scenarios used in the formal experiment, with one lane-changing scenario and one braking scenario. The HMI type for TORs in one practice trial was the peripheral HMI, and that in the other was the HUD or instrument panel. This arrangement was intentional, as the icons displayed on the HUD were identical to those on the instrument panel, while the icons on the peripheral HMI were significantly different. During automated driving, participants were required to fully immerse themselves in the Tetris game. To further enhance their motivation, they were informed that their game performance in the formal experiment, along with their takeover performance, would influence the experiment's reward, although all participants ultimately received a fixed compensation regardless of performance. Additionally, participants were required to play the game continuously throughout the experiment and were not allowed to start a new game unless they "lost" the current one. However, few participants "lost" the game during automated driving, as the game's difficulty level was set to moderate. Moreover, drivers were told to prioritize driving safety over game performance when they received TORs and could take control of the vehicle without pausing the game. In the next takeover trial, participants would start a new game. At the end of the practice session, the experimenter helped participants to put on their eye-tracking glasses and calibrate them.

During the formal experiment section, participants were required to complete three blocks corresponding to the three HMI types, which were balanced using a Latin square. Each block contained four trials, so participants had to complete a total of 12 trials. In each trial, participants played the Tetris game for approximately 2 to 3 mins before the TOR was issued to prevent participants' from anticipating the takeover. At the end of each block, participants completed the NASA TLX to assess their workload during the takeover process and gave their usefulness and satisfaction ratings for the HMI type used for the block. There was a short break between blocks to prevent fatigue. The whole experiment lasted approximately 70 mins. All participants were thanked and compensated with 60 RMB for completing the experiment.

3. Results

We used IBM SPSS 25.0 and a linear mixed model (LMM) for data analysis. In this model, the TOR type and HMI type were treated as fixed factors, and participants were treated as a random effect. We adopted the least significant difference method for post hoc pair-wise comparisons. All significance levels were set at 0.05.

3.1 Takeover performance

3.1.1 Takeover time

The LMM analysis showed that the main effect of the TOR type on takeover time was marginally significant (F(1, 28) = 3.63, $p = 0.07$). The main effect of the HMI type ($F(2, 318) = 12.13$, $p < 0.001$) and its interaction effect ($F(2, 318) = 4.58$, $p = 0.01$) with the TOR type both reached statistical significance. That is, informative TORs ($M = 2.46 \pm 0.04$ s) led to a shorter takeover time than generic TORs ($M = 2.75 \pm 0.05$ s, $p = 0.07$). Furthermore, the post hoc test for the main effect of the HMI type showed that the peripheral HMI ($M = 2.45 \pm 0.06$ s) resulted in a shorter takeover time than the instrument panel ($M = 2.69 \pm 0.06$ s) and HUD ($M = 2.67 \pm 0.05$ s, $ps < 0.001$). There was no significant difference in takeover time between the instrument panel and HUD, as shown in Figure 4a. The simple effect analysis showed that when presenting generic TORs, there was no obvious difference among the three HMI types. However, when presenting informative TORs, the peripheral HMI led to a significantly shorter takeover time than the other two HMI types ($ps < 0.001$), as shown in Figure 4b.

