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Insights for the Future of Car Rental and Ridesharing: Driving Behavior Across Different Levels of Automation

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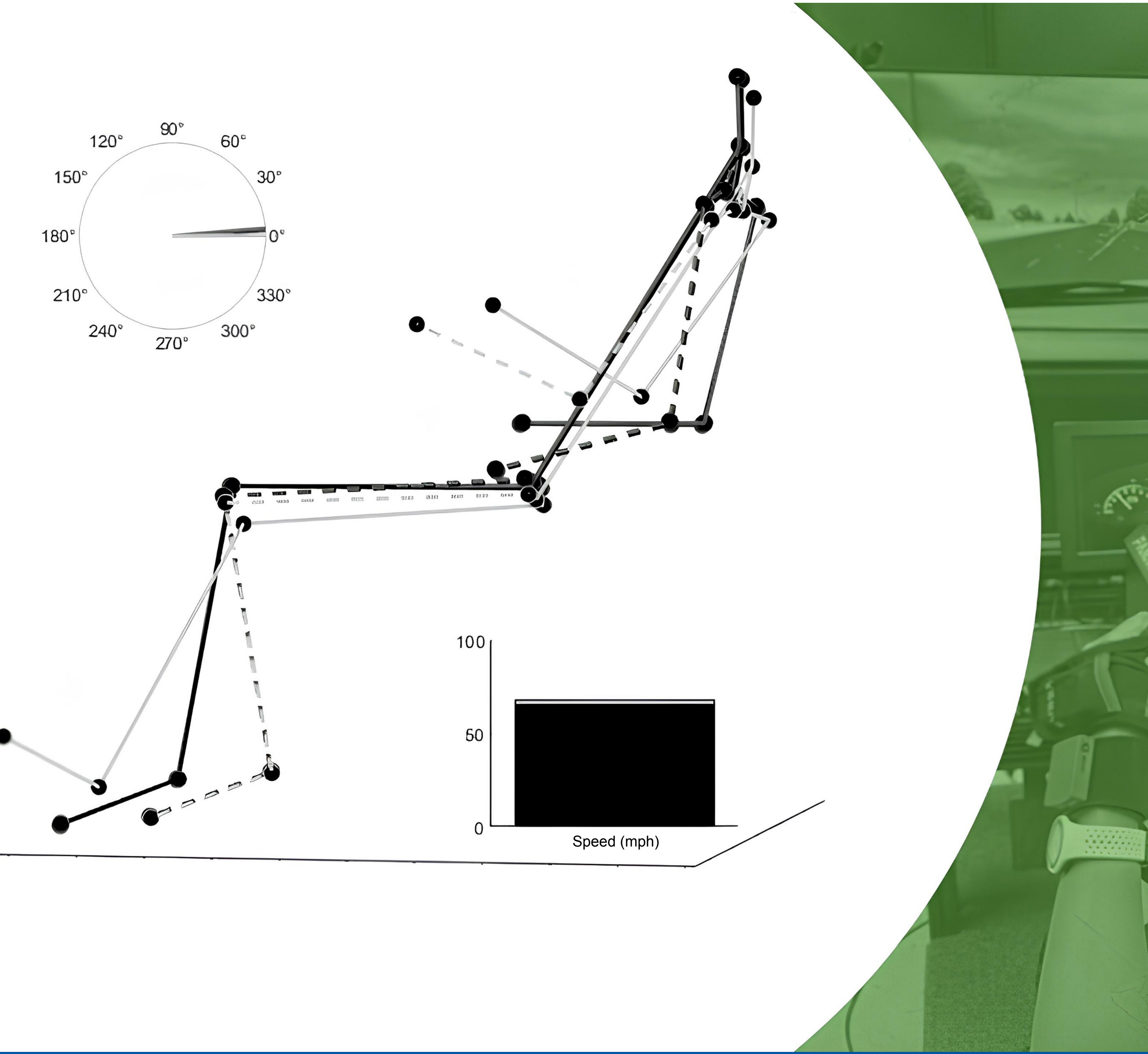

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16. Abstract

Autonomous vehicles are reshaping the car rental and ridesharing industries, potentially leading to a unified model of on-demand transportation suitable for both uncommon (e.g., business trips) and daily commuting. An exploratory study of human behavior towards autonomous vehicles can uncover the challenges and opportunities inherent in different levels of vehicle automation. This study aims to (a) identify behavioral differences in drivers operating vehicles at various levels of automation and (b) explore how these behaviors vary with different assistance feature styles, specifically between risky and conservative modes. Human-subject experiments were conducted among twelve participants (aged 21 to 29, including four women) to complete simulated driving trials under different levels of automation (Levels 0, 3, and 5), assistance features (risky and conservative modes), and driving activities (lane keeping and lane changing). Measures of driving performance, body posture, and eye movement were recorded during each trial. The data implied that: (1) driving performance: drivers exhibited stable speed and steering control at Levels 0 and 5, while speed decreased and steering variability increased obviously at Level 3; (2) driving posture: a tense posture was noted at Level 0, with potential posture preparation needed for takeover actions at Level 3; (3) eye movement: active scanning and continuous control were maintained at Level 0, with notable shifts in attention at Levels 3 and 5. Further research could focus on conducting on-road tests, using equipment designed for on-road tests and broadening the demographic range of participants.

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Executive Summary

An exploratory study of human behavior towards different levels of vehicle automation can inform the challenges and opportunities in the future car rental and ridesharing industries. Therefore, this study aims to identify behavioral differences in drivers operating vehicles at different levels of automation (Levels 0, 3, and 5) and how they vary among assistance feature styles (risky and conservative modes) and driving activities (lane keeping and lane changing).

Human-subject experiments with twelve participants were conducted to observe simulated driving behaviors. The findings highlighted:

- Driving performance: Drivers maintained stable speed and steering at Levels 0 and 5. However, at Level 3, there was a noticeable decrease in speed and an increase in steering variability.

- Driving posture: A tense posture was noted at Level 0, with potential posture preparation needed for takeover actions at Level 3.

- Eye Movement: Active scanning and continuous control were consistent at Level 0, while attention shifts were observed at Levels 3 and 5.

Based on these observations, the study recommends the implementation of multimodal interfaces and alarm systems, the enhancement of vehicle ergonomics, and the development of training programs to increase driver awareness. These are designed to address the short-term behavioral changes identified in this study and improve overall vehicle design and driver training.

1. Introduction

The advent of autonomous vehicles is reshaping the future trends of the car rental and ridesharing industries. A prime example is Waymo, which emerged as a leading force in the autonomous driving industry. Waymo has logged over 7.1 million driverless miles across major cities including San Francisco, Los Angeles, and Phoenix (Hawkins, 2024) and has consistently surpassed 100,000 weekly bookings in the U.S. (Kolodny, 2024). As this technology matures, it promises to transform urban mobility with safer, more seamless, and potentially more cost-effective alternatives to conventional transportation methods. This evolution could lead to a blurring of the lines between car rental and ridesharing services under uncommon commuting (e.g., business trip) or even daily commuting, potentially culminating in a unified model of on-demand transportation.

Additional reasons to investigate a unified model of on-demand transportation lie in a growing reliance on car rental and ridesharing services for a variety of needs, from business trips and vacations to daily activities. The flexibility of these services allows individuals to choose vehicles that best fit their immediate needs. This is important in areas with limited public transit or extensive geographical expanses: vehicle rental and ridesharing services can meet the diverse and changing transportation needs of communities that may not rely heavily on personal vehicles (L. Zhang et al., 2021). However, increased traffic accidents associated with these services cannot be ignored. Research indicates that rental cars tend to have a higher collision rate compared to private vehicles (Tay et al., 2017), often resulting in more severe injuries (Al-Balbissi, 2001). Additionally, ridesharing has been associated with a 3% increase in fatal accidents, impacting both vehicle occupants and pedestrians (Barrios et al., 2023). This trend is particularly pronounced in areas that heavily rely on these services, such as tourist destinations and airport vicinities, where there has been a significant rise in accidents involving both rental cars (Kwon et al., 2017) and ridesharing vehicles (Chaudhry et al., 2018).

For industry stakeholders, analyzing these trends and adapting business strategies to the new model of on-demand transportation that combines car rental and ridesharing services through autonomous vehicles holds great promise. However, before proceeding, it is beneficial to first take an exploratory approach to understand human behaviors and attitudes towards new autonomous driving vehicles. Gaining insights into how drivers interact with and adjust to various levels of vehicle automation can help identify potential challenges and opportunities that arise in both the aforementioned uncommon commuting and even daily commuting practices.

Human driving behavior and attitudes vary significantly by the assistance features available in vehicles and the drivers' trust in their capabilities. Utilizing advanced measurement devices, research has provided deep insights into how drivers engage with in-vehicle assistance features such as Adaptive Cruise Control (ACC) (Yu & Wang, 2022). For example, motion capture can reveal changes in posture as drivers transition from active control to monitoring roles (Wu et al., 2020), while eye trackers can show shifts in gaze patterns (Zhou et al., 2021), highlighting how frequently and where drivers look when ACC is engaged compared to when it is not. In this study, we will utilize wearable measurement devices to explore drivers' behaviors as they interact with a new transportation system that incorporates vehicles with varying levels of automation and different driving assistance features.

