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Mental States and Machine: Enhancing Driver Engagement in Automated Vehicles for Safer Transitions

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16. Abstract
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Mental States and Machine: Enhancing Driver Engagement in Automated Vehicles for Safer Transitions

Abstract

The current automated vehicles are not perfect, which means that human intervention, known as a takeover, is still necessary. For signaling takeover requests, informative (contralateral) displays were investigated and proven effective compared to instructional (ipsilateral) displays. However, how drivers interpret the information can vary based on the driver's mental state, which remains unclear in earlier research. To address this, the current study aims to investigate the effect of modality (visual and tactile signal), scenario (lane-changing and lane-keeping scenario), mental state (control (baseline), anger, sadness, happiness, internal distraction (mind-wandering), external distraction, and fatigue), on the takeover performance and physiological data. As an exploratory pilot study, six participants were engaged in the current study. Three participants were assigned to the scenario with a visual takeover request, while the other three were assigned to the scenario with a tactile takeover request. The results reveal that lane-keeping was associated with lower decision-making accuracy than lane-changing scenarios. Additionally, the tactile signal request had marginally higher decision-making accuracy than the visual signal. Lastly, the visual signal was associated with a marginally greater change in wrist joint angle compared to the tactile signal in a lane-keeping scenario. Overall, the findings of this study could guide the development of human-machine interfaces to enhance safety under various mental states in future automated vehicles.

List of Key Terms

Driver Mental State, Takeover Request, Human-machine Interface, Safety, Automated Driving

Chapter 1: Introduction and Background

The development of automated vehicles has gradually matured in recent years. Some automated assistance features have begun to be integrated into vehicles, such as Tesla Autopilot or Full Self-Driving (Supervised) (Yang et al., 2023). However, the current level of automated vehicles (SAE L3) has its limitations, and due to ethical and technological concerns (Cascetta et al., 2022; Fagnant & Kockelman, 2015), full automation (SAE L5) seems unlikely in the near future. Therefore, when the automated vehicle reaches its operational limits (e.g., lane markings missing or unexpected accidents), human intervention is still necessary (Chu et al., 2020; Deo & Trivedi, 2018). This intervention is known as a takeover, which has two main phases, each phase consisting of several steps (Huang & Pitts, 2022a; Petermeijer et al., 2016) (Figure 1). After the automated system delivers the takeover request, drivers are required to perceive these warnings and process the information accordingly. Next, the driver must adjust their position and prepare to regain manual control (e.g., placing their foot on the pedal and their hands on the steering wheel). Once the transition is complete, the driver will execute the appropriate action. The takeover task requires significant perception and cognitive ability; however, drivers have only a few seconds to take the right action to prevent a collision or maintain control of the vehicle (Huang & Pitts, 2022a; McDonald et al., 2019). Therefore, ensuring a safe and smooth transition during the takeover is crucial. To achieve this, previous studies suggest that developing an effective takeover request interface is a promising solution (McDonald et al., 2019).

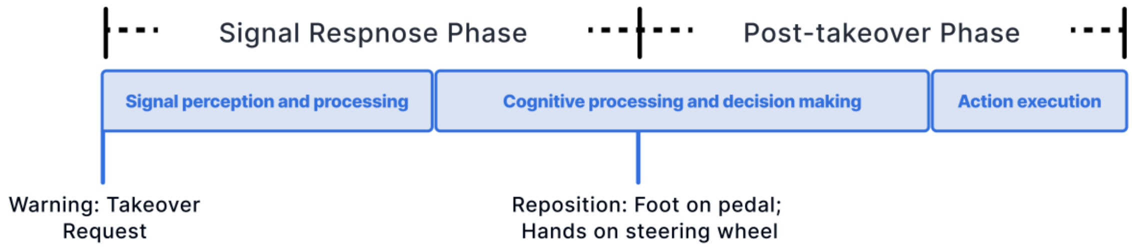

Figure 1. The takeover model (adapted from Huang & Pitts, (2022b) and Petermeijer et al. (2016)).