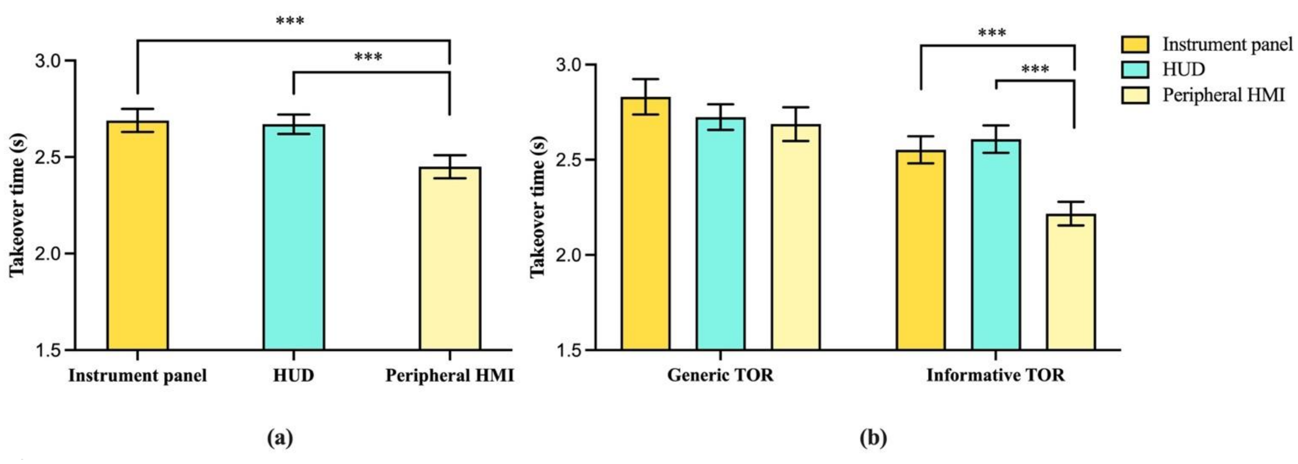

Figure 4. (a) Means of takeover time per human–machine interface type. (b) Means of takeover time as a function of human–machine interface type and takeover request type. (Notes: Error bars indicate standard errors; ***$p < 0.001$.)

3.1.2 Maximum resultant acceleration

The LMM results for maximum resultant acceleration showed a significant main effect for the TOR type ($F(1, 28) = 5.08$, $p = 0.02$). The main effect of the HMI type

($F(2, 318) = 0.22$, $p = 0.80$) and its interaction effect with the TOR type ($F(2, 318) = 1.16$, $p = 0.31$) were insignificant, though. Moreover, maximum resultant acceleration with informative TORs ($M = 4.46 \pm 0.17$ m/s^2) was less than with generic TORs ($M = 5.71 \pm 0.15$ m/s^2, $p = 0.02$) (see Figure 5).

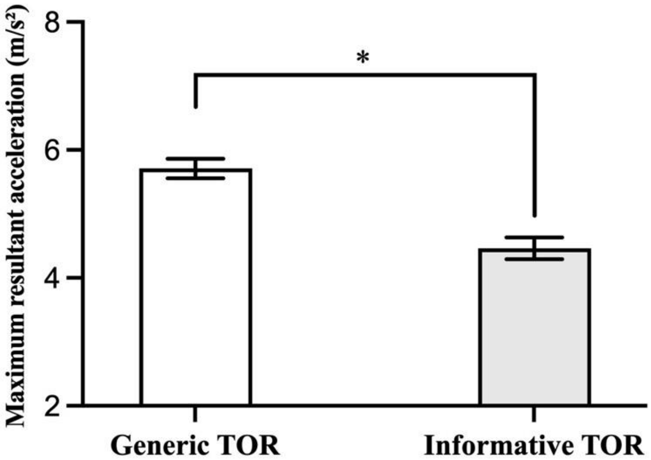

Figure 5. Means of maximum resultant acceleration under the conditions of generic and informative takeover requests. (Notes: Error bars indicate standard errors; $^*p < 0.05$.)

3.2 Eye-tracking metrics

3.2.1 Road gaze proportions

The main effect of the TOR type on road gaze proportions was insignificant ($F(1, 3) < 0.01$, $p = 0.99$), whereas the main effect of the HMI type ($F(2, 624) = 2.85$, $p = 0.06$) and its interaction effect with the TOR type ($F(2, 624) = 2.49$, $p = 0.08$) were marginally significant. Specifically, participants in the peripheral HMI condition ($M = 68.40 \pm 1.80$ %) had greater road gaze proportions than those in the instrument panel ($M = 64.09 \pm 1.99$ %) and HUD ($M = 64.27 \pm 1.97$ %, $ps < 0.05$) conditions (see Figure 6a). There was no significant difference in road gaze proportions between the instrument panel and HUD conditions, though. The simple effect analysis showed that when presenting generic TORs, there was no significant difference in road gaze proportions among the three HMI types; however, when presenting informative TORs, participants in the peripheral HMI condition had greater road gaze proportions than those in the instrument panel ($p = 0.002$) and HUD ($p = 0.07$) conditions, as shown in

Figure 6b.

