Open-Loop Naturalistic Driving: An Assessment of Human Behavior, Performance, and Physiology to Support the Development of Shared Control Strategies

Maya S. Luster and Brandon J. Pitts
Purdue University, West Lafayette, IN

Advanced systems that require shared control are becoming increasingly pervasive. One advantage of a shared control approach is that the human and machine work together to accomplish safe operations. However, data about the human is needed to implement successful strategies. The goal of this study was to quantify naturalistic driving by collecting performance and physiological data during manual, open-loop driving. Sixteen participants performed a single drive that included four sudden obstacles of increasing difficulty (road debris, construction, inclement weather, and an animal). Participants were asked to traverse each obstacle using self-employed judgement and strategies. Action selection, lane deviation, speed, and heart rate data were recorded. Results showed two distinct driving strategies for avoiding the moving obstacle/animal (left vs. right lane navigation). Also, maximum speed was affected by obstacle type, but heart rate variability was not. Results can be used to inform shared control algorithms designed to combat poor driving performance.

INTRODUCTION

The past decade has witnessed the introduction of advanced systems that require shared control. For example, semi-autonomous vehicles are assuming more control of driving dynamics, while there are still portions of the driving task that are the responsibility of human drivers. Shared control has the potential to provide additional roadway safety to drivers by taking over vehicle operations during critical situations. For example, if a driver maneuvers to avoid road objects, e.g., debris, such action can result in serious accidents. A report found that "nearly 37[%] of all deaths in road debris crashes resulted from the driver swerving to avoid hitting an object" (Tefft, 2016). Thus, in this setting, shared control can help to ensure safety by deploying swift and accurate interventions during off-nominal, adverse events.

Marcano et al. (2020) adapted Abbink et al. (2018)'s definition of shared control to the driving context and suggests that: "The driver and the steering assistance system interact congruently in a perception-action cycle to execute a dynamic driving task that either the driver or the system could execute individually under ideal circumstance." Many researchers are investigating how to model shared control for driving tasks to better design vehicle control algorithms (e.g., Guo et al., 2019; C. Huang et al., 2021; Marcano et al., 2020; Terken & Pfleging, 2020). They acknowledge the need to understand both drivers' state and performance under a variety of complex situations. To do so, it is important to first characterize naturalistic driving behaviors in the absence of any automated assistance to understand how the human responds to unexpected events. This knowledge can enable the modeling and predicting of human actions as a function of dynamics of the environment and, in turn, be used to implement real-time control strategies to counteract poor driving performance.

Wang et al. (2020) and others posit that there are no agreed-upon methods for determining which and when functions should be assigned to the automation versus the human. One approach is task-level shared control, such as an adaptive cruise control (ACC) function, where the human operator allocates a subtask to the automated agent while executing other subtasks (Wang et al., 2020). A second architecture is servo-level shared control that involves autonomous agents automatically assuming task-specific control via direct or indirect shared control. For direct shared control, the human and the automated agent work simultaneously to execute an action, where the vehicle receives inputs from both the human and the automatic controller (e.g., the human turns the steering wheel and the controller adds more torque). In the case of indirect shared control, for example, an automated vehicle estimates the driver's desired steering wheel angle and applies that value directly to the control module of the wheels (without direct human input) (Wang et al., 2020). Researchers have modeled servo-level decision-making strategies of automated driving agents by applying concepts such as rule-based piecewise functions, exponential functions, and U-shape functions, in addition to game-theory based models, such as Nash and Stackelberg equilibriums (e.g., Benloucif et al., 2019; Y. Li et al., 2015). However, these approaches focus on vehicle dynamics and have not considered the role and behavior of the driver – which is a critical component of a shared control system.

Wang et al. (2020)'s review paper also highlights approaches to modeling human driving behavior, including sensory dynamics (e.g., visual and auditory), cognition, and neuromuscular-skeletal dynamics. Sensing techniques for understanding visual sensory dynamic information, e.g., eye gaze/tracking, have been used to access driver-related behavior such as intent, fatigue, and readiness to take-over during conditional driving automation (X. Li et al., 2018; Mandal et al., 2016; Zhou et al., 2021). But, other psychophysiological methods, such as heart rate monitoring, electroencephalography (EEG) and galvanic skin response (GSR), have not yet been fully exploited for use in shared control contexts. Wang et al. (2020) proposes that in the context of shared authority "exploiting brain-related signals could directly offer rich information about human driver intent, ability, and thus allow us to optimize the allocation of authority and reduce the conflict between two agents."