1.1 Meaningful Human-Machine Interface for Takeover Requests

According to the previous literature review (Martinez & Huang, 2022), there are two typical human-machine interfaces (HMIs) designed to present meaningful information regarding takeover requests that represent complex driving situations during a takeover (Figure 2): (1) instructional (ipsilateral) display. This interface design is based on stimulus-response compatibility (SRC) (Fitts & Deininger, 1954; Proctor & Reeve, 1990), and indicates that the signal aligns spatially with the needed action (e.g., Lo & Huang, 2024, 2025; Meng et al., 2015; Petermeijer et al., 2017). Instructional displays provide navigational guidance, including whether to turn left or right, as well as cues for speed regulation, such as acceleration and deceleration. For example, they may show an arrow icon to indicate recommended maneuver directions. (2) Informative (contralateral) display. This interface design is the opposite of the ipsilateral display, meaning that the signal does not align spatially with the needed action (reversed SRC) (e.g., Chu et al., 2024; Huang & Pitts, 2023; Martinez & Huang, 2024). Informative displays provide details about the driving environment, including the location and status of nearby vehicles or pedestrians. For example, displaying an obstacle icon to represent the dangerous surroundings. Previous studies have shown that, in the context of a takeover request, informative displays were associated with better takeover performance when compared to instructional displays. For instance, Martinez & Huang (2024) examined how takeover requests impact younger and older adults in a lane change scenario, focusing on different modalities (tactile versus visual-tactile) in both instructional (ipsilateral) and informative (contralateral) displays. The results indicated that an informative display was associated with higher situation awareness and faster information processing time compared to an instructional display. Similarly, Huang and Pitts (2023) investigated the effects of baseline, instructional, and informative signals on vibrotactile takeover requests while the driver was required to perform a lane change during the takeover. The findings showed that the instructional signal performed worse (e.g., longer response time and larger maximum resulting acceleration) in takeovers compared to the baseline signals. However, despite the informative display seeming to be an effective takeover request, the impact of such requests under different mental states needs further investigation. This gap is critical, as earlier research indicates that a driver's mental state can significantly affect how they interpret and respond to information (Hameed & Sarter, 2009). For example, forward collision warning systems are more beneficial for visually distracted drivers than for those who are not (Abe et al., 2011).

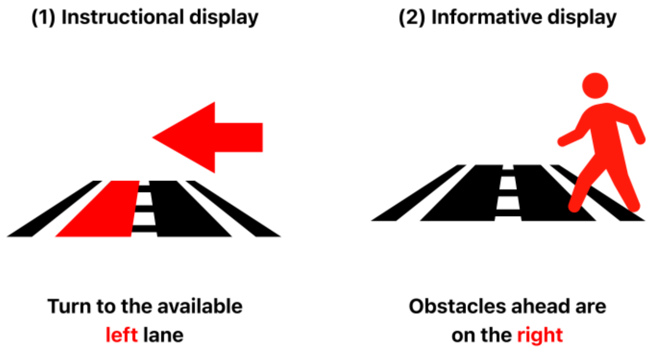

Figure 2. Two common human-machine interfaces (HMIs) for presenting information.

