Enhancing Human-Autonomous System Interaction and Team Dynamics in Automated Driving Systems

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Abstract

As Automated Driving Systems (ADS) advance toward higher levels of automation (SAE Levels 3-5), the role of human drivers is shifting from active control to supervision and intervention. However, traditional human-automation interaction frameworks do not fully account for the dynamic team-based coordination required for effective ADS integration. Poor adaptability and coordination between drivers and ADS can result in critical safety failures, as seen in real-world incidents. This research focuses on human-autonomy teaming (HAT) in ADS, focusing on collaborative adaptation, shared decision making, and real-time interaction metrics to improve safety and user experience. By incorporating team cognition theory and layered dynamical models, this research aims to develop human-machine teaming metrics that facilitate adaptive and context-aware cooperation. Key research questions include: (1) How do human drivers and ADS dynamically interact? (2) What team cognition metrics effectively measure human ADS adaptability? (3) How can real-time analytics improve driver-ADS collaboration and safety?

Introduction

vehicle relationship, shifting responsibilities from manual control to shared autonomy (Figure 1). SAE defines six levels of driving automation, ranging from Level 0 (fully manual) to Level 5 (fully autonomous) (SAE, 2021). While higher levels of automation promise increased efficiency and safety, real-world implementation is fraught with challenges related to human-ADS coordination, adaptability (Flemisch et al., 2012; Tinga et al., 2023), and trust (Kraus et al., 2020; Lee and See, 2004; Walke et al., 2016). The transition to full autonomy requires robust interaction models that account for the evolving role of human drivers in a human-machine teaming framework.

Human-autonomy teaming (HATs) presents a promising paradigm for addressing these challenges by treating human drivers and ADS as interdependent team members rather than separate entities. Research highlights that failures in human-automation coordination—rather than system malfunctions—are a major cause of ADS-related accidents. In the well-documented 2018 Arizona fatal crash, the lack of real-time adaptability between the driver and the automated

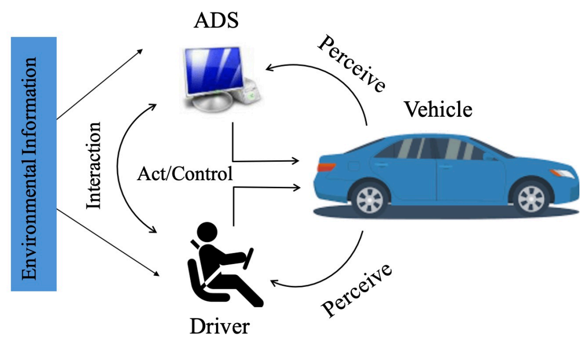


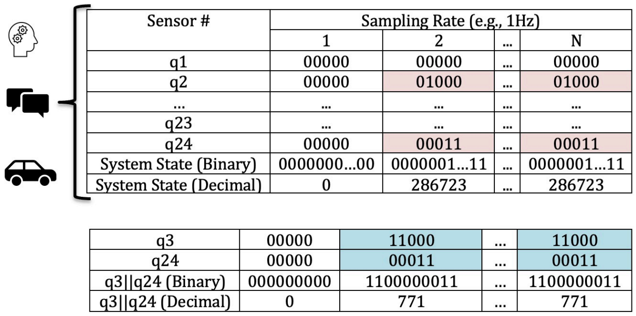
Figure 1: presents a driver-vehicle system where the human driver and automated driving agents cooperatively share and achieve the same driving task as a team.

system contributed to the collision (Stanton et al., 2019). To mitigate such risks, this study proposes the integration of team cognition theory and real-time adaptation metrics to enhance human-ADS collaboration. By understanding and modeling these dynamics, we aim to develop practical contributions for designing ADS interfaces that foster safe, effective, and satisfactory teamwork between humans and automation.

Background

HATs in ADS research emphasize coordination, cooperation, and collaboration between drivers and automated systems (Lee et al., 2023). Poor coordination has been linked to maladaptive responses in critical driving situations, while effective teamwork can improve safety and operational efficiency (Gorman and Wiltshire, 2024). Given the dynamic nature of driving, both the human driver and the ADS must adapt to each other as well as to evolving environmental conditions (Kolekar et al., 2020).