To provide empirical data that can be used to design driving-related shared control, we developed a study to observe naturalistic driving behaviors. Our specific goal was to quantify driving strategies and cognitive states when drivers experience unexpected obstacles. To this end, an experiment was designed that involved driving with various unexpected events hidden in the environment that could be encountered during daily driving. Also, to begin addressing the research gaps related to the use of sensing techniques that can help to characterize driving behavior, we employed cardiological-related physiological methods. Ultimately, this work can be used to inform the development of algorithms to create more robust shared control strategies implemented within the context of emerging human-autonomy systems across a wide range of complex environments.

METHOD

Participants

Sixteen participants (8 males, 7 females, 1 non-binary), with a mean age of 21.63 years (SD = 4.79), volunteered for this study. Participants were students recruited from Purdue University. The average number of years driven within the U.S. across participants was 4.53 years (range: 1.5 to 10), and the average of years driven outside of the U.S. was 5.22 years (range: 1.5 to 15). For the three miles driven categories: five out of the 16 participants reported driving less than 10k miles/year, nine drove an average of 12k miles/year, and two reported driving more than 15k miles/year (all pre-COVID-19 travel estimations). This study was approved by the Purdue University Institutional Review Board (IRB-2020-755).

Equipment

This study used a fixed-based medium-fidelity driving simulator developed by the National Advanced Driving Simulator (NADS), miniSIM^{TM}. The system is equipped with three 48-inch monitors and one 18.5-inch monitor for displaying the driving environment and the vehicle dashboard display, respectively. There are also two foot-pedals and a steering wheel to capture driver inputs. The miniSIM^{TM} system's sampling rate is 60Hz.

In addition, heart rate-related data was collected using the Polar H10 heart monitor that was placed on participants' chest under the sternum, above the stomach. The RR interval series was measured throughout the driving experiment at a sampling rate of 130Hz.

Driving Scenario and Independent Variable

The driving scenario was a two-lane rural road environment. The roadway topography consisted of multiple curves, hills, and straight, flat segments. Four obstacles (the independent variable) were placed throughout the drive and appeared approximately 5-8 minutes apart from one-another (see Figure 1 for a sample road network). The obstacles were intentionally selected to represent increasing levels of difficulty, in terms of how drivers might avoid the obstacle (see Table 1), as identified as "unexpected/relevant objects derived from normal driving scenarios" in Thorn et al. (2018)'s NHTSA report.

Table 1: Independent variable (obstacle: 4 levels) ordered in terms of difficulty

Level of Difficulty	Description	Obstacle Type
1	*Tire* – an old tire in the center of the subject's driving lane to mimic road debris	Small static object
2	*Construction Zone* – road signs, barriers, workers, and a cement truck	Large static objects
3	*Rain & High Winds* – a brief (~ 5 sec) onset of heavy rain and high velocity wind gusts	Small dynamic event
4	*Deer* – initially hidden by stalled 18-wheeler, emerged into road, crossed driver's lane, and stopped in middle of road	Large dynamic object

A 4 x 4 Latin Square Design was utilized to counterbalance ordering effects across participants. On-coming vehicles, in the left adjacent lane, were randomly presented throughout the drive, but not when the subject's vehicle was approaching an obstacle event. Also, obstacles were hidden in the environment until participants approached them. To help make the obstacles less visible, stalled vehicles were present along the shoulder of the road during the drive, two of which were decoys, and the other was an 18-wheeler tractor trailer (which masked the deer obstacle). This was done to ensure that participants did not see the upcoming obstacle (deer), before it suddenly walked into the middle of the road. There was only one leading vehicle during the drive, which related to the construction zone obstacle (more details in Procedure section below).