1.2 Impact of Driver Mental States on Takeover Performance in Automated Driving

In addition to information interpretation, drivers' mental states (Figure 3) including emotions, distractions, or fatigue, may negatively impact their performance (e.g., longer reaction times) (Jafarpour & Rahimi-Movaghar, 2014). For example, emotions play a significant role in negatively impacting driver performance. Previous research has indicated that such emotional states, including anger, sadness, and crying, increase the risk of a crash by nearly 9.8 times (Dingus et al., 2016). This pattern is also observed in automated driving scenarios. Previous studies have demonstrated how the two dimensions (i.e., valence and arousal (Russell, 1980)) of the emotion affect takeover performance. For example, Du et al. (2020) investigated the effect of emotion on takeover performance, with thirty-two participants participating in the driving simulator study. In this study, eight 4-minute movie clips were used to induce different emotions (i.e., Sadness, Anger, Happiness, and Calmness). Results showed that the positive valence emotions (i.e., happiness) were associated with better takeover quality (e.g., smaller maximum resulting acceleration and a smaller maximum resulting jerk) compared to other emotions. In addition to emotional factors, 68.3% of all crashes were associated with significant distractions, with engaging in non-driving-related tasks being one of the primary reasons for these distractions (Oviedo-Trespalacios et al., 2016). Previous studies indicated that talking on the phone while driving increases the crash risk by a factor of four (Redelmeier & Tibshirani, 1997). Although drivers do not need to perform driving tasks in highly automated vehicles, the distractions caused by non-driving-related tasks also pose safety concerns in these vehicles. For example, Eriksson & Stanton (2017) compared the takeover performance in a scenario involving external distractions (i.e., reading a newspaper) with a scenario without distractions (i.e., monitoring the system) with twenty-six participants. The findings indicated that when performing the secondary task (i.e., with external distraction), the reaction time for takeovers was significantly longer than in the scenario without the secondary task. Besides emotional factors and distractions, fatigue also plays a significant role in traffic accidents (Zhang et al., 2016). Previous reports revealed that fatigued driving accounts for 16.5% of fatal accidents and 12.5% of injury-related collisions in the U.S. (Tefft, 2010). Given that prolonged and monotonous automated driving can lead to fatigue (Körber et al., 2015), understanding how fatigue affects takeover performance is also critical. Jarosch et al. (2019) investigated how task-related fatigue affects takeover performance during extended conditional automated driving involving seventy-three participants. The results showed that performing takeover tasks after prolonged automation correlates with worse takeover performance (e.g., longer reaction times) compared to performing takeover tasks after short automation. Although previous studies have separately explored the impact of different mental states on takeover performance, these effects have not been concurrently evaluated within a single experimental framework. In addition to the mental state, the effectiveness of takeover requests may be significantly affected by the scenarios in which an automated vehicle is encountered (Du et al., 2024; Naujoks et al., 2021). For example, Yun and Yang (2020) reveal that the reaction time for exact takeover requests was slower when the vehicle planned to exit the highway than when it faced a sudden obstacle. However, earlier studies of informative takeover requests primarily focused on one specific scenario, lateral steering scenarios, which require the driver to make a lane change during takeover; the effectiveness of informative displays in longitudinal braking scenarios, which require the driver to brake or reduce the speed during takeover, remains unknown.

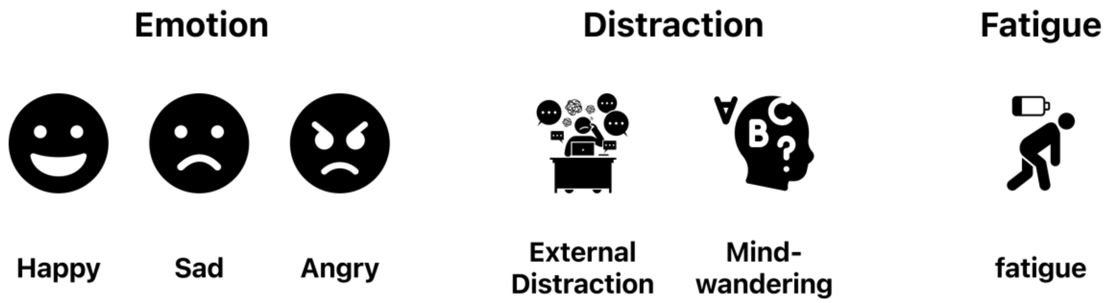

Figure 3. Emotion at three levels (anger, sadness, happiness), internal distraction (mind-wandering), external distraction, and fatigue.

Therefore, the goal of this study was to evaluate the impact of informative takeover requests on takeover performance in lateral (i.e., lane-changing) and longitudinal (i.e., lane-keeping) scenarios across various mental states. Participants were divided into two groups and presented with an informative takeover request in different modalities (i.e., visual and tactile). They were required to perform a takeover task in a driving simulator in a two-lane urban scenario. Both groups experienced scenarios corresponding to seven mental states (i.e., control (baseline), emotion at three levels (anger, sadness, happiness), internal distraction (mind-wandering), external distraction, and fatigue). They were asked to make a decision based on the traffic situation, either to change lanes or stay in the lane. The findings of this study could help develop human-machine interfaces that enhance safety across different mental states and scenarios for future automated vehicles.