Studies suggest that adaptability is crucial for effective ADS deployment. A team that quickly and effectively adapts to unexpected situations can maintain operational robustness and mitigate risks (CFR, 2021). However, adaptability in the human-ADS interaction is difficult to measure directly. Researchers have proposed simulation-based experiments that evaluate adaptability through behavioral and physiological indicators, including reaction time, steering response, and



Sensor #	Sampling Rate (e.g., 1Hz)			
	1	2	...	N
q1	00000	00000	...	00000
q2	00000	01000	...	01000
...	...	...	...	...
q23	...	...	...	...
q24	00000	00011	...	00011
System State (Binary)	0000000...00	0000001...11	...	0000001...11
System State (Decimal)	0	286723	...	286723

q3	00000	11000	...	11000
q24	00000	00011	...	00011
q3||q24 (Binary)	000000000	1100000011	...	1100000011
q3||q24 (Decimal)	0	771	...	771

Figure 2: The layered dynamics approach (Gorman et al., 2019)

eye tracking data (Petermeijer et al., 2015; Louw et al., 2017). To enhance human-ADS teamwork, dynamic team cognition models have been introduced, integrating real-time metrics that assess reorganization and adaptability in response to environmental stressors (Gorman et al., 2020).

Existing ADS frameworks focus primarily on binary task allocation between humans and automation, rather than fostering a dynamic, interdependent team structure. This limitation is especially problematic for SAE Levels 2 and 3, where manual and automated driving tasks are blended. The design of driver-ADS teams should consider not only task distribution, but also the interdependent nature of their relationship. Research suggests that a layered dynamics approach, using computational models to track real-time team states, can provide valuable insights into human-vehicle coordination and adaptability (Gorman et al., 2019).

Layered dynamics offer a computationally efficient way to track team states without requiring prior specification (Gorman et al., 2019). The model processes denoised and time-synchronized data by converting it into symbolic time series, which represent the evolving states captured by sensors over time. A dynamical system is generally characterized as a collection of trajectories (velocity vectors) mapped over a state space of variables. These trajectories follow a function that correlates system behavior at time $t(i)$ with behavior at time $t(i+n)$, where $t(i)$ is the current time and $t(i+n)$ is a future point in time.

In the context of team cognition, the dynamical system is defined as a set Q of interacting elements q_i, where $q_i \epsilon Q$, and $\cup q = Q$, while $q_i \bigcap q_j = \phi$ for all $i \neq j$(i.e., exhaustive and mutually exclusive). Each element qi corresponds to a sensor (e.g., speech sensor, physiological sensor, machine sensor) that monitors the changing states of system elements over time (e.g., at a 1 Hz sampling rate). By ensuring that qi is mutually exclusive, every possible combination of elemental states results in a unique team state $Q^{'}$. The symbolic states (e.g., on/off) of each qi are concatenated (e.g., $q_i \parallel q_j$) to generate new states. Figure 2 illustrates the layered dynamics approach (Gorman et al., 2019), showing how this model produces time series of team/system states $Q^{'}$ to track the ongoing reorganization of team states over time. Additionally, it enables the analysis of joint states across subsets of system elements (e.g., $q_i \parallel q_j$) to assess the impact

System (Q)	Sensor	Active State
Vehicle (q_v)	q_1 (alarm/warning)	10000
	q_2 (adaptive cruise control)	01000
	q_3 (keeping distance)	11000
	q_4 (lane keeping assist)	00100
	q_5 (speed)	10100
	q_6 (direction)	01100
Human (q_h)	q_7 (Eye tracking)	11100
	q_8 (ECG)	00010
	q_9 (SC)	10010
	q_{10} (fNIRs)	01010
	q_{11} (Respiration)	11010
Vehicle Control (q_{cv})	q_{12} (vehicle uses flasher)	00110
	q_{13} (vehicle accelerates)	10110
	q_{14} (vehicle decelerates)	01110
	q_{15} (vehicle moves steering wheel)	11110
	q_{16} (vehicle brakes)	00001
	q_{17} (vehicle changes speed)	10001
Human Control (q_{ch})	q_{18} (human driver uses flasher)	01001
	q_{19} (human driver accelerates)	11001
	q_{20} (human driver decelerates)	00101
	q_{21} (human driver moves steering wheel)	10101
	q_{22} (human driver brakes)	01101
	q_{23} (human driver changes speed)	11101