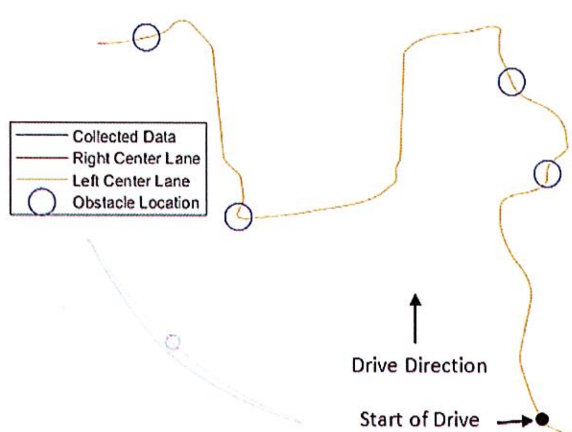

Figure 1. Bird's-eye view of sample road network of driving scenario with right and left reference lanes and driver (collected) data; zoomed in reference window (left-side image)

Procedure

Participants were first asked to sign a consent form. Next, the heart rate sensor was placed on them. Afterwards, they were given a practice drive on an open highway (different from the actual drive) to familiarize themselves with the driving simulator. The actual driving scenario was comprised of the four obstacles that unexpectedly appeared along the drive, precipitating the need for an avoidance task. Participants were instructed to drive along the rural road (see Figure 2) and avoid any obstacles in the roadway that might be present. Specifically, each participant was given the same set of instructions: (1) drive as you normally would on the road, (2) drive at 60 mph, or any other posted speed sign, and if anything in the environment makes you cautious, do what you think is best, for example, (3) you can steer or go around an obstacle to ensure that you maintain control of your vehicle at all times, (4) however, do not come to a complete stop and do not pass any traffic/leading vehicles. The only leading vehicle in the driving scenario was a leading cement truck that merged into traffic and led the participant to the construction zone obstacle. This truck was designed to keep the construction zone hidden until participants reached the zone and, at that time, the cement truck exited to the shoulder and the obstacle (signs, barricades, and construction workers) was revealed.

Each participant drove the scenario only once and was not made aware of the (different types of) obstacles nor when they would occur. Participants were also not guided on how they should avoid any obstacle. The drive lasted approximately 30 minutes, with three intermediate breaks, during which they completed a NASA-TLX subjective workload assessment (Hart & Staveland, 1988) (Hart & Staveland, 1988) after each obstacle occurrence.

Figure 2. Sample participant driving on rural road

Dependent Measures and Data Analysis

The dependent measures in this study included: driving performance measures, i.e., maximum speed and deviation during obstacle avoidance, subjective workload ratings (via NASA-TLX), and heart rate variability (HRV).

Driving performance. Maximum speed was measured by the subject vehicle's center of gravity velocity during obstacle avoidance. The maximum deviation (in feet) represented the farthest distance traveled away from the obstacle within the avoidance trajectory (distance between the subject vehicle and the obstacle at the time of avoidance). These measures were captured in a ± 5-second time window before and after the location of the obstacle in order to capture behavior when approaching the obstacle and clearing the obstacle, respectively.

Subjective data. Workload was measured subjectively using an unweighted NASA-TLX workload assessment (Hart & Staveland, 1988) to record perceived workload for avoiding each obstacle event. Each participant rated each of the six items using a 0-20 scale after every obstacle encounter.

Heart Rate Variability. HRV was used to measure objective workload. HRV is a physiological measure often used in Human Factors research to assess mental workload, including reactions to external stimulus (Charles & Nixon, 2019). For HRV, data was captured using a ±15-second time window before and after the obstacle stimulus, while maintaining an interval of time adequate for a ultra-short term (UST) period of analysis (Shaffer & Ginsberg, 2017). Data was also collected for 15 seconds of straight drive time (no external elements), which was used to assess baseline HRV that could be compared to the obstacle segments. HRV can be analyzed using time-domain, frequency-domain, and non-linear metrics. Shaffer & Ginsberg (2017) suggests that time-domain metrics are better for measuring mental workload in regards to sudden stimulus. Thus, we utilized the root mean square of successive RR interval difference (RMSSD) metric, which is conventionally analyzed during 5 minute segments, but has been proposed for UST periods (Baek et al., 2015).

Data Analysis. Observational and statistical analysis was performed on the subjective workload measurement. Also, repeated-measures analysis of variances (ANOVAs) were conducted on the driving performance data (one-way), subjective workload (two-way), and HRV (one-way) using IBM SPSS Statistics 28. Bonferroni corrections were applied for multiple comparisons. Mauchly's test of sphericity and normality were used to evaluate assumptions and were not violated. Results were considered significant at $p < 0.05$.