Chapter 2: Methodology

2.1 Participants

This study included six college students who were recruited through San Jose State University's Research Pool (SONA) system. As part of a larger-scale ongoing study, this pilot study recruited six participants: three in the visual signal group (mean age = 19.33, mean driving experience = 2 years) and three in the tactile signal group (mean age = 20.33, mean driving experience = 3 years). For compensation, each participant received four hours of class credit for their time and participation. All participants must meet the following inclusion and exclusion criteria: (1) possess a valid driver's license, (2) drive at least once a week, (3) have no cognitive or neurological impairments affecting touch, (4) have normal or corrected-to-normal vision, and (5) report no motion sickness symptoms. This study received approval from the Institutional Review Board of San Jose State University (IRB Protocol ID: 23-388).

2.2 Apparatus

This experiment includes the following devices to collect data and conduct the experiment:

Driving Simulator. The fixed-base medium-fidelity driving simulator – miniSim (Figure 4), developed by the University of Iowa Driving Safety Research Institute (DSRI), was utilized in this experiment. This system features three 42-inch monitors (1920 × 1080) to showcase the simulated driving environment, along with an 18.5-inch monitor functioning as the in-vehicle dashboard. Additionally, the system features various accessories, including driving pedals (accelerator and brake), a steering wheel, and a standard adjustable driver's seat for a realistic driving simulation. The driving data were recorded at 60 Hz.

Figure 4. Experimental apparatus.

Visual and tactile signals (Figure 5). The visual signal (V) was a 400 × 300 pixel icon, combined with the black road and red pedestrian vector graphics, presented in the center of the windshield. The tactile signal (T) was delivered through six C-2 tactors (developed by Engineering Acoustics, Inc., with dimensions of 1" × 0.5" × 0.25") positioned on the seat belt. Specifically, three tactors were located on the right side, while three were on the left. The frequency of the tactile feedback was set to 235 Hz (Wersényi, 2022).

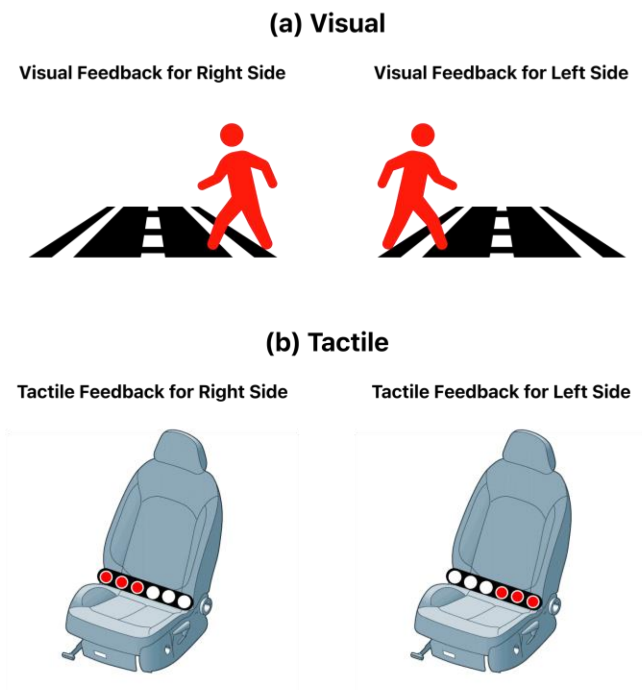

Figure 5. (a) Visual and (b) tactile signals.

Eye Tracking (Figure 6*a).* This study employed the Tobii Pro Fusion eye-tracking system (Tobii Technology AB, Sweden). The eye movement data were recorded at 60 Hz. The pupil size, measured in millimeters, is calculated from the camera image, referencing the distance between the sensor and the eyes.

Skin Response and Optical Pulse Sensor (SROPS) (Figure 6b). This study utilized the Shimmer3 GSR+ unit (Shimmer, MA, USA), which collects Galvanic Skin Response (GSR) and skin temperature data at a rate of 60.01 Hz.