Table 1: Overview of the sensors in the Human-Autonomous Driving System Vector (Q)/ Layered Dynamics in human-ADS teaming

of individual elements on overall team/system reorganization. Binary symbols are employed to enhance the computational efficiency of mapping individual states to team states for real-time analysis. As long as the set of binary symbols is both mutually exclusive and exhaustive, binary addition across individual states at each time point yields a unique team state (Gorman et al., 2019). We adapted this model to the human-ADS teaming (see Table 1).

Approach

This study applies team cognition theory to model the real-time dynamics of human-ADS interaction. The layered dynamics approach enables team state tracking through sensor data, capturing how the driver and ADS jointly navigate driving tasks. Two key interactive states—reorganization and influence—will be computed from the layered dynam-

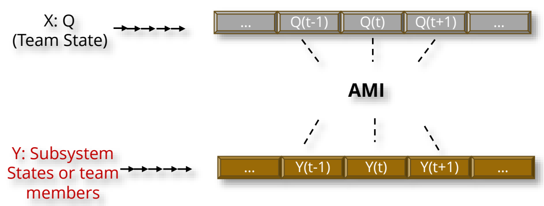


Figure 3: Influence is calculated as the average mutual information (AMI) between "lower level" and "higher level"

ics time series. Reorganization will be measured using moving window entropy (Equation 1) to assess adaptation and recovery, while influence will be calculated using mutual information metrics to quantify the degree to which individual components affect the system state.

General Adaptive Response (GAR): The general adaptive response (GAR; Gorman et al., 2018; Gorman et al., 2020) is a response mechanism that predicts survival and success in living systems and systems that interact with living components. GAR metrics are computed from reorganization time series (Stevens et al., 2018). A reorganization time series is computed as the moving window (ws = window size) entropy (Shannon and Weaver, 1949) of the team state time series.

$$\text{Entropy} = -\sum_{k}^{K} p_k \times \log_2 p_k \tag{1}$$

Influence: Influence is the degree to which individual actions change patterns at the system level (Reitman et al., under review). Our influence metric is rooted in the information theoretic quantity mutual information (Cover and Thomas, 2006), which is how much process Y (e.g., an individual's actions) tells us about process X (e.g., change in system state) and vice versa. Influence will be computed using the mutual information (AMI; Cover and Thomas, 2006) between the time series inputs using a moving win-dow of size ws (Figure 3).

$$\begin{aligned} \text{AMI}_{XY} &= \sum_{x,y} P_{XY}(x_i, y_j) \log_2\Big[\frac{P_{XY}(x_i, y_j)}{P_X(x_i) P_Y(y_j)}\Big] \\ &= \text{Infl}(X, Y) \end{aligned} \tag{2}$$

To evaluate our model, we developed a modifiable scenario that can be run in the driving simulator to achieve the research objectives. Experiment introduces a driving scenario with unexpected events requiring variable amounts of adaptation across human and system layers within human-ADS teaming to overcome unexpected events. Physiological and behavioral data, including reaction time, gaze tracking, and driver intervention rates, will be collected and analyzed to validate the layered dynamics model. Within the experiment, we will analyze GAR metrics and influence distributions to examine the validity of adaptation and reorganization measures in human autonomous driving systems. These experiments will include two driving scenarios—neutral and stressful (Figure 4)—each designed to introduce controlled