In the subsequent section of the introduction, we will provide a brief overview of the current levels of automation and some automation/assistance features associated with it, along with a summary of metrics used to quantify human cognitive and physical driving behaviors.

1.1 Levels of Driving Automation and Assistance Features

In the context of motor vehicles and their operation on roadways, degrees of automation in vehicles are classified from 0 to 5 to describe the extent to which a vehicle can automatically handle driving tasks and drivers' responsibility during operation: Level 0 (No Automation), Level 1 (Driver Assistance), Level 2 (Partial Automation), Level 3 (Conditional Automation), Level 4 (High Automation), and Level 5 (Full Automation) (SAE International, 2021). The assistance features offered by vehicles vary significantly across different levels of automation. At Level 0, the human driver is responsible for controlling functions such as steering, braking, accelerating, and continuously monitoring the vehicle and road conditions. Simple alert systems could be the assistance feature for drivers' awareness. At Level 3, vehicles can handle all driving operations under certain conditions such as highway driving. However, the human driver must remain alert and be prepared to take over when the system requests or fails to handle a task. Systems such as Audi AI traffic jam pilot can manage vehicle speed and lane keeping in slow-moving traffic. Moving up to Level 5, vehicles do not require human attention or intervention at any time. Conceptually, Level 5 technology would be a fully autonomous vehicle that could travel without any human input, equipped with systems that handle everything from navigating dense urban environments to adjusting to unexpected road incidents.

Research indicates that the development of autonomous driving technologies has primarily reached Level 3 automation (Cho et al., 2021; Kyriakidis et al., 2019), with exploration and development efforts actively pushing toward Level 4 automation (Kusano et al., 2024; Schwall et al., 2020). This implies that human drivers are still responsible for regaining control of the vehicle or initiating a takeover in instances where the autonomous system is unable to handle the situation. Here, the takeover process is defined as a process involving the perception and information processing of the takeover request and the resulting action by taking control and resuming manually driving (Huang & Pitts, 2022b, 2022a). Driving behavior, characterized by takeover performance in Level 3 automation—which includes metrics such as information processing time, takeover time, and lane-keeping performance—varies according to personal and environmental factors. This study aims to investigate how driving behavior during these takeover scenarios contrasts with manual driving at Level 0 and with fully automated vehicle operation at Level 5.

1.2 Driving Posture from Motion Capture Systems

Maintaining proper body posture while driving is essential for the comfort and safety of drivers. For instance, the position of the hands on the steering wheel impacts arm fatigue and vehicle control (Z. Wang et al., 2020). It is recommended to position the hands at either the "9 and 3 o'clock" or "8 and 4 o'clock" positions to optimize control and minimize strain. Additionally, keeping a natural bend in the knees and ankles allows for more efficient and comfortable pedal operation (Gao et al., 2022). The seat position is critical as it influences how easily drivers can reach both the pedals and the steering wheel, affecting hand and foot posture. Moreover, several other factors also play crucial roles, such as the adjustments of the backrest and headrest (Q. Wang et al., 2023). In this study, we extend our investigation beyond the vehicle's interior layout to consider how the level of vehicle automation and the activation of different assistance features can further influence driver posture.

Motion capture systems have demonstrated their ability to detect changes in drivers' posture during transitions between different roles within a vehicle under varying levels of vehicle automation. Inertial measurement units (IMU), in particular, are effective in monitoring and analyzing subtle postural shifts while driving. This system excels at tracking complex, real-world motions in meticulous detail with its lightweight and unobtrusive features (Fan, 2024; Lueken et al., 2020). Van Der Kruk and Reijne (2018) emphasize the adaptability of IMU systems for dynamic settings, such as driving, where an active environment is a significant factor to consider. Su and Jia (2022) demonstrate that these wearable sensors are effective in integrating physiological and movement data, enabling real-time analysis of certain driving behaviors such as steering, gear adjustments, and posture adjustments. The same study has also validated the use of wearable sensors in studying human comfort and organizational behaviors in autonomous vehicles (Su & Jia, 2022). For this study, we are interested in capturing small movements that commonly occur while driving, such as arm motions during the rotation of a steering wheel and rapid foot movements as the driver engages with the brake.

1.3 Eye Movement Metrics from Eye Tracking System

Observing eye movement patterns during driving can reveal information about drivers' status that might otherwise go unnoticed. Changes to eye movement matrices, such as pupil diameter, reflect physiological reactions to circumstance that may elicit discomfort (e.g., fatigue or cognitive overload) (Morad et al., 2000). Frequent shifts in gaze away from the road could indicate distraction (Fernández et al., 2016). Similarly, the duration and fixation on specific objects such as navigation devices or smartphones can provide insights into drivers' engagement with potentially distracting activities. Additionally, the rate of blink and the duration of eye closures can be used to monitor subtle signs of drowsiness (Massoz, 2019), enabling proactive safety measures before drivers' status compromises road safety.

Eye tracking systems are extensively utilized to capture the eye movement matrices (Nordhoff et al., 2020). Such systems serve to monitor drivers' attention and identify distractions effectively (Le et al., 2020). This technology also plays a crucial role in detecting drivers' emotional states; for example, stress, which significantly impacts driving performance, can be inferred from changes in pupil diameter recorded by eye tracking systems (Vintila et al., 2017). Additionally, eye tracking is useful in assessing the driving performance and user experience of newly developed human-machine interfaces (S. Li & Hao, 2024; W. Li et al., 2022). Moreover, the metric, percent road center (PRC), measured by eye tracking systems, which quantifies the percentage of fixations considering spatial and temporal information, is a validated indicator of cognitive load (Khan & Lee, 2019). This is particularly important in scenarios where driving responsibilities are shared between the vehicle and human drivers, highlighting the importance of managing cognitive demands effectively. In the current study, we are investigating pupil diameters and gaze coordination across various levels of automation and assistance features. Our goal is to identify the physiological responses elicited by these driving environments.

1.4 Driving Simulation and Driving Performance Metrics

As mentioned above, driving behavior varies based on personal and environmental factors. At Level 0, behavior may be influenced by drivers' experience, often resulting in increased vigilance while manually navigating traffic. At Level 3, drivers may show reduced vigilance due to over-reliance on automation, potentially leading to slower reaction times when manual takeover is necessary. At Level 5, driver behavior transitions from active participation to passive monitoring, engaging in non-driving related activities. Driving simulations are naturally at the forefront of automated vehicle research as they provide a safe, controlled environment to test and analyze the impact of levels of vehicle automation on driver behavior. These simulations allow researchers to systematically introduce and vary conditions, such as traffic scenarios, without the risks associated with on-road testing. This makes them invaluable tools for studying how automation affects driving decisions and the overall interaction between human drivers and automated systems.

Driving performance in simulations is typically assessed using spatial and temporal metrics. Key measures include speed, reaction time, braking behavior, and lane-keeping ability. Speed data evaluates a driver's consistency in maintaining appropriate velocities, while reaction time metrics assess drivers' responsiveness to unexpected road incidents. Braking and lane-keeping behavior offer insights into drivers' control and precision. Collectively, these performance indicators are essential for gauging how effectively the assistance features in automated vehicles can facilitate safe driving when required. In the current study, we are focusing on speed management, reaction time-related measures, and the force exerted on pedals and steering wheels to explore changes in driving parameters under various driving scenarios.

1.5 Study Objectives

This study aims to incorporate human behavior measures of body posture, eye movement metrics, and overall driving performance to explore two main objectives: (a) to examine drivers' behavioral differences when operating vehicles at various levels of automation and (b) to investigate how these behavioral responses vary between different assistance feature styles, specifically risky versus conservative modes. To address these objectives, human-subject experiments were conducted focusing on three critical research questions: (1) what biomechanical differences are evident under varying driving conditions that engage different levels of automation and assistance features, (2) what cognitive differences arise under these varied driving conditions, and (3) how do these biomechanical and cognitive differences interrelate, and what impact do they have on drivers' reactions to unexpected accidents or incidents? By answering these questions, the study seeks to explore drivers' behavioral differences in various driving conditions and inform the design of a new transportation system that incorporates vehicles with varying levels of automation and different driving assistance features.

2. Method

2.1 Participants

The study recruited a total of 12 participants, comprising 4 males and 8 females, all of whom were college graduate students. Participants ranged in age from 21 to 29 years old. Recruitment was conducted through social media engagement and word of mouth to ensure a diverse sample within the specified criteria. Inclusionary criteria required participants to hold a valid driver's license and be at least 18 years of age. Individuals with visual or cognitive impairments that could potentially impact their driving behavior were excluded to ensure consistency and reliability in the data collected. This sample provided a focused demographic of young adult drivers with varied driving experiences, aligning with the study's objectives to evaluate driver behavior and performance. The study protocol was approved by the San José State University Institutional Review Board (IRB#: 23-378). All participants gave their consent by signing the provided informed consent form.