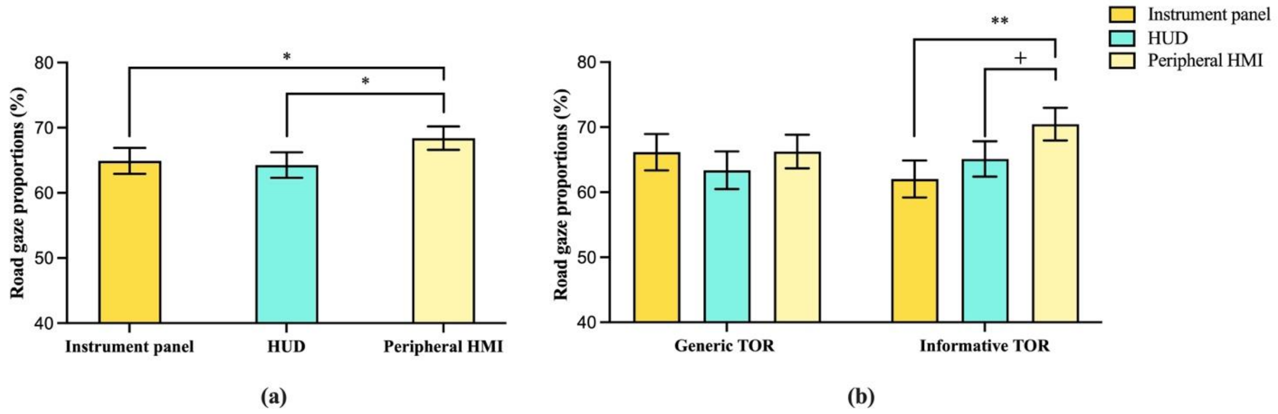

Figure 6. (a) Means of road gaze proportions per human–machine interface type. (b) Means of road gaze proportions as a function of human–machine interface type and takeover request type. (Notes: Error bars indicate standard errors; *$p < 0.05$, +$p < 0.1$.)

3.2.2 Rear-view mirror gaze proportions

Only the main effect of the TOR type ($F(1, 22) = 5.62$, $p = 0.03$) on rear-view mirror gaze proportions was significant. The main effect of the HMI type ($F(2, 241) = 1.21$, $p = 0.30$) and its interaction effect ($F(2, 241) = 0.29$, $p = 0.75$) were both insignificant. The post hoc test revealed that informative TORs ($M = 6.51 \pm 0.95$ %) led to a smaller rear-view mirror gaze proportion than generic TORs ($M = 12.42 \pm 1.02$ %, $p < 0.05$), as shown in Figure 7.

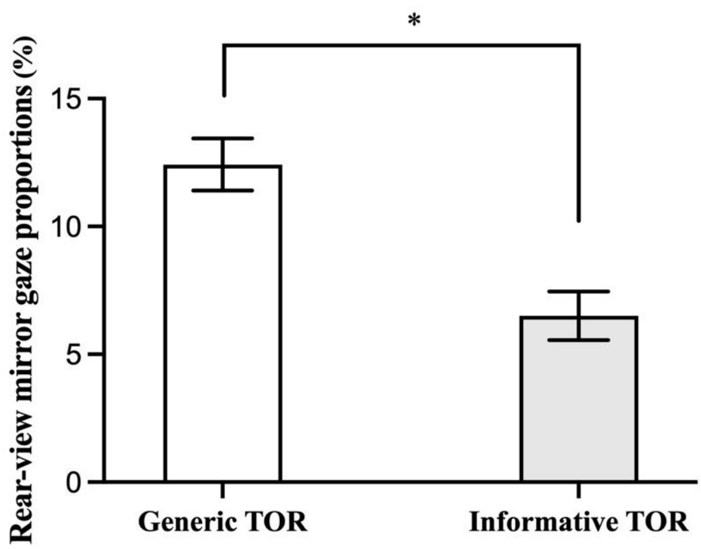

Figure 7. Means of rear-view mirror gaze proportions under the conditions of generic and informative takeover requests. (Notes: Error bars indicate standard errors; *$p < 0.05$.)

3.2.3 Broken-down vehicle gaze proportions

The LMM results revealed a significant main effect of the HMI type ($F(2, 495) = 6.79$, $p = 0.001$) on broken-down vehicle gaze proportions. The main effect of the TOR type ($F(1, 3) = 0.19$, $p = 0.70$) and its interaction effect ($F(2, 495) = 0.50$, $p = 0.61$) were both insignificant, however. The post hoc test showed that those in the HUD condition ($M = 16.66 \pm 1.56$ %) had smaller broken-down vehicle gaze proportions than those in the peripheral HMI ($M = 20.11 \pm 1.53$ %) and instrument panel ($M = 21.73 \pm 1.52$ %, *ps* < 0.01) conditions, as shown in Figure 8.