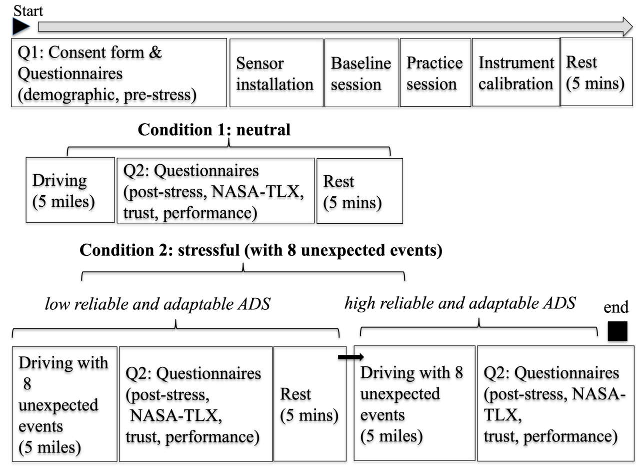


Figure 4: Experiment Process

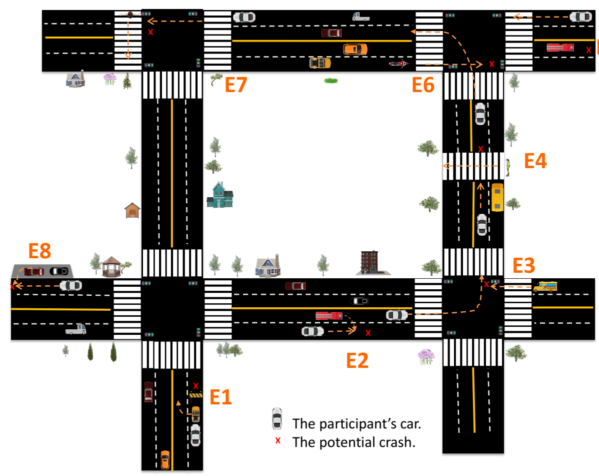


Figure 5: Driving Scenario

perturbations to assess how well human-ADS teams adapt to environmental changes. The experiment will conduct in a driving simulator. A series of designed events would happen in the neutral and stressful scenarios when the participants approached specific places. These events imitated real-life traffic conditions. Only eight of the unexpected events differed between the neutral and stressful scenarios in the response of other road users; other road designs and events were the same. The eight events are illustrated in Figure 5. Additionally, this study will explore subjective experiences such as trust and workload, alongside objective team performance scores, to determine whether reorganization and influence metrics can predict human-ADS teaming effectiveness. Machine learning classifiers, including neural networks and support vector machines, will be used to analyze the collected data, enabling the development of predictive models for adaptive human-ADS interaction.

Expected Outcomes

This research aims to develop real-time adaptation metrics that enhance the effectiveness of human–Automated Driving System (ADS) teamwork. We anticipate that mean entropy values—or reorganization—during perturbations will be higher than in normal (non-perturbed) segments, reflecting variations in team members' influence distributions. These findings can inform real-time metrics that enable drivers and ADS to interact and adapt more effectively, thereby helping to prevent potential crashes. Key expected outcomes include:

- Real-time adaptation metrics: Objective measures for assessing adaptability in human-ADS interaction, including entropy-based reorganization and mutual information-based influence metrics.
- Enhanced driver-ADS coordination: Insights into how predictive analytics can optimize system behavior and improve dynamic interaction between human drivers and automation.
- Increased trust and transparency: Design guidelines for ADS interfaces that foster intuitive collaboration and strengthen driver confidence in automation.
- Improved safety and efficiency: Practical recommendations for integrating adaptive teaming models into ADS design, ensuring more robust and resilient automated driving experiences.

Conclusion

This study underscores the importance of modeling human-ADS interaction through a team-based approach that emphasizes adaptability, coordination, and shared decision-making. By applying real-time cognition metrics and machine learning techniques, we aim to develop robust indicators of human-ADS teamwork that can be used to enhance automation safety and efficiency. Future work will extend these findings by developing an adaptive agent that can dynamically evaluate human-ADS performance and provide real-time assistance during demanding situations. This work will leverage validated team cognition metrics to optimize human automation collaboration, ultimately leading to more intuitive and reliable ADS systems.

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