2.2 Instrumentation

In this study, a medium-fidelity driving simulator known as MiniSim, developed by the Driving Safety Research Institute (DSRI) at the University of Iowa, was employed to simulate driving scenarios. The MiniSim replicates real-world driving environments, allowing for the precise measurement and analysis of driver behavior under varied conditions (Figure 1). Driving scenarios were crafted using ISAT software on a Windows-operated desktop computer to generate the necessary (.scn) files.

To capture driving posture and eye movement metrics, we utilized wearable measurement devices, specifically a motion capture system (Movella/Xsens) and an eye tracking system (Pupil Core) (Figure 1). The Movella/Xsens system, an advanced inertial measurement unit (IMU), is an effective device used in research studies for capturing human movement. This system captures data on joint angles, segment positions, and dynamic orientation changes, which are crucial for analyzing drivers' biomechanics. For eye movement tracking, we employed the Pupil Core eye-tracking glasses from Pupil Labs, which stands out due to their use of open-source software. These glasses can record gaze and pupil behavior in real-time with the Pupil Capture desktop application enabling device calibration and real-time viewing of the camera feeds and the recording scene.

During the experiment, pre-study questionnaires, NASA-TLX questionnaires, and post-study questionnaires were planned. The pre-study questionnaire contained a demographic survey and 16 questions related to frequency of renting vehicles, general driving experience, style of driving behavior, familiarity with various driving systems such as in-vehicle information displays, warning systems, adaptive cruise control, and prior experience with automated driving systems. The NASA-TLX questionnaire was administered after every drive trial via iPad. The post study questionnaires were adopted from The Unified Theory of Acceptance and Use of

Technology (UTAUT2), which is a widely validated questionnaire (Nordhoff et al., 2020). We utilized two versions to ascertain prior levels of trust, acceptance, and familiarity of autonomous driving systems. One version focused on acceptance of conditionally automated vehicles and another version focused on fully automated vehicles.

In addition, desktop workstations and laptop computers were utilized to operate the MiniSim, calibrate devices, collect data, and administer questionnaires.

2.3 Procedure

The study was conducted in the Human Factors Laboratories at San José State University. Upon arrival, participants were provided with an overview of the study and the tasks they would be performing. If participants had not signed the informed consent form, they were asked to do so at this time. Following consent, participants completed an initial set of questionnaires (i.e., pre-study questionnaires) to gather demographic information and their current level of driving experience and driving style.

Figure 1. Demonstration of the Driving Simulator, Motion Capture System, and the Eye Tracking System During One Driving Trial

Next, researchers equipped the participants with the necessary devices, including a motion capture system and an eye tracking system, and performed system calibrations to ensure accurate data collection. Sensor attachment involved fitting the motion sensor straps and adjusting the eye tracking glasses to align with the participant’s pupils. System calibration involved body measurements, body motion calibration, and eye gaze calibration.

Before starting the main driving trials, participants spent time familiarizing themselves with the equipment and the driving simulator through practice trials. Once the participants indicated to the researchers that they felt confident and ready, they proceeded to begin the main driving trials.

The main experiment consisted of six driving trials, each approximately 6 minutes long, across different levels of automation: two trials at Level 0 (manual), two at Level 3 (conditional automation), and two at Level 5 (full automation). In this study, we used Level 3 to represent driving situations that require human intervention only at critical moments, a scenario not fully addressed by Level 2 automation. Level 5 was selected to illustrate scenarios where vehicles operate with full control, in contrast to Level 4, which remains subject to specific driving restrictions and conditions. During these trials, participants encountered scenarios requiring them to maintain their lane (lane keeping) or change lanes (lane changing) when faced with unexpected situations. The assistance features in Levels 3 and 5 were activated in these situations, offering either conservative (early indication/action) or risky (late indication/action) intervention. Driving performance, driving posture, and eye movement metrics were recorded during each driving trial.

Between each trial, researchers checked in with the participant to ensure comfort and address any concerns. The participant was afforded a 1-minute break during each trial after they completed the NASA-TLX questionnaires. To simulate a partially and fully autonomous experience, the miniSIM driving simulator allowed the participant to “start” the car’s engine and initiate a self-driving mode using an easily accessible button to the left side of the steering wheel. Control of the system can be regained by engaging with the brake pedal at any time.

After completing all trials, participants were debriefed, and all sensors were removed. They then filled out the post-study questionnaire. Throughout the study, participants had the freedom to take breaks as needed. Photos and videos were taken for research purposes, with prior consent included in the form they signed at the beginning of the study.

The sequence of events involving lane keeping and lane changing, as well as the order of assistance features (risky versus conservative), were counterbalanced to minimize potential learning effects that could impact data analysis. This study employed a within-subjects design, enabling each participant to experience all variations of the three independent measures—level of automation (L0, L3, L5), assistance features (risky, conservative), and driving activities (lane keeping, lane changing)—across six trials.

2.4 Data Processing and Analysis

The study investigated human behavior through three types of dependent measures related to driving performance and driving behavior through a physiological lens: (1) driving performance parameters, covering spatial and temporal control of driving tasks; (2) body posture measures, examining the positioning and movements of drivers’ body; and (3) eye movement metrics, focusing on drivers’ gaze and pupil changes. The influence of automation levels, aka SAE levels (Level 0 – No Automation, Level 3 – Conditional Automation, and Level 5 – Full Automation), and assistance features (conservative vs. risky) on human driving behavior were compared using these measures during lane keeping and lane changing activities.

Using MATLAB (version R2022b) (Luo et al., 2022), data was extracted starting at the onset of these activities and continuing for 15 seconds to ensure a comprehensive capture of the driving responses. Human behavior data across the three automation levels were analyzed by comparing the average values over 15 seconds and the values in each frame throughout the 15-second window. Additionally, data was segmented and compared at specific intervals: at the start, at 5 seconds, and at 10 seconds, in order to assess temporal changes and patterns in the driving behavior under different conditions. This segmentation allows for a detailed analysis of how drivers respond immediately after a task begins, as well as their adaptation over a short period.

2.4.1 Driving Performance Parameters

Two driving performance parameters were analyzed: driving speed (in mph) and steering wheel angles (in degrees) across SAE levels, assistance features, and driving activities. These parameters were evaluated over a 15-second window and at designated time intervals. In addition, the time taken for information processing was calculated by measuring the time interval between the appearance of the "take over" indicator and the moment participants pressed the brake pedal to regain control. This measurement was specifically calculated and compared at Level 3 automation.

2.4.2 Body Posture Measures

Body positioning was visualized at designated time intervals, focusing on body parts including the (1) head, (2) neck, (3) pelvis, (4–5) right and left shoulders, (6–7) right and left upper arms, (8–9) right and left forearms, (10–11) right and left hands, (12–13) right and left upper legs, (14–15) right and left lower legs, (16–17) right and left feet, and (18–19) right and left toes (Luo et al., 2021, 2022). Additionally, the average flexion angles of the right wrist and right ankle were calculated and compared within a 15-second window. Wrist flexion, indicated by a positive (+) value, involves curling the wrist towards the palm, while wrist extension, indicated by a negative (–) value, refers to moving the back of the hand towards the forearm. Similarly, ankle dorsiflexion (+) occurs when the foot is raised upward toward the shin, and ankle plantarflexion (–) occurs when the foot points downward away from the shin (Luo et al., 2021; J. T. Zhang et al., 2013).

2.4.3 Eye Movement Metrics

Eye movement patterns were analyzed using two metrics: eye gaze coordination and pupil diameters (Chen et al., 2022; Zheng et al., 2020). Eye gaze coordination was captured from the world video at specific frame intervals. Meanwhile, the pupil diameters of the right eye (in millimeters) were averaged over the 15-second window for comparison. Although raw numerical data on eye gaze coordination are available, they were not included in this study's analysis. Instead, video clips of eye gaze were used, as they can provide a more straightforward and intuitive approach for this exploratory study. Visual representations from the eye gaze data and graphs of the pupil diameters were compiled to facilitate comparisons across SAE levels, assistance features, and driving activities.

2.4.4 Driving Performance Comparison

As mentioned, time series were extracted over a 15-second window for all 12 participants. Time-series line charts, complete with mean and standard deviation, were employed to depict this data. Box-and-whisker plots were used to illustrate the averaged data for all participants. Furthermore, to enhance understanding of the dataset, samples of driving performance, body posture, and eye movement from one participant (Participant #10) were demonstrated in figures and compared at specific time points: at the beginning, at 5 seconds, and at 10 seconds.

3. Results and Discussion

3.1 Participants' Characteristics

Among the 12 participants, two were reported to be left-handed. The driving behavior self-assessments revealed that 11 participants categorized themselves as safe drivers, while one identified themselves as a risky driver. Other related information about the participants is included in Table 1.