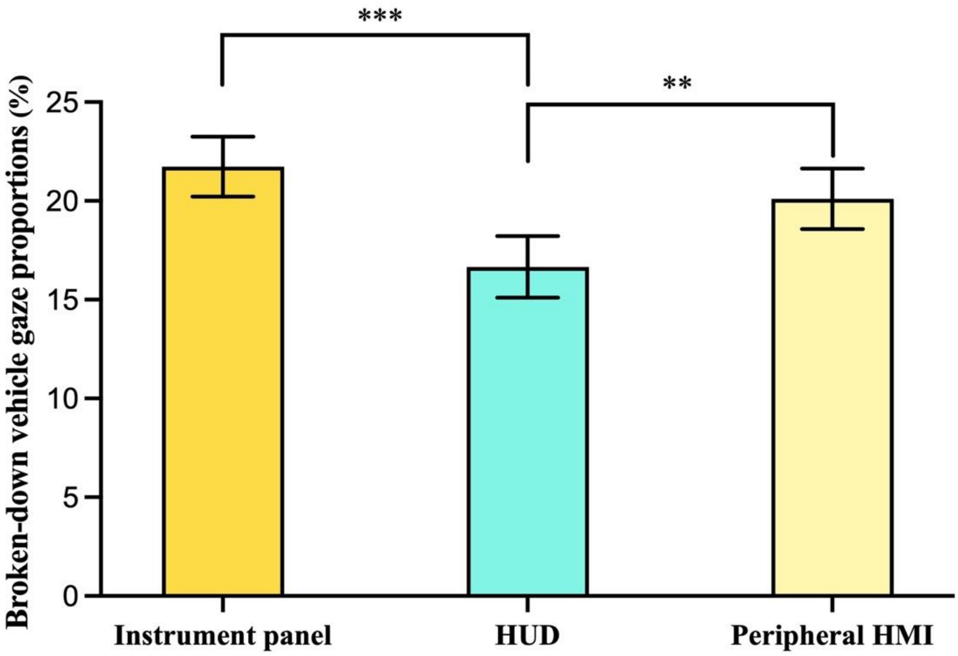

Figure 8. Means of broken-down vehicle gaze proportions per human–machine interface type. (Notes: Error bars indicate standard errors; *$p < 0.05$, **$p < 0.01$.)

3.2.4 Takeover request gaze proportions

The main effects of the TOR type (F(1, 21) = 10.97, $p = 0.003$) and the HMI type ($F(2, 243) = 42.63$, $p < 0.001$) and their interaction effect ($F(2, 243) = 10.97$, $p < 0.001$) reached statistical significance. Notably, informative TORs ($M = 5.65 \pm 0.80$ %) resulted in greater TOR gaze proportions than generic TORs ($M = 2.70 \pm$

0.67 %, $p = 0.003$), as shown in Figure 9a. For the HMI type, participants in the HUD condition ($M = 7.59 \pm 1.16$ %) had greater TOR gaze proportions than those in the instrument panel ($M = 4.78 \pm 0.96$ %) and peripheral HMI ($M = 0.41 \pm 0.18$ %, $ps < 0.01$) conditions. The differences in TOR gaze proportions between the instrument panel and peripheral HMI conditions were also significant ($p = 0.002$) (see Figure 9b). The simple effect analysis showed that when presenting generic TORs, participants in the HUD condition had greater TOR gaze proportions than those in the instrument panel and peripheral HMI ($ps < 0.001$) conditions, but no obvious difference was observed between the instrument panel and peripheral HMI conditions. However, when presenting informative TORs, participants in the instrument panel and HUD conditions had greater TOR gaze proportions than those in the peripheral HMI condition ($ps < 0.001$), but there was no obvious difference in TOR gaze proportions between the instrument panel and HUD conditions, as shown in Figure 9c.