RESULTS

Driving Strategies and Performance

Participants completed a single drive that included four different obstacle types. Though maximum deviations across obstacles were analyzed, due to the lack of similarity of each obstacle type, direct comparisons of values were not made. For example, the small dynamic obstacle, i.e., rain and wind, would not prompt significant lane deviations compared to a tire in the road, which could cause a collision if not avoided (see Table 2 for average deviation values). Therefore, only driving strategies for each obstacle were examined.

Of the four obstacles, the deer obstacle yielded two distinctive avoidance patterns. In particular, participants either went around by moving into the left lane (in front of the deer) or by staying in the current lane and driving closely between the deer and the stalled 18-wheeler on the shoulder (which had less available vehicle clearance). Seven out of the 16 participants drove behind the deer, while the remaining eight drove in front of the deer. One participant collided with the deer.

Table 2. Average maximum lane deviation per obstacle event

Obstacle Type	Max Deviation (ft)
Tire	10.18
Construction Zone	15.14
Rain & Wind	2.46
Deer (left vs right)	15.37 vs 5.15

Maximum speed (mph). There was a significant main effect of obstacle type on maximum speed, ($F(3, 45) = 11.073$, $p < .001$, partial $\eta^2 = 0.425$). Post-hoc comparisons revealed that drivers' speed was significantly higher for the rain and wind obstacle compared to the tire obstacle (mean difference (M_{diff}) = 6.94 mph, standard error of the mean (SEM) = 2.202, p = 0.039), the construction zone (M_{diff} = 12.41 mph, SEM = 2.034, $p < .001$), and the deer obstacle (M_{diff} = 14.826, SEM = 2.740, $p < .001$) (see Figure 3).

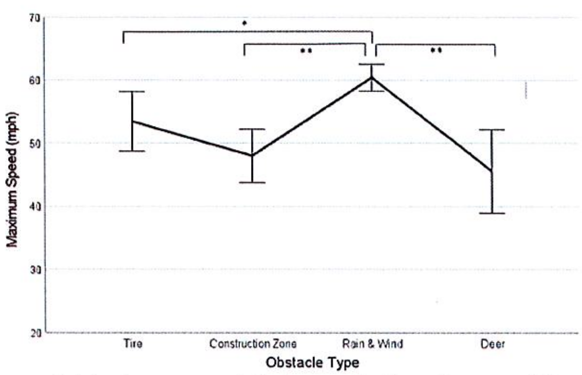

Figure 3. Maximum speed during each obstacle event (*Note.* *: $p < 0.05$, **: $p < .001$, Error bars indicate 95% CI)

Subjective Workload

A two-way repeated-measures ANOVA was conducted on the 4 obstacle types (tire, construction zone, rain and wind, deer) x 6 NASA-TLX un-weighted subscales (mental demand, physical demand, temporal demand, performance, effort, and frustration) (similar to Huang et al., 2019). There was a significant main effect of obstacle type ($F(1, 15) = 28.967$, $p < .001$, partial $\eta^2 = 0.659$) and subscale ($F(1, 15) = 10.325$, $p = .006$, partial $\eta^2 = 0.408$) on workload (see Figure 4). For obstacle type, post-hoc comparisons showed that drivers experienced a significantly higher level of perceived workload during the deer obstacle compared to the tire (M_{diff} = 4.50, SEM = 0.913, p = .001). For workload, drivers perceived the driving task to be more mentally and temporally demanding (mean (M) = 9.31, SEM = 0.684 and M = 11.64, SEM = 0.791, respectively) compared to all other subscales. There was no significant obstacle type x subscale interaction.

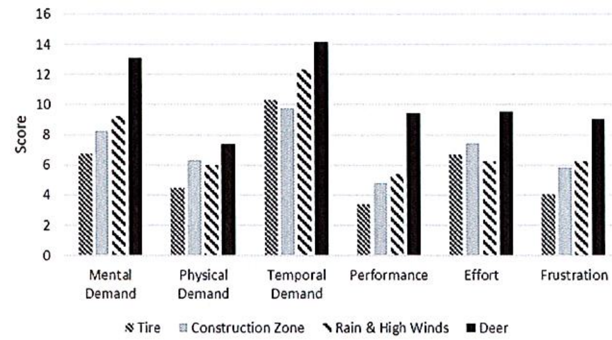

Figure 4. Unweighted NASA-TLX subscale scores for each obstacle type

Heart Rate Variability (RMSSD)

HRV was not significantly affected by obstacle type ($F(4,60) = 0.657$, $p = 0.624$, partial $\eta^2 = 0.042$) (see Figure 5).