Table 1. Participants' Characteristics

Characteristics	Gender	
	Female	Male
Demographic		
Counts (N)	8	4
Age (years)	21–29	23–26
Weight (kg)	52kg–127kg	61kg–77kg
Driving Experience		
How many years have you been driving?	1–5 years: 5 5–10 years: 1 > 10 years: 2	1–5 years: 2 > 10 years: 2
Trust in Automated or Self-Driving Vehicles (Scale of 1 to 5; 1 = Complete Avoidance; 5 = Complete Trust)	1 out of 5: 12.5% 2 out of 5: 25% 3 out of 5: 25% 4 out of 5: 37.5%	2 out of 5: 50% 3 out of 5: 25% 4 out of 5: 25%
Risky vs. Safe Driver	Safe: 100%	Safe: 75% Risky: 25%

3.2 Conditional Automation – L3

Driving performance, body posture, and eye movement were compared while 12 participants were prompted to take over and regain control of the vehicle (L3) under conditions requiring lane keeping (Section 3.2.1) and lane changing (Section 3.2.2). These metrics were also compared across two takeover request modes: conservative versus risky.

3.2.1 Lane Keeping

Figure 2 presents a comparative visual analysis of driving performance under two takeover request modes, conservative and risky modes, in an L3 condition. It features trajectory plots of body parts, video snapshots capturing drivers' eye gaze, and charts showing vehicle speed and steering wheel angle. The data were extracted in three instances, at three key moments: at the onset, at 5 seconds, and at 10 seconds following the takeover request.

Figure 2. Sample of a Participant's Driving Behavior (Vehicle Speed and Steering Wheel Angle), Body Trajectory, and Eye Gaze in an L3-Lane-Keeping Condition

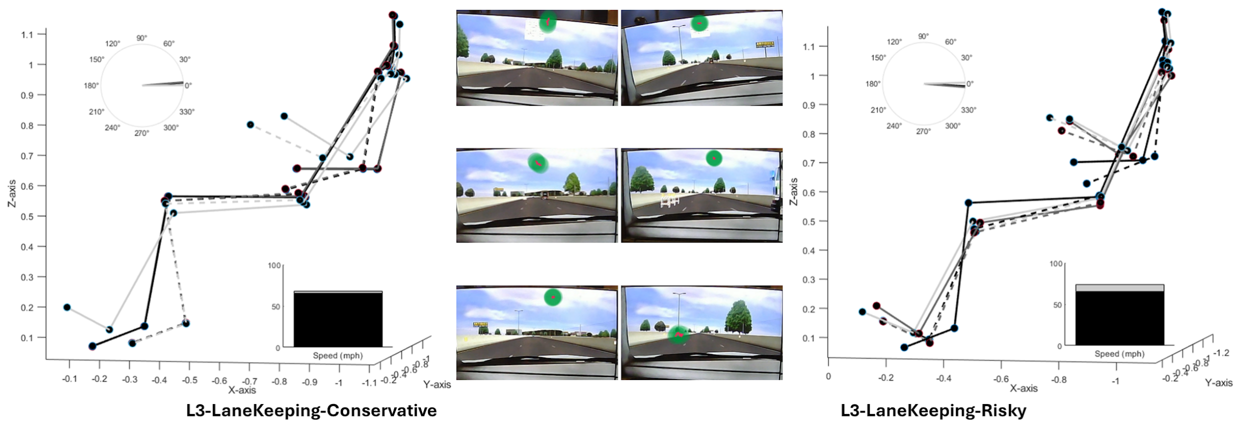
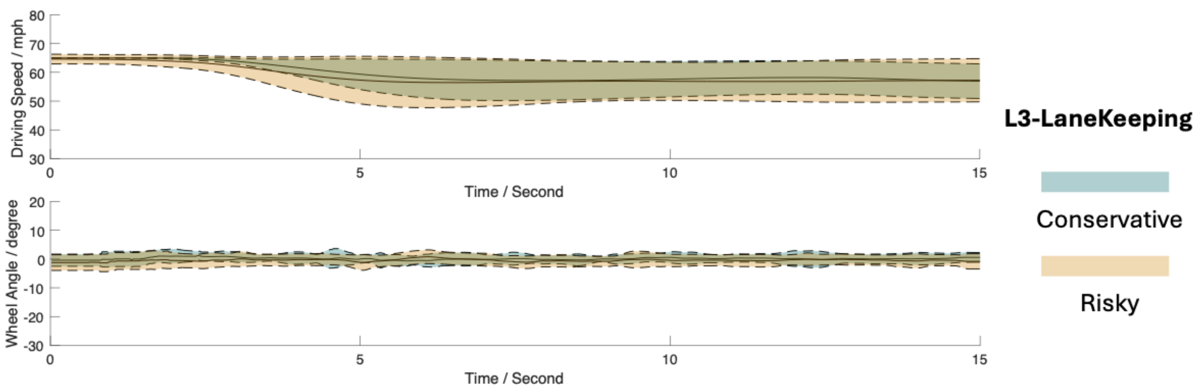


Figure 3 displays line charts during L3-lane keeping tasks, comparing driving speed and steering wheel angle under two takeover request modes. The figure illustrates a consistent pattern in driving speed and steering behavior with minimal deviation between the two modes throughout the L3 lane-keeping scenario. The average driving speed remained constant at 65 mph for approximately two seconds at the beginning, then gradually declined towards 60 mph during lane keeping, regardless of the request mode. The speed variance was notably higher in the risky mode while decreasing the speed when compared to the conservative mode. As for the steering wheel angle, the line charts show that both modes exhibited similar behavior, with lines overlapping and minor oscillations around zero degrees. Both request modes demonstrated minimal steering deviations, with consistent average values and variances.

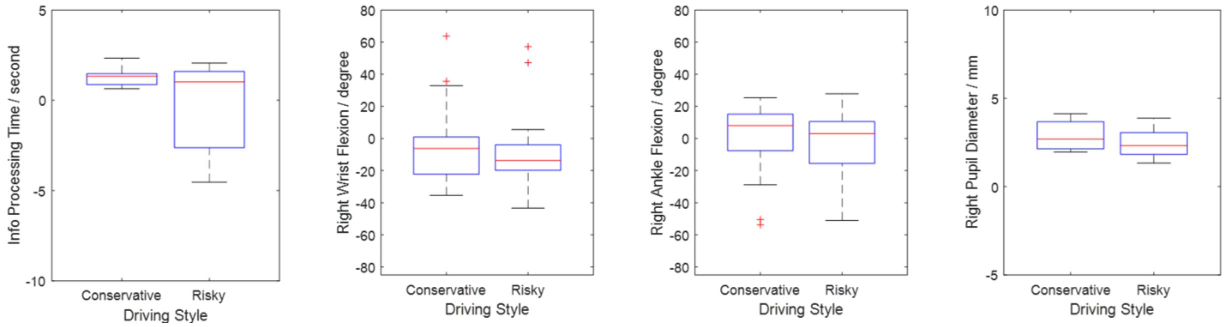
Figure 3. Driving Speed and Steering Wheel Angle for 15 Seconds Following a Takeover Request in an L3-Lane-Keeping Condition



Two request modes, conservative and risky takeover mode, are also included in the comparison. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 4 presents box-and-whisker plots that reveal the impact of two request modes on the three categories of human behavior metrics. Each chart targets one variable, comparing how each request mode impacts these metrics. The first plot shows the time participants took to execute an action (i.e., stepping on the brake pedal) to take over the vehicle. The median information processing time is slightly shorter under the risky mode than the conservative mode, with greater variability (a wider interquartile range (IQR)) as well. Here negative values indicated that participants took actions before the takeover indicator was shown to them. The second plot presents the flexion angle of the right wrist. Here, the median value is smaller in the risky mode, with a narrower range of deviations than in the conservative mode. Negative values in this plot represent a joint extension of the wrist. The third plot focuses on the flexion angle of the right ankle. The median value is lower in the risky mode and shows a wider range of deviations, compared to the conservative mode. Negative values in this plot indicated an ankle plantarflexion. The fourth plot compares the right pupil diameter. The median pupil diameter is smaller in the risky mode than in the conservative mode.

Figure 4. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in an L3-Lane-Keeping Condition



The metrics are averaged over a 15-second window and compared across two request modes among all participants.

3.2.2 Lane Changing

A comparative visual analysis under conservative and risky takeover requests is presented in Figure 5.

Both requests resulted in a decrease in driving speed, with the conservative mode consistently maintaining a marginally higher speed than the risky mode (Figure 6). Notably, the decline in driving speed was initiated earlier under the risky mode compared to the same mode under the lane-keeping condition in Section 3.2.1. The data also revealed more pronounced fluctuations in steering behavior for both modes (compared to lane-keeping), with these fluctuations occurring earlier and more abruptly in the risky mode and more continuously and evenly in the conservative mode (Figure 6).

The box-and-whisker plots in Figure 7 illustrate patterns in information processing time similar to those observed in the lane-keeping condition (Section 3.2.1). The median information processing time was slightly shorter under the risky mode. However, no differences were observed in the mean flexion angles of the right wrist and the right ankle, as well as the right pupil diameter between the two request modes.