Motion Capture System (Figure 6c). This study utilized the Xsens Motion Tracking System (MTw Awinda, Movella Inc., Henderson, NV, USA) to capture human movement. This system captures movement data at 60 Hz from seventeen inertial sensors placed on participants' bodies, from head to toe, specifically focusing on joint angles, segment positions, and changes in dynamic orientation.

Figure 6. (a) Eye tracker; (b) SROPS; (c) Motion capture.

2.3 Procedure

Once participants agreed to participate in the study and finish the consent form, they were given an overview of the study and were required to complete the pre-experiment questionnaire. Participants were randomly assigned to the scenario with visual or tactile signals and asked to wear the physiological device. Afterward, they engaged in a 20-minute training session to familiarize themselves with the takeover task and the experimental device. During the experiment, upon receiving an informative takeover request, participants were required to press the brake first, assess the traffic situation, and decide whether to change lanes or stay in their current lane. Once they decided, they needed to press one of two buttons corresponding to their chosen action: one button indicated lane-changing, while the other referred to lane-keeping. During the main experiment, each participant completed eight drives: six short drives (control (baseline), anger, sadness, happiness, internal distraction, and external distraction) lasted about seven minutes with two takeover events and two prolonged (fatigue) drives, which were approximately twenty minutes and included one takeover event (e.g., lane-changing or lane-keeping) (Figure 7). To prevent the order effect, the sequence of short and long drives was randomized. In both lane-changing and lane-keeping scenarios, participants received only the informative signal as a takeover request, meaning that both the visual and tactile displays indicated only the obstacles in the environment (Figure 5). The scenario involving the visual takeover request was displayed on the windshield, featuring a red pedestrian icon to indicate the location of the approaching obstacle (Figure 5a). Similarly, the scenario with the tactile signal was delivered through the seatbelt, accompanied by a three-stroke vibration warning (Carcedo et al., 2016; Liao et al., 2016) on either the right or left side to show where the obstacle is approaching (Figure 5b).

In addition to the control (baseline) scenario, which represented normal driving conditions without any added stimuli, several methods from previous studies were used to induce different mental states for each scenario. For the drive with the emotion state, participants listened to music suited to each state: anger (Holst - The Planets (Maciantowicz & Zajenkowski, 2021)), sad (Chopin - 24 Preludes, Op. 28 (Poon & Schutz, 2015)), and happy (Bach - Orchestral Suite No. 1 in C Major (Park et al., 2019)). For external distraction, the operator asked random questions and kept the conversation going until the drive ended, while participants were expected to engage thoughtfully (Heenan et al., 2014). In contrast, mind-wandering involved questions played by the speaker every 20 seconds (to induce task-irrelevant thoughts), with no need for responses (Huang et al., 2019). During two long, fatigue-inducing drives, automated driving lasted at least twenty minutes before the takeover event (Thiffault & Bergeron, 2003). To minimize cumulative fatigue and interaction effects between mental states, 5-minute breaks were implemented between each drive (Figure 7). During these breaks, participants were asked to complete NASA-TLX questionnaires regarding the drive they had just completed. Once all eight drives were finished, participants were asked to complete the post-experiment questionnaire. Overall, the study lasted approximately 200 minutes.

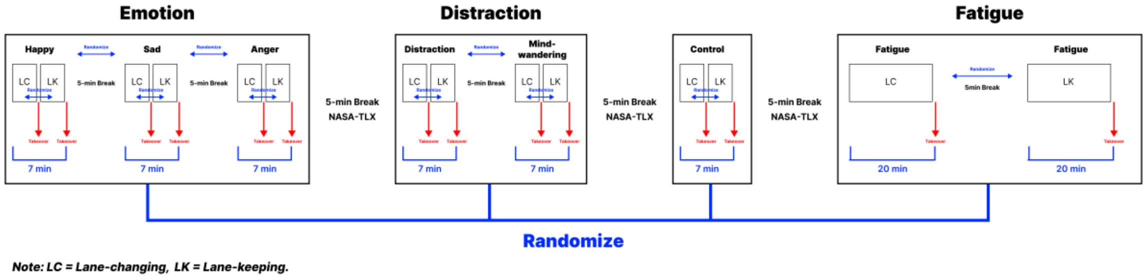

Figure 7. The design and procedure of the experiment (LC=lane-changing, LK=lane-keeping).