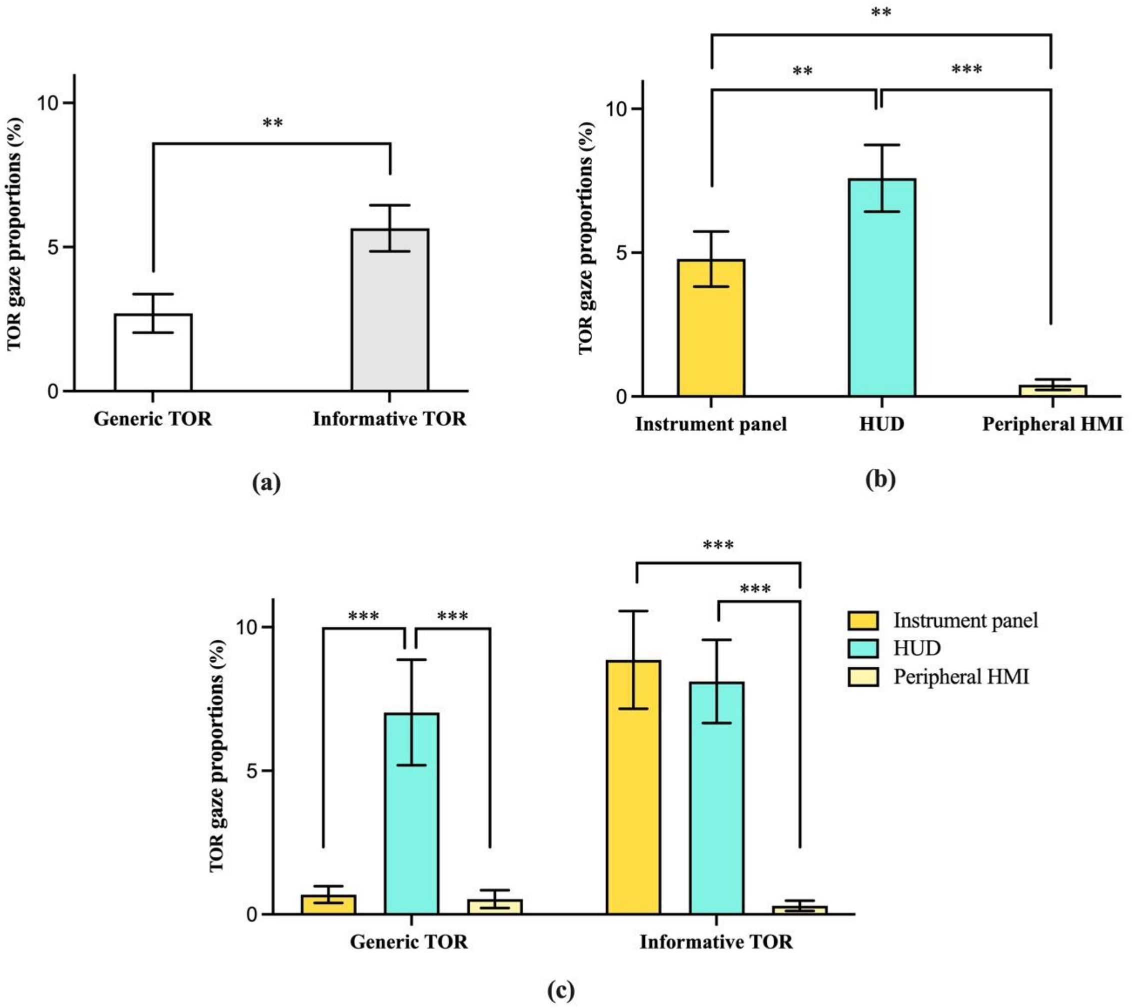

Figure 9. (a) Means of takeover request gaze proportions under the conditions of generic and informative takeover requests. (b) Means of takeover request gaze proportions per human–machine interface type. (c) Means of takeover request gaze proportions as a function of human–machine interface type and takeover request type. (Notes: Error bars indicate standard errors; $**p < 0.01$, $***p < 0.001$.)

3.3 Subjective metrics

3.3.1 Usefulness ratings

The LMM analysis showed significant main effects of the TOR type ($F(1, 28) = 5.18$, $p = 0.03$) and HMI type ($F(2, 56) = 6.47$, $p = 0.003$). However, the interaction effect ($F(2, 56) = 1.57$, $p = 0.22$) was insignificant. Specifically, informative TORs ($M = 1.36 \pm 0.08$) received higher usefulness scores than generic TORs ($M = 0.83 \pm 0.15$, $p = 0.03$), as shown in Figure 10a. For the HMI type, the peripheral HMI ($M = 1.46 \pm$

0.08) received higher usefulness scores than the instrument panel ($M = 0.82 \pm 0.18$) and HUD ($M = 0.99 \pm 0.17$, $ps < 0.01$). However, no significant difference in usefulness scores between the instrument panel and HUD was observed (see Figure 10b).