Figure 5. Sample of a Participant's Driving Behavior (Vehicle Speed and Steering Wheel Angle), Body Trajectory, and Eye Gaze in an L3-Lane-Changing Condition

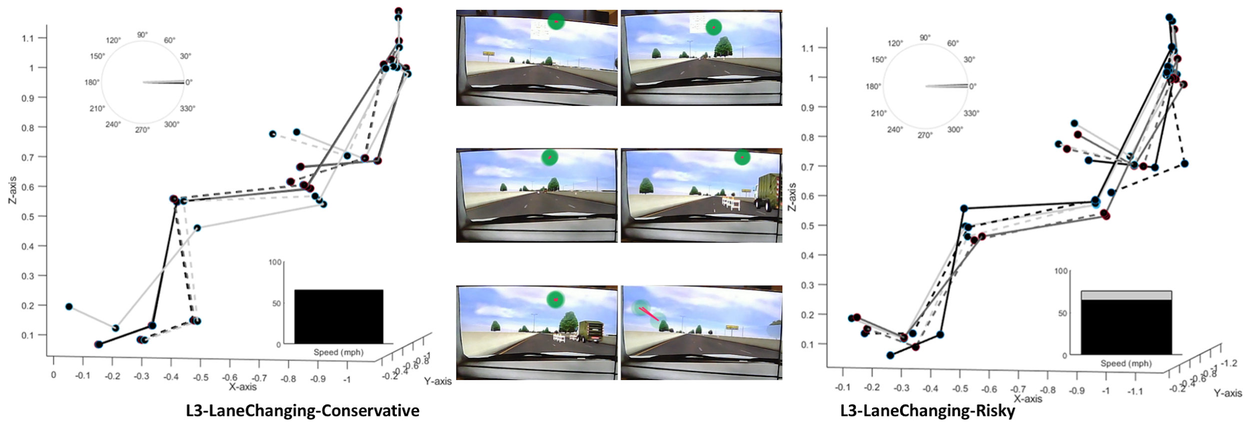
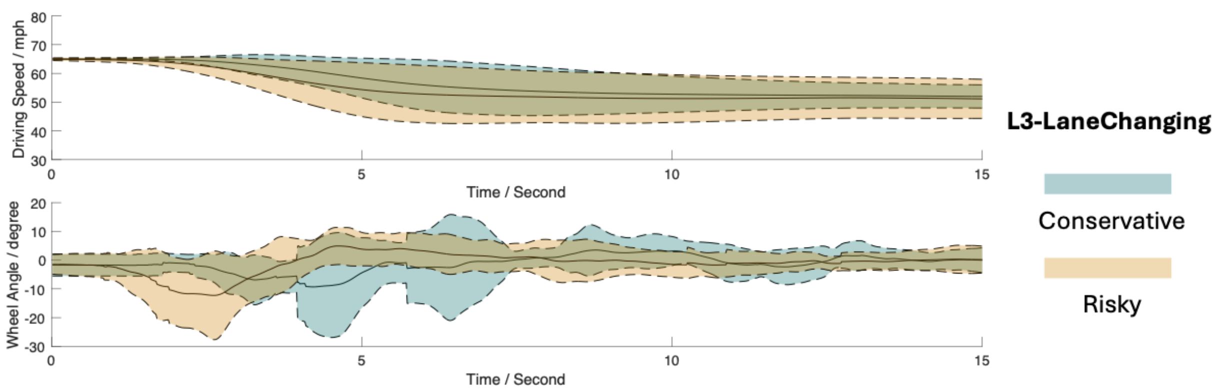
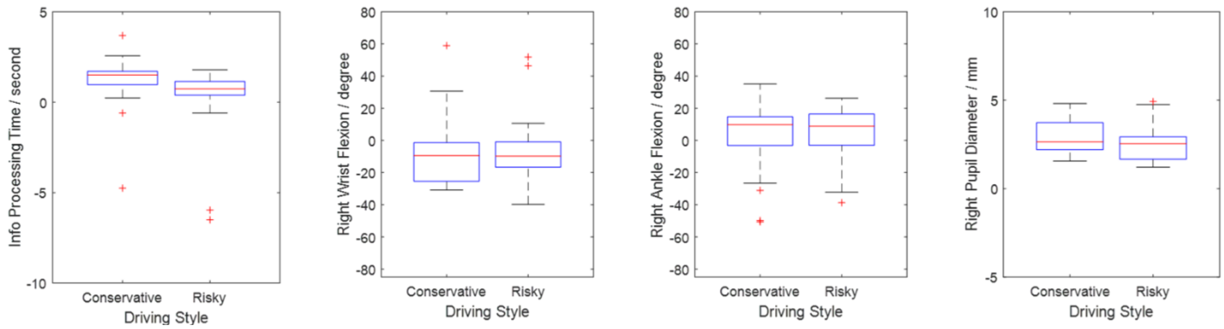


Figure 6. Driving Speed and Steering Wheel Angle for 15 Seconds Following a Takeover Request in an L3-Lane-Changing Condition



Two request modes, conservative and risky takeover mode, are also included in the comparison. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 7. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in an L3-Lane-Changing Condition



The metrics are averaged over a 15-second window and compared across two request modes among all participants.

3.3 Full Driving Automation – L5

Under the scenarios of full driving automation (L5), the vehicle's driving parameters, along with observations of participants' body posture and eye movement, were compared during lane keeping (Section 3.3.1) and lane changing (Section 3.3.2) conditions. These metrics were also compared across two vehicle behavior modes: conservative versus risky.

3.3.1 Lane Keeping

From the comparative visual analysis of a sample participant presented in Figure 8, there were no obvious changes observed in the vehicle's driving parameters or the participant's body posture across conservative and risky driving modes. In this condition, the vehicle maintained a steady driving speed and there were no adjustments to the steering wheel angle while maintaining lane position, as shown in Figure 9. However, when comparing participants' body posture (Figure 10), there was noticeably greater variability in wrist flexion and a slightly lower median value in ankle flexion in the risky mode compared to the conservative mode. Additionally, the pupil diameters of participants' right eyes were generally larger, both in median and overall trends, in the risky mode than in the conservative mode (Figure 10).

Figure 8. Sample of a Participant's Driving Behavior (Vehicle Speed and Steering Wheel Angle), Body Trajectory, and Eye Gaze in an L5-Lane-Keeping Condition

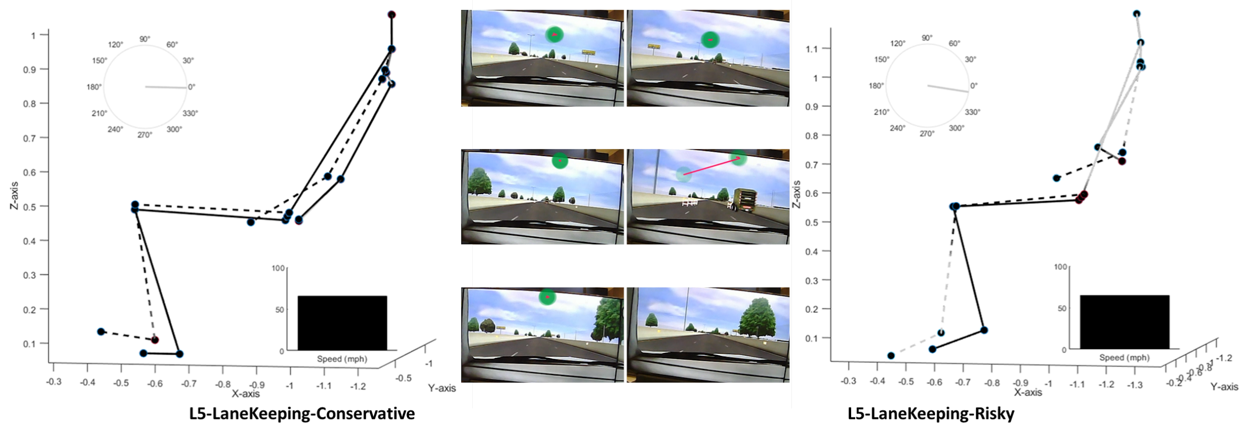
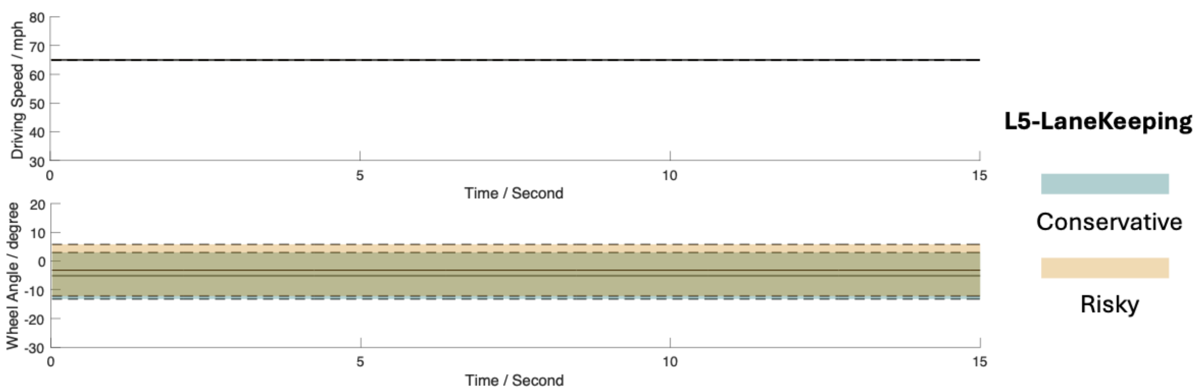
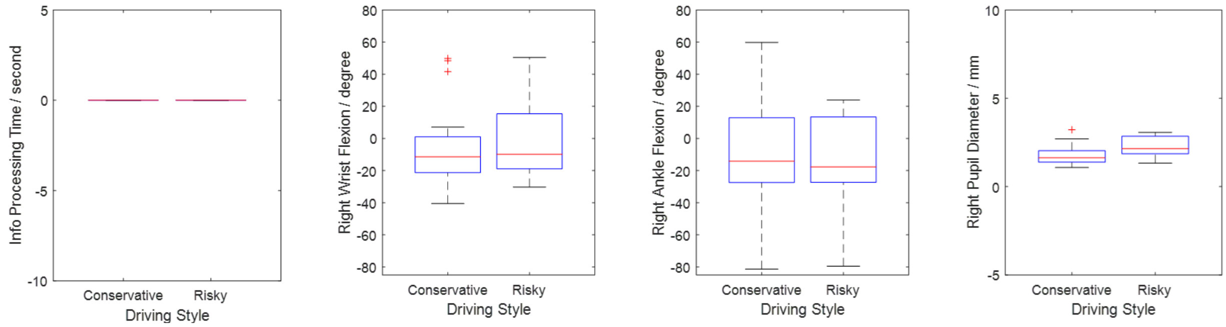