2.4 Dependent variable

2.4.1 Takeover performance

Three dependent variables were used to assess takeover performance (McDonald et al., 2019). Reaction time (in seconds) (Dogan et al., 2017) measured the duration from the start of the takeover request until participants deactivate automation. By pressing the brake pedal, participants deactivate automation, allowing us to measure how quickly they perceive and process takeover requests (i.e., visual or tactile signals). Next, decision-making time, known as indicator time (in seconds) (Li et al., 2018), measured how long it takes participants to decide whether to change lanes or remain in their lane, followed by pressing one of the two predefined buttons that correspond to their chosen action. Lastly, the decision-making accuracy evaluated participants' ability to accurately identify and press the correct buttons for the appropriate actions in a given scenario.

2.4.2 Physiological data

In addition, five dependent variables were used to assess physiological data. A 5-second observation window was used to measure all physiological data (e.g., Gruden et al., 2024; Liao et al., 2025), comparing the average values from the 5 seconds before the takeover request was activated to the average values from the 5 seconds after the driver reactivated the automation mode. For the eye-tracking data, pupil dilation was used to estimate pupil size (in millimeters). The skin response data included galvanic skin response (GSR) and skin temperature. Motion data captured the flexion angles of the right wrist and right ankle. Wrist flexion (+) refers to curling the wrist toward the palm, whereas wrist extension (−) refers to moving the hand back toward the forearm. Similarly, ankle dorsiflexion (+) refers to lifting the foot toward the shin, while ankle plantarflexion (−) involves pointing the foot downward toward the shin.

2.5 Data analysis

This study employed a 2 (signal modality: visual and tactile signal) × 2 (scenario: lane-changing and lane-keeping scenario) × 7 (mental state: control (baseline), emotion at three levels (anger, sadness, happiness), internal distraction (mind-wandering), external distraction, and fatigue) full factorial design. The independent variables included signal modality (between-subjects), scenario (within-subjects), and mental state (within-subjects). The dependent variables included takeover performance (i.e., reaction time, decision-making time, and decision-making accuracy) and physiological data (i.e., pupil diameter, right wrist joint angle, right ankle joint angle, GSR, and skin temperature). For reaction time, decision-making time, and physiological data, differences across modality, scenario, and mental state were analyzed using a three-way mixed analysis of variance

(ANOVA). In addition, a post hoc analysis with Bonferroni correction was conducted to assess significant differences and interactions across multiple comparisons. For decision-making accuracy, differences across modality, scenario, and mental state were analyzed using a generalized linear mixed model (GLMM) with a binomial distribution and logit link function. Statistical analyses were conducted using SPSS, with significance set at $p < 0.05$. Partial eta squared (η_p^2) served as the measure of effect sizes.

Chapter 3: Results and Discussion

3.1 Takeover performance

There was a significant main effect of scenario (χ^2 (1) = 4.98, p = .029) on decision-making accuracy (**Error! Reference source not found.**). In particular, lane-changing scenarios (mean (M) = 0.987, standard error of the mean (SEM) = 0.019) were correlated with higher decision-making accuracy than lane-keeping scenarios (M = 0.869, SEM = 0.121). In addition, there was a marginally significant effect of modality (χ^2 (1) = 3.21, p = .077) on decision-making accuracy. Specifically, tactile signals (M = 0.98, SEM = 0.026) resulted in slightly greater decision-making precision than visual signals (M = 0.907, SEM = 0.094). However, no significant main effect of mental state on decision-making accuracy was found.

We also investigated how modality, scenario, and mental state influence reaction and decision-making times. However, none of these factors had a significant impact on reaction or decision-making time.