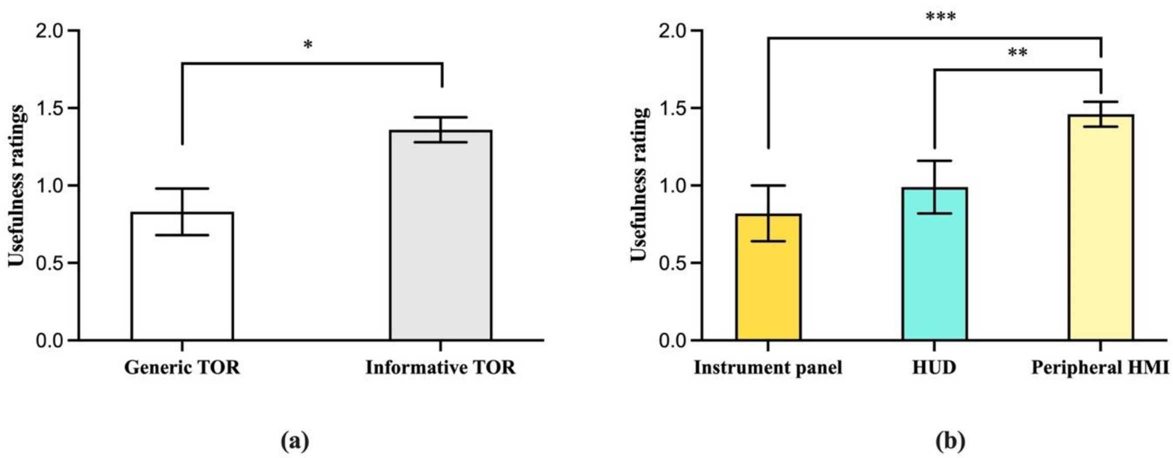

Figure 10. (a) Means of usefulness ratings under the conditions of generic and informative takeover requests. (b) Means of usefulness ratings per human–machine interface type. (Notes: Error bars indicate standard errors; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.)

3.3.2 Satisfaction ratings

Only the main effect of the HMI type was significant ($F(2, 88) = 4.02$, $p = 0.02$); the main effect of the TOR type ($F(1, 20) = 2.16$, $p = 0.16$) and its interaction effect ($F(2, 88) = 0.99$, $p = 0.38$) were both insignificant. The participants were more satisfied with the peripheral HMI ($M = 1.34 \pm 0.11$) than the instrument panel ($M = 0.86 \pm 0.17$) and HUD ($M = 1.04 \pm 0.16$, $ps < 0.05$). In addition, satisfaction ratings for the instrument panel and HUD did not significantly differ, as shown in Figure 11.

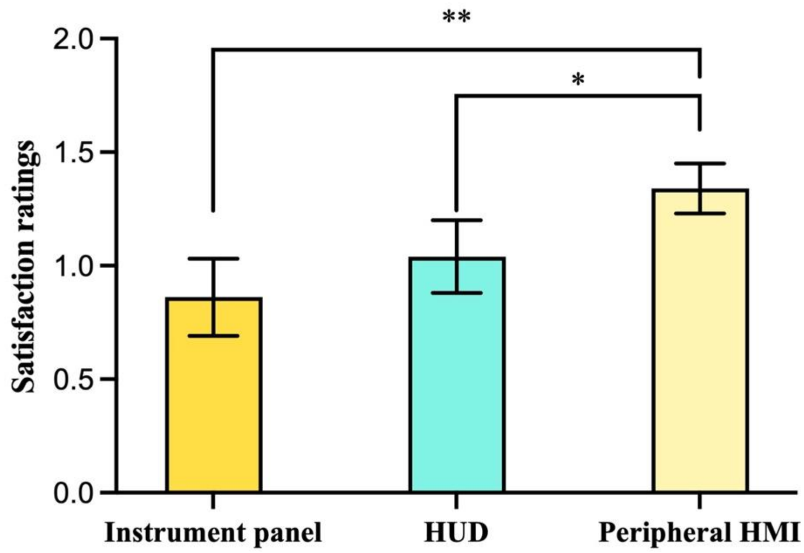

Figure 11. Means of satisfaction ratings per human–machine interface type.

(Notes: Error bars indicate standard errors; $*p < 0.05$, $**p < 0.01$.)

3.3.3 Workload ratings

Neither the main effects of the HMI type ($F(2, 56) = 0.13$, $p = 0.88$) and TOR type ($F(1, 28) = 2.33$, $p = 0.14$) nor their interaction effects ($F(2, 56) = 1.63$, $p = 0.21$) on the workload during the takeover process were significant. The means of the workload ratings for each condition are shown in Table 2.

Table 2. Means and standard errors of workload ratings as a function of human–machine interface type and takeover request type

Informative takeover request			Generic takeover request		
Instrument panel	Head-up display	Peripheral human–machine interface	Instrument panel	Head-up display	Peripheral human–machine interface
42.19 ± 5.01	48.06 ± 5.45	40.29 ± 4.49	49.26 ± 4.33	50.28 ± 3.78	54.17 ± 3.82

4. Discussion

The present study involved a simulated driving experiment to explore the effects of various HMIs on takeover performance while considering the type of TORs. Moreover, we used eye-tracking technology to investigate drivers' gaze patterns during the takeover process while using various HMI and TOR types. The findings of the present study provide some references for guiding relevant practitioners in designing HMIs for presenting TORs that get drivers back into the control loop efficiently in automated vehicles.