Figure 9. Driving Speed and Steering Wheel Angle for 15 Seconds Following a Takeover Request in an L5-Lane-Keeping Condition



Two request modes, conservative and risky takeover mode, are also included in the comparison. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 10. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in an L5-Lane-Keeping Condition



The metrics are averaged over a 15-second window and compared across two request modes among all participants.

3.3.2 Lane Changing

The outcome of driving parameters and participant observation during the lane-changing task mirrored those seen in the lane-keeping tasks under the L5 condition. No obvious changes were noted in the driving parameters or the body posture between the conservative and risky driving modes, as depicted in Figure 11. The vehicle maintained a relatively steady driving speed (slight changes observed) and minimal adjustments to the steering wheel angle (Figure 12). When comparing participants' body posture (Figure 13), a higher median value and increased variability were found in wrist flexion under the risky mode, together with a larger variability in ankle flexion. Additionally, the pupil diameters of participants' right eyes were slightly larger in the risky mode compared to the conservative mode (Figure 13).

Figure 11. Sample of a Participant's Driving Behavior (Vehicle Speed and Steering Wheel Angle), Body Trajectory, and Eye Gaze in an L5-Lane-Changing Condition

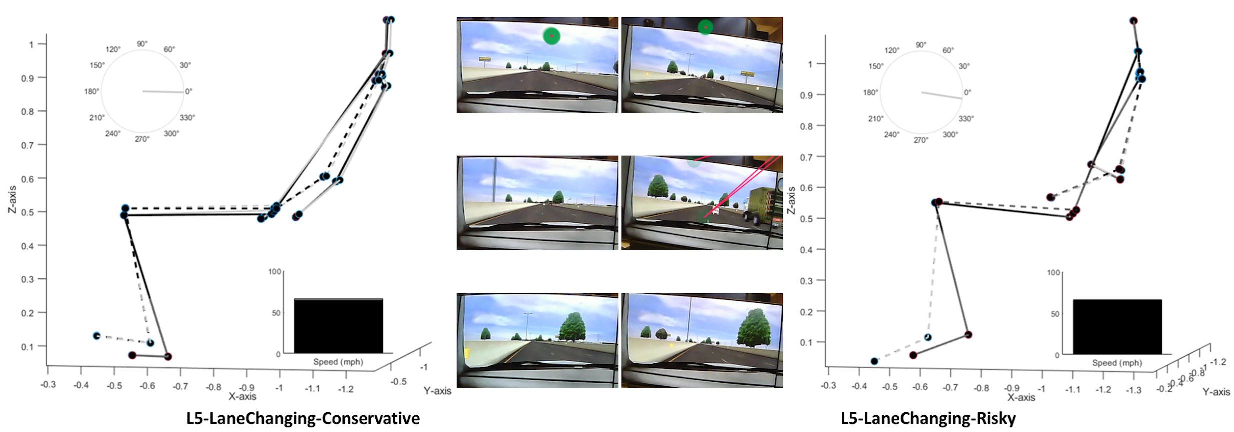
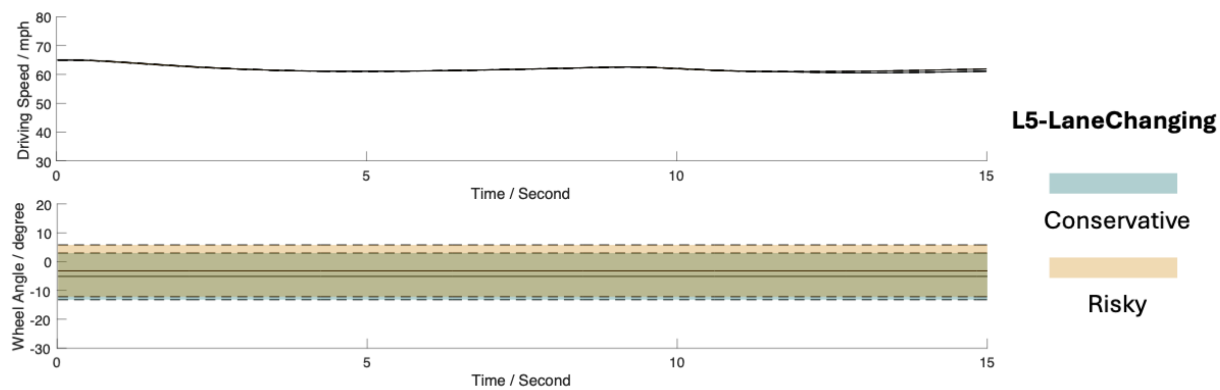
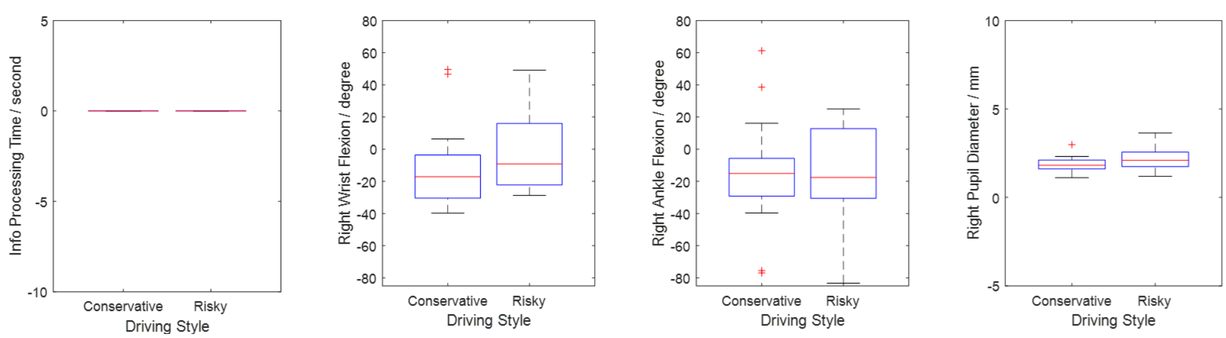


Figure 12. Driving Speed and Steering Wheel Angle for 15 Seconds Following a Takeover Request in an L5-Lane-Changing Condition



Two request modes, conservative and risky takeover mode, are also included in the comparison. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 13. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in an L5-Lane-Changing Condition

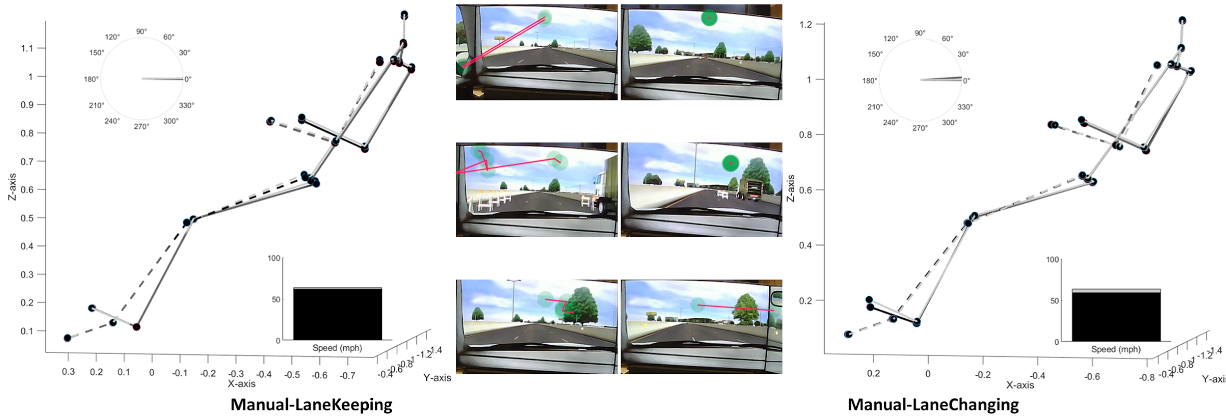


The metrics are averaged over a 15-second window and compared across two request modes among all participants.