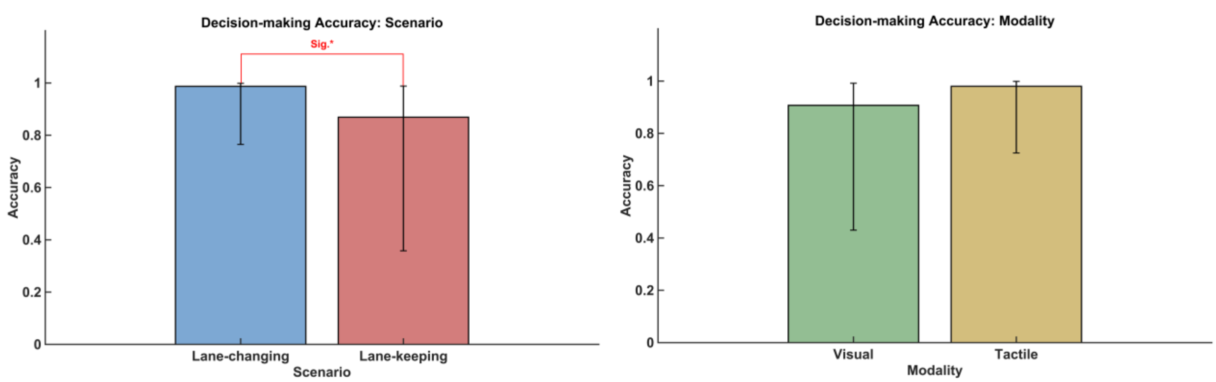

Figure 8. Decision-making accuracy for the scenario (left) and modality (right).

3.2 Physiological data

We examined how modality, scenario, and mental state affect pupil diameter, right wrist joint angle, right ankle joint angle, GSR, and skin temperature. However, none of these factors significantly affected pupil diameter, right wrist joint angle, right ankle joint angle, GSR, or skin temperature.

While the main effect was not observed among various independent variables, there was a marginal scenario × modality interaction effect (F (1, 4) = 5.727, p = 0.075, η_p^2 = 0.589) on the right wrist joint angle (Figure 9) . In a lane-keeping scenario, the visual signal (M = 4.658°, SEM = 1.449) was correlated with a slightly greater change in the joint angle of the wrist when compared to the tactile signal (M = -.043°, SEM = 1.449).

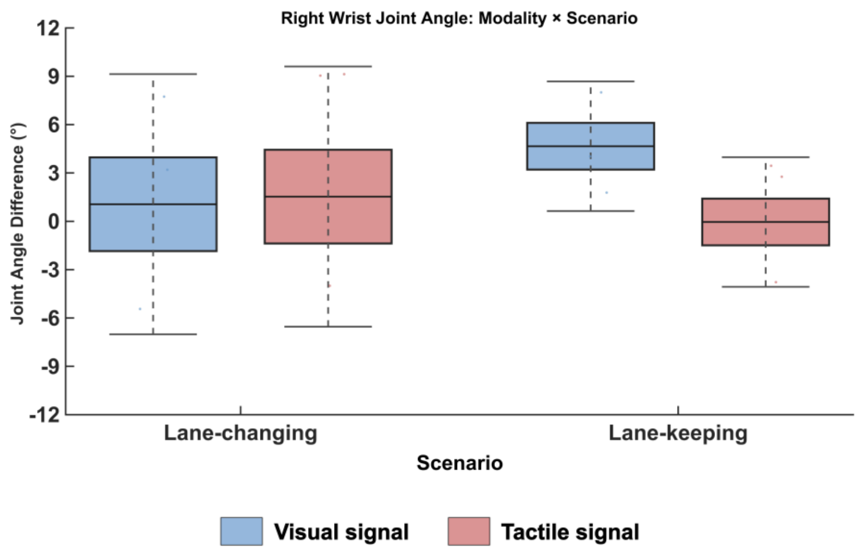

Figure 9. Right wrist joint angle as a function of modality and scenario.