It was found that the peripheral HMI not only shortened takeover time compared to the HUD and instrument panel, but it was also rated as more useful and satisfactory. This finding confirms the advantage of peripheral HMIs for conveying TORs to drivers, with several studies having proposed using peripheral HMIs in automated vehicles (Borojeni et al., 2016; Hecht et al., 2022; Kunze et al., 2019; Yang et al., 2018). Notably, when presenting informative TORs, the peripheral HMI's shortened takeover time is even more evident than when presenting generic TORs. This may be because we used an auditory beep TOR, in addition to the visual TOR displayed on the HMI, to improve the experiment's ecological validity since many vehicles currently on the market provide both visual and auditory warnings to alert drivers (e.g., Tesla). When TORs displayed on HMIs do not contain additional supportive information, the auditory beep alert may be sufficiently effective for drivers, allowing them to depend less on visual HMIs to complete their takeover actions. This was also revealed in the eye-tracking metrics, where drivers spend less time gazing at the generic TOR than the informative TOR. Therefore, when presenting generic TORs, the advantage of the peripheral HMI over the HUD and instrument panel was smaller in the present study.

In addition, although the resolution of drivers' peripheral vision is much lower than their central vision due to anatomical differences, and they struggle to perceive and process detailed information in their peripheral vision (Wolfe et al., 2017), the results above verify the potential of peripheral HMIs to support drivers with informative TORs, in addition to pure warnings. This is important for the application of peripheral HMIs, as drivers' situational awareness is at an extremely low level when engaging in NDRTs during automated driving (de Winter et al., 2014), and it is necessary to provide drivers with informative TORs to help them recover situational awareness and support their takeover actions (Petermeijer et al., 2016; Zeeb et al., 2015).

The analysis of drivers' eye movement data revealed a greater road gaze proportion and a smaller TOR gaze proportion with the use of peripheral HMIs than HUDs and instrument panels. This may be the attention mechanism behind the advantage of peripheral HMI in the takeover performance. In accordance with Wickens' (2002) multiple resources theory, drivers' cognitive resources for peripheral and central vision are independent, so they can simultaneously process information in the two vision areas without mutual interference. After TORs are issued, drivers can use their peripheral vision to perceive and understand TOR information displayed on the peripheral HMI without needing to gaze at it directly. Concurrently, they can use their central vision to gaze at the road ahead and evaluate the takeover situation. These two processes occur in parallel and do not compete for cognitive resources. Contrastingly, with the use of HUDs and instrument panels to present TORs, drivers can only use their central vision to obtain and process TOR information, which will be at the expense of gazing at the front road to evaluate the situation (Gonçalves et al., 2022). Therefore, the peripheral HMI can improve drivers' TOR information processing efficiency and prompt them to gaze for longer at the road, which is of great significance for improving driving safety, as the less time is spent gazing at the road, the greater the risk there is of having a traffic accident (Harbluk et al., 2007).

In addition, the HUD results in a greater TOR gaze proportion than the instrument panel, which is especially obvious when presenting generic TORs. The broken-down vehicle gaze proportion with the HUD is also lower than with the instrument panel. These results may be related to the attention tunnel phenomenon typical of HUDs. That is, drivers suffer from slight attentional distribution damage between the HUD and external scenery (Karar et al., 2018). This phenomenon has been found in the field of manual driving. For example, Gabbard et al. (2014) argued that when drivers focus on the information displayed on the HUD, they ignore some information in the actual driving scenario. Recently, Wang et al. (2022) found that HUDs increase drivers' inattentional blindness to hazards on the road, and this blindness is more significant when drivers are in a high workload state. The present study also showed that HUDs pose a potential threat to drivers' attention distribution during the takeover process in automated vehicles. This issue should be emphasised when utilising HUDs because drivers' visual attention distribution plays an important role in their recovery of situational awareness and successful takeover of the vehicle's control (Louw et al., 2017).