3.4 Manual Driving – L0

The participants were also asked to conduct manual driving without the aid of assistive driving features (L0) for both lane-keeping and lane-changing tasks. During these tasks, data on participants' driving performance, body posture, and eye movements were collected. No significant changes were noted in body posture across different stages of the lane-keeping and lane-changing tasks. However, subtle but more noticeable differences were observed in driving speed and steering wheel angles during the lane-changing tasks compared to the lane-keeping tasks, as shown in Figure 14.

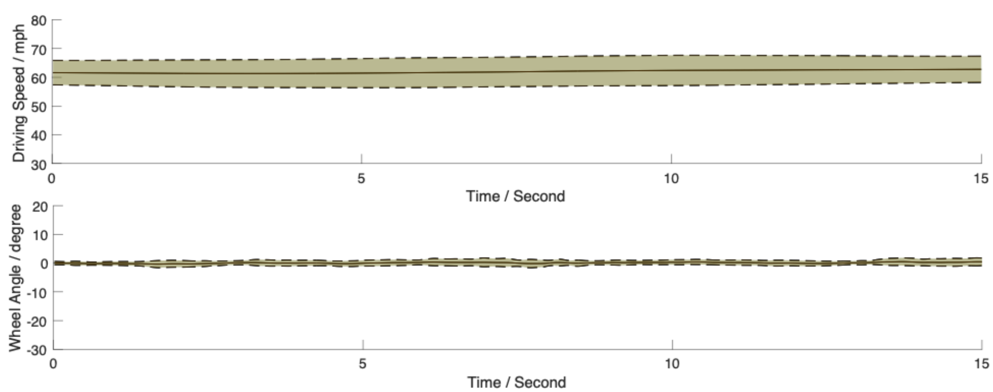
Figure 14. Sample of a Participant’s Driving Behavior (Vehicle Speed and Steering Wheel Angle), Body Trajectory, and Eye Gaze in an L0-Manual-Driving Condition



3.4.1 Lane Keeping

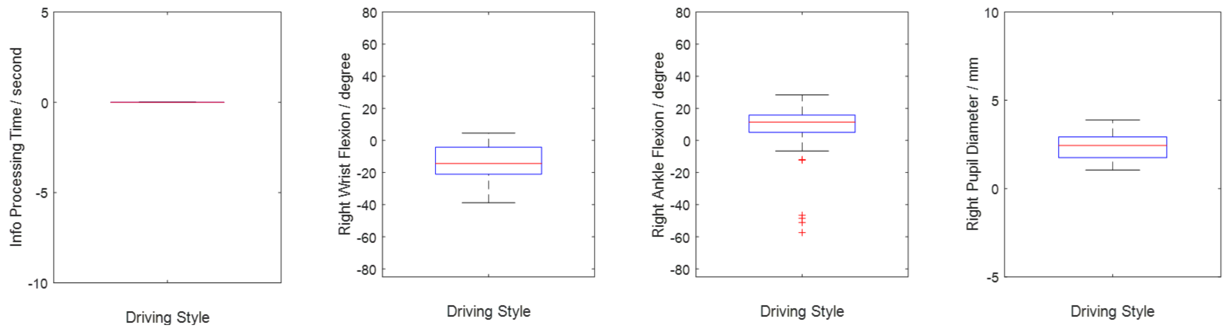
For the lane-keeping task, it is observed that the driving speed remained nearly constant (around 65 mph) across the time interval with minimal fluctuation (Figure 15). And the steering wheel angle also remained consistent and nearly flat across the 15 seconds (Figure 15). The steering wheel angles hovered around zero degrees, indicating that very little or no steering activity was required to maintain lane position during the task. During their lane keeping tasks, most of the participants displayed a negative wrist flexion and a positive ankle flexion, and all the pupil diameters were less than 5 mm (Figure 16).

Figure 15. Driving Speed and Steering Wheel Angle for 15 Seconds During Manual Lane Keeping



The data record started at the time of a risky takeover request that was about to be issued in an L3 condition. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 16. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in a Manual Lane-Keeping Condition

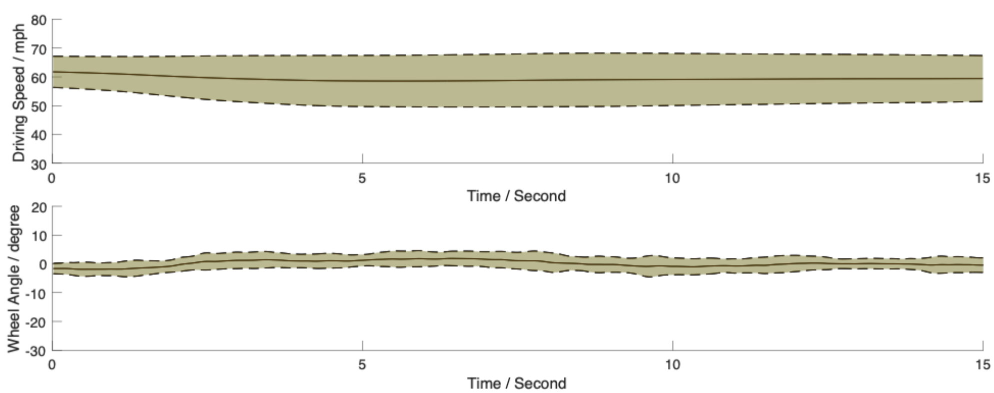


The metrics are averaged over a 15-second across all participants.

3.4.2 Lane Changing

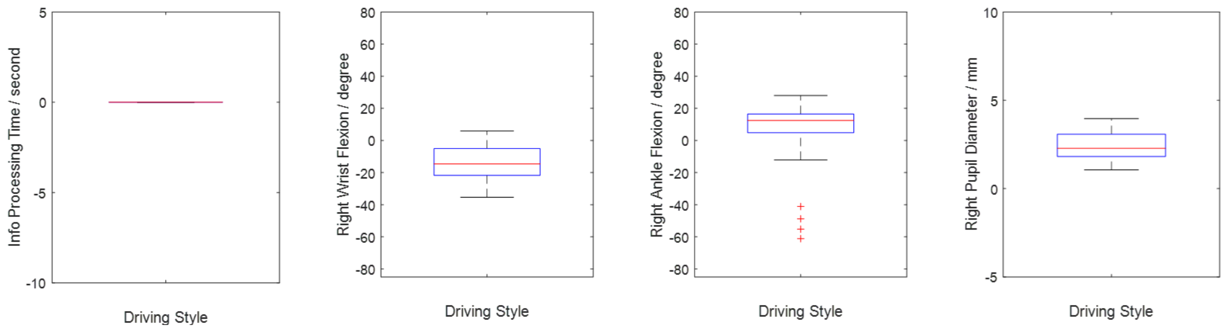
For the lane-changing task, participants maintained a relatively steady driving speed as illustrated in Figure 17. However, there was a noticeably larger variance in driving speed compared to the lane-keeping condition (Section 3.4.1). The steering wheel angle also exhibited more noticeable fluctuations (Figure 17). Similar trends were observed between lane-changing and lane-keeping, as evidenced by similar mean and standard deviation values for wrist flexion angle, ankle flexion angle, and pupil diameters (Figure 18). The manual action of lane changing did not result in significant differences in flexion angles or pupil diameters.

Figure 17. Driving Speed and Steering Wheel Angle for 15 Seconds During Manual Lane Changing



The data record started at the time of a risky takeover request that was about to be issued in an L3 condition. The solid line represents the mean and the shaded areas denote the standard deviation for the specific condition across all participants.

Figure 18. Selected Metrics from Driving Performance, Body Posture, and Eye Movement in a Manual Lane-Changing Condition



The metrics are averaged over a 15-second across all participants.

3.5 Short-Term Behavioral Changes When Switching Between Driving Modes

Transitions between manual driving (L0), conditional automation (L3), and full driving automation (L5) presented notable changes in how drivers interact with the vehicle and their overall driving behavior.

In manual driving (L0), drivers exerted full control over steering, braking, and acceleration, which generally resulted in stable driving speeds and consistent steering during simple tasks such as lane keeping, but variability increased with more complex tasks like lane changing. Upon transitioning to L3, where the vehicle takes over all driving functions under certain conditions but still requires driver readiness for potential interventions, a shift in driving performance metrics is observed. Notably, in L3, both conservative and risky modes showed a tendency towards a gradual decrease in speed and increased steering variability during takeover scenarios compared to manual driving. The onset of speed reduction and steering fluctuations tends to be more pronounced in the risky mode. This indicates that automation may introduce a different pattern of response depending on the timing of the takeover request being issued. Moving to L5, where the vehicle assumes complete control, leads to highly precise and consistent management of driving speeds and steering.