Chapter 4: Conclusions and Recommendations

This study examined how informative takeover requests affect takeover performance in lane-changing and lane-keeping scenarios across visual and tactile modalities under seven mental states. First, this study examined how lane-changing and lane-keeping scenarios impact takeover performance. The findings suggest that the scenario that required changing lanes resulted in higher decision-making accuracy compared with the scenario that required maintaining the lane. However, Dogan et al. (2019) suggested that although lane-changing scenarios (i.e., obstacles ahead) were associated with shorter reaction times than lane-keeping scenarios (i.e., missing lane markings), the increased mental workload in lane-changing scenarios may not lead to effective decision-making. The different environmental settings used in these two studies might lead to this conflict (i.e., Dogan et al. (2019) adopted highway scenarios, and the current study adopts urban scenarios). For example, Du et al. (2024) indicated that dealing with lane-changing situations on highways resulted in poorer takeover performance (e.g., higher collision risk, higher arousal and stress) than similar situations in urban scenarios. On the other hand, encountering lane-keeping scenarios on highways resulted in better takeover performance (e.g., lower arousal and stress) compared with urban scenarios. Another explanation is that in the lane-changing scenario, drivers receive an informative takeover request about the danger and perceive the obstacle in their current lane, providing sufficient cues to make the appropriate decision. However, during the lane-keeping scenario, obstacles are often located in adjacent lanes, which overlap the effectiveness of the informative display (Martinez & Huang, 2022), leaving drivers without clear cues to rely on and resulting in decreased accuracy. Additionally, this study also evaluated the effects of visual and tactile takeover requests on takeover performance. The results indicated that tactile signals were associated with slightly higher decision-making accuracy than visual signals. One explanation is that tactile informative displays engage both sides of the body, helping users identify obstacles more effectively than visual signals do. This finding aligns with earlier studies indicating that tactile stimuli can effectively direct a user's attention to a particular area compared with visuals (Lehtinen et al., 2012; Lüttgen & Heuer, 2012). Another possibility could be that the visual cue on the windshield might block part of the driver's view. In contrast, the tactile display features a "gaze-free" benefit (Graham, 1999), enabling the driver to perceive the real-life environment and the takeover request simultaneously. The results among different mental states reveal no significant differences in takeover performance. This finding suggests the informative display may help maintain driver situation awareness across mental states, supporting decision-making in dynamic autonomous environments. Additionally, the findings across signal modality, scenario, and mental state on physiological measurements also reveal no significant differences, suggesting that, when developing such takeover requests, objective performance metrics, such as decision-making accuracy, could be prioritized.

Some limitations need to be addressed in this study. First, as an exploratory pilot study, the sample size may not provide enough statistical power. For example, although the results show some trends in decision-making accuracy, the non-significant findings in physiological data might be due to the limited sample size. Future research should increase the sample size to confirm these findings. Additionally, the participants were primarily recruited from a specific college and within a specific age range (i.e., 18–24 years old). However, the design of the human-machine interface, such as takeover requests, is intended for the general population. To further validate this study, future research should investigate the effects among different user groups, such as younger versus older adults or novice drivers versus experienced drivers. Next, due to the experiment's duration, we could only examine the effects of visual and tactile modalities using a between-subjects design. To gain a better understanding of both modalities, future studies should consider employing a within-subjects design to examine the effects of each modality on individual participants. Lastly, although the current study employed some validated methods, such as playing music or chatting with participants to induce mental states, it remained unclear whether the mental state was successfully induced. To address this, future studies could consider adding a brief survey during the induction process to verify whether participants are in the corresponding mental state.

The findings of this study provide insights for developing human-machine interfaces that enhance safety across various mental states for future automated vehicles. Based on these insights, when developing the informative takeover request, tactile feedback should be prioritized over visual feedback due to its advantages in redirecting attention to a specific area. In addition, the differences in takeover performance shown in different scenarios indicate that it is important to create an adaptive warning system for the various situations drivers encounter. Moreover, the non-significant result between different mental states might indicate that the effectiveness of adopting informative displays in the takeover request is stable and reliable. Given that this study is solely a pilot study with a minimal sample size, the results should be interpreted cautiously. Overall, these results deliver crucial evidence for engineers and designers to create advanced human-machine interfaces in automation systems that enhance safety.

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