In terms of the TOR type, the results showed that informative TORs improve takeover performance (with shorter takeover times and less maximum resultant acceleration) and were rated as more useful by drivers than generic TORs, which is in line with the studies of Shi et al. (2023) and Heo et al. (2022). Moreover, the eye-tracking results showed that drivers spend less time gazing at their rear-view mirrors with informative TORs than with generic TORs. To our knowledge, only Gonçalves et al. (2022) have investigated the impact of the information displayed on HMIs on drivers' gaze behaviour during the takeover process, and in their simulated driving experiment, they found that the information displayed on HMIs does not affect drivers' gaze at the rear-view mirror. This discrepancy may be attributed to time pressure. In their study, the takeover operation was a discretionary lane change without a TOR warning, and drivers were not under any pressure, so they only checked their mirrors as part of a routine, regardless of the information displayed on the HMI. However, in the present study, drivers had to react to TOR warnings within 7 s; otherwise, the ego vehicle would collide with the broken-down vehicle ahead. Since drivers' situational awareness was low due to NDRT engagement (de Winter et al., 2014), there was relatively high time pressure for drivers to make a decision to act. Therefore, in the present study, drivers had to depend more on the TORs, especially informative TORs, to recover their situational awareness and complete the takeover, which led to fewer rear-view mirror-checking behaviours.

In summary, the present study validates the potential performance advantage of using peripheral HMIs to present TORs in improving takeover performance. Moreover, the attention mechanism behind this was revealed by using eye-tracking technology. Specifically, the peripheral HMI can improve drivers' gaze patterns between the TOR information and the road ahead, which can be of great value in enhancing driving safety. However, although several studies have proposed using peripheral HMIs in automated vehicles (Borojeni et al., 2016; Hecht et al., 2022; Kunze et al., 2019; Yang et al., 2018), most current studies have used a conventional instrument and HUD to convey relevant information to drivers (see Bengler et al., 2020, for a review). The benefits of using peripheral HMIs are thus underestimated. Relevant practitioners should be encouraged to use the peripheral HMI as a complement to conventional HMIs. In addition, the HUD was found to have a risk of capturing drivers' attention. Relevant practitioners should also be cautious with this phenomenon and optimise the HUD design to overcome this issue by, for example, finding a more suitable place for the HUD (Yang et al., 2020).

5. Limitations and future work

Although the present study was carefully prepared, it still has some limitations. First, the present study was conducted in a fixed driving simulator, which inevitably differs from the actual driving scenario. Future studies should explore the effects of various HMIs in an actual driving environment to replicate the results of the present study. Second, the participants in the present study were relatively young. However, Laurin et al. (2019) found that older people devote more resources toward central vision when processing visual information than young people. The effect of the in-vehicle peripheral HMI on older people deserves future research, and it is necessary for future studies to consider drivers of different ages when evaluating the peripheral HMI. Third, in the present study, we only collected data on participants' percentage of gaze time spent looking at various AOIs. Future studies could benefit from recording both the number and duration of drivers' fixations on these AOIs, in addition to the percentage of gaze time. This would provide a more nuanced understanding of drivers' gaze patterns when using different HMIs during the takeover process. Finally, we did not collect data on participants' Tetris game performance during automated driving. Although participants were instructed to fully immerse themselves in the game, collecting performance data could further confirm their engagement in the NDRT. Additionally, recent studies have shown that transitions from an NDRT to driving often involve interleaving between the two tasks before fully switching (Nagaraju et al., 2021; Janssen et al., 2019). In our study, participants were required to prioritize driving safety over game performance upon detecting TORs, and the game was set to a moderate difficulty, making it somewhat challenging for drivers to look away without immediately losing. Furthermore, the 7-second lead time for TORs was relatively short, limiting opportunities for interleaving (Nagaraju et al., 2021). Consequently, few participants were observed interleaving between the Tetris game and driving during the takeover process in the recorded videos. Nonetheless, the phenomenon of interleaving is intriguing and warrants further investigation in future studies, as it could offer deeper insights into the transition from various NDRTs to the driving task.

6. Conclusions

The present study involved a simulated driving experiment conducted to investigate the effects of various HMIs (instrument panel, HUD, and peripheral HMI) and TOR type (informative and generic) on drivers' takeover performance and gaze behaviour during the takeover process in an automated vehicle. The peripheral HMI was found to be capable of shortening takeover time compared to conventional HMIs (instrument panel and HUD), especially when presenting informative TORs. It was also rated as more useful and satisfactory. The eye-tracking analysis revealed the attention mechanism behind its performance advantage. That is, the peripheral HMI can reduce the time drivers gaze at the TOR information and prompt them to spend more time gazing at the road ahead. The HUD, on the other hand, seemed to have a risk of capturing drivers' attention, resulting in an attention tunnel when presenting TORs, as compared to the instrument panel. Moreover, informative TORs were associated with improved takeover performance and prompted drivers to spend less time gazing at their rear-view mirrors than generic TORs. The findings of the present study highlight the benefits of using the peripheral HMI as a complement to conventional HMIs in automated vehicles. Our findings also provide some insights into designing in-vehicle HMIs that present TORs for interested practitioners.

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