Changes in body posture are particularly indicative of drivers' state and readiness during the transitions. In manual driving, negative wrist flexion (indicating wrist extension) and consistent ankle movements suggest a more physically tense posture. Conversely, during L3, increased wrist flexion, particularly in conservative mode, and more variable ankle movements are observed, indicating a preparatory postural need for potential vehicle takeover. Transitioning from L3 to L5 shows less wrist flexion in conservative modes and more in risky modes, suggesting that drivers' expectations of the vehicle's actions influence their physical readiness. It is important to note that the terms "conservative" and "risky" have different implications in L3 and L5: at Level 3, these terms refer to the timing of takeover requested by vehicles, whereas at Level 5, these terms indicate the timing of the actions initiated by vehicles.

Eye movement patterns changed with different levels of vehicle automation, reflecting shifts in drivers' role. In manual driving (L0), eye movements are typically consistent, reflecting active scanning of the environment and continuous vehicle control. However, with L3 automation, there may be periods when drivers' visual engagement decreases as the vehicle takes over primary driving functions. As drivers transition from manual (L0) through L3 to full automation (L5), the variability in pupil diameter tends to increase. This suggested that there are shifts in cognitive load or changes in the focus of attention, as drivers adjust from actively managing the driving process to possibly engaging in secondary tasks while monitoring the vehicle's autonomous operations.

Considering the observed changes in driving performance, body posture, and eye movement across different levels of vehicle automation, there are several recommendations for vehicle design and training that can effectively address these short-term behavioral shifts. Firstly, adaptive interface and alarm systems should be implemented to effectively capture drivers' attention across all automation levels. These systems should utilize multimodal cues—visual, auditory, and haptic—to ensure drivers can quickly and easily understand when intervention is needed, thus improving response time and accuracy. Secondly, the ergonomic design of vehicle controls should be enhanced to ease the physical and posture demands during transitions between different SAE automation levels, which includes developing adjustable seating and steering mechanisms that adapt to drivers' physical state, promoting readiness and comfort. Additionally, training programs focusing on cognitive load management should be developed to facilitate drivers' multitasking capabilities, complemented by workshops that increase driver awareness about the behavioral impacts of transitioning between different levels of automation.

3.6 Study Limitations and Future Research Directions

The study has limitations regarding the sample and the technological constraints of the equipment. While the use of convenience samples from the university student body provides insight into a segment of the driving population (predominantly younger individuals), it does not fully represent the diverse spectrum of drivers on the road. Future studies could enhance participant diversity by recruiting individuals across a broader range of ages, cultural backgrounds, and other demographic characteristics. Although driving simulators work well for controlled experimental conditions, they do not completely capture the complexities of real traffic situations, which could impact the generalizability of the findings. On-road studies, though more challenging to implement, could provide valuable complementary data to simulator-based findings. Regarding equipment, the motion capture systems and eye trackers used are well-suited for laboratory settings but adapting them for on-road testing might require careful consideration. Future research, in this case, could address these limitations by conducting on-road studies, expanding the demographic range of participants, and utilizing equipment suitable for on-road testing.

Additionally, this study did not include an in-depth analysis of the questionnaire responses collected from participants; it only reported basic data such as handedness, years of driving experience, level of trust in automated vehicles, and self-assessed driving behavior. Specifically, the self-assessments revealed that 11 participants identified themselves as safe drivers, while one considered themselves a risky driver. These assessments were based on responses to the question, "Would you consider yourself to be a safe driver or take more risks?" The motivations behind one participant's identification as a risky driver and the reliability of this self-reporting require further exploration. To validate these self-perceptions and achieve a deeper understanding of drivers' behaviors, future studies could analyze participants' driving histories in more detail, correlate self-assessments with actual driving data, and consider attitudes toward driving. Integrating physiological data collected via smartwatches, such as heart rate and blood volume pulse, could also provide insights into the correlations between physiological responses, subjective assessments (of driving experience, trust in automated vehicles, and others), and actual driving behaviors under varying conditions.

4. Summary & Conclusions

Autonomous vehicles are transforming car rental and ridesharing industries, potentially merging them into a unified model of on-demand transportation for both uncommon (e.g., business trips) and daily commuting. Understanding human behavior towards these autonomous driving vehicles through an exploratory study can reveal the challenges and opportunities associated with varying levels of vehicle automation. This study investigated human behavior, including body posture, eye movement metrics, and overall driving performance, to accomplish two main objectives: (a) identifying behavioral differences in drivers operating vehicles at various levels of automation and (b) exploring how these behaviors vary with different assistance feature styles, specifically between risky and conservative modes.

To accomplish these goals, we conducted human-subject experiments and found the following: (1) driving performance: drivers exhibited stable speed and steering control at Levels 0 and 5, while speed decreased and steering variability increased more obviously at Level 3; (2) driving posture: a tense posture was noted at Level 0, with potential posture preparation (i.e., posture transition) needed for takeover actions at Level 3 and posture readiness influenced by assistance features at Level 5; and (3) eye movement: active scanning and continuous control were maintained at Level 0, with notable shifts in attention at Levels 3 and 5.

From these findings, we recommend: (i) implementing interfaces and alarm systems with multimodal cues—visual, auditory, and haptic—to enhance drivers' attention and response across all levels of automation; (ii) enhancing vehicle ergonomics to reduce physical demands during transitions between SAE levels; and (iii) developing training programs for cognitive load management and conducting workshops to increase driver awareness of the effects of transitioning between automation levels.

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About the Authors

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Pranav Meda is a second-year student in San José State University's Human Factors & Ergonomics MS program, concentrating in User Experience. He received his B.A. from University of California, Los Angeles in Psychology and Cognitive Science in 2017 and is a lead graduate researcher for the Biomechanics and Ergonomics in Environment-Persons Interaction and Collaboration Laboratory (BE-EPIC) Lab. His research focuses on digital design usability, substance abuse /public health and human-device interaction. This involves projects ranging from the usability of an e-commerce mobile application to human driving behavior in autonomous vehicular systems. This spectrum of versatility represents Pranav's expertise in qualitative and UX design work to experimental research quantified with physiological data obtained with the assistance of devices such as motion capture systems, heart rate monitors, and eye-tracking systems, and through subjective measures such as questionnaires. Pranav has authored two papers: one about substance use disorders and the other about the application of upper limb exoskeletons for use in pediatric rehabilitation.

Aubrey Victoria Contreras

Aubrey Victoria Contreras is a graduate student majoring in M.S. Human Factor Ergonomics at San José State University. She received her B.A. in Psychology from University of California, Davis in 2017. She has 7+ years of public service experience working with the Department of Transportation in a Project and Program Management capacity. Her research interests include automotive and driver behavior, patient safety and healthcare, and consumer applications to better improve the usability, accessibility, safety and enjoyment of these products and environments.

Wei-Hsiang Lo

Wei-Hsiang Lo is a graduate student majoring in M.S. Human Factors Ergonomics at San José State University. He received his B.A. in Industrial Design from Shih Chien University in 2021. He currently works as a research assistant and lab manager in the Behavior, Accessibility, and Technology (BAT) Lab. He is passionate about developing inclusive solutions and assistive tools for diverse user groups, such as older adults and individuals with hearing impairments. His research focuses on creating human-machine interfaces (HMIs) that connect human capabilities with automation and AI systems to enhance human performance and promote inclusivity. His work aims to ensure that all users can safely access and benefit from technology.

Gaojian Huang, PhD

Dr. Gaojian Huang is an Assistant Professor in the Department of Industrial and Systems Engineering at San José State University and the director of the Behavior, Accessibility, and Technology (BAT) Lab. He specializes in human-centered automation systems, human-machine interfaces, human-AI collaboration, and inclusive design. His research focuses on the design of adaptive human-automation/AI systems that enhance human decision-making and performance. He develops and evaluates technologies to improve accessibility for diverse user populations, including older adults and individuals with disabilities, by creating adaptive systems tailored to user capabilities and context, such as multimodal interfaces integrating augmented reality and haptic feedback. His research is supported by grants from the National Science Foundation, the U.S. Department of Transportation, the National Institutes of Health (NIH), and industry, and is disseminated through more than 50 research publications.

Yue Luo, PhD

Dr. Yue Luo is an Assistant Professor from the Department of Industrial and Systems Engineering at San José State University. She is the lab director for the Biomechanics, and Ergonomics in Environment-Persons Interaction and Collaboration Laboratory (BE-EPIC) Lab. Her research focuses on human-centered evaluation in multi-agent systems. This includes assessment of physical and physiological interactions between non-human agents (e.g., robots and autonomous vehicles) and individuals from diverse demographics (e.g., older adults). These interactions are quantified and analyzed by objective data collected via wearable technologies (e.g., motion capture systems, electromyography, and eye-tracking systems) and through subjective measures, such as questionnaires. Dr. Luo has authored more than thirty papers on human-robot interaction, digital human modeling, motor behavior and control, and inclusive design. Part of her research is supported by grants from the National Science Foundation and the U.S. Department of Transportation.

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