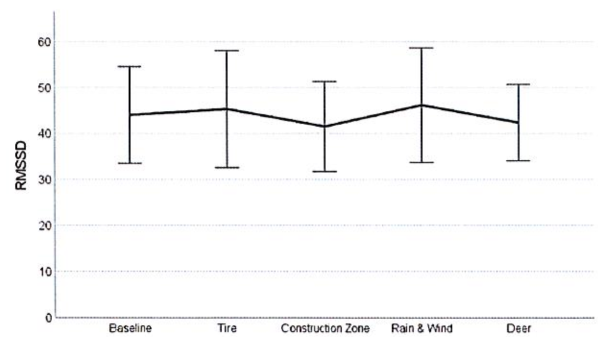

Figure 5. Average square root of mean squared difference between successive RR intervals (RMSSD) (*Note.* Error bars indicate 95% CI)

DISCUSSION

The goal of this study was to observe and quantify naturalistic driving behavior and strategies deployed during the appearance of sudden stimulus. In addition, physiological measures, specifically heart rate variability, was used to collect data about the state of the driver as a prerequisite for designing shared control strategies that can intervene during adverse driving events.

During the dynamic deer obstacle, there were two notable driving strategies of avoidance that emerged: 1) merging into the left lane (driving in front of the deer) and 2) staying in the current lane (going behind the deer), except for one driver who collided with the deer. Czarnecki (2018) reviewed roadway driving behavior based on the size of domestic animals and wildlife that may come into contact with vehicles. This study found that most severe animal-vehicle crashes involved large wild animals, such as a deer. Kaplan & Prato (2012) noted that the "majority of drivers fail to take action when [faced with critical events]," possibly due to objective infrastructural, behavioral, or psychological constraints that result in delayed recognition of and reaction to the critical event. This was partly observed in our study as five of the 16 participants experienced complete stops or collisions with the deer obstacle, though instructed not to.

This may also explain why drivers experienced a significantly higher level of perceived workload, as measured by the NASA-TLX assessment, during the deer obstacle compared to the tire obstacle. The inherent characteristics of the tire obstacle are smaller and less consequential, in terms of damage to the vehicle, if hit. Also, more mental workload may be required to traverse the deer obstacle due to the constant evaluation of the deer's position when deciding how/when to safely overtake it. The objective physiological workload measure, HRV, however, was not significantly affected by obstacle type. This could be due to the UST segments chosen for analysis that, though logical to use for sudden stimulus, may not be enough to capture statistically different HRV effects. Future work will investigate if varying the length of time of obstacle events influences HRV responses.

Maximum speed was affected by the wind and rain obstacle. Czarnecki (2018) explains that drivers' speed selection is often dependent on many factors, including road configurations, traffic, and weather. We speculate that participants traveled at higher speeds during the rain and wind obstacle compared to any of the other obstacles because they may have felt it was less risky to generally maintain speed than to apply hard braking and potentially lose control of the vehicle. Also, compared to the other obstacles, there was no visible sign of imminent collision, given that the duration of obscurity for the rain was approximately 5 seconds and did not fully impair visibility (i.e., the road was still visible through the rain drops on the windshield).

Finally, the lane deviation metric, although not directly compared across obstacles in this study, did provide some insight into the drivers' intent by revealing individual path selection. One common theoretical approach to modeling driving behavior is predictive modeling, i.e., the creation of optimal and/or highly probable trajectories, to help train control algorithms that will be used to develop future automated controllers. The knowledge gained through the metrics explored in this paper support the notion that these methods should be further explored in other contexts.

CONCLUSION

In summary, our study collected data regarding naturalistic behavior during manual, open-loop driving, which can be used to predict actions and develop shared control algorithms for intervening in unsafe, off-nominal conditions. This study represents one area of activity within a larger NSF-funded (NSF # 1836952) Cyber-Physical Systems (CPS) project that seeks to integrate human behavior, performance, and physiological data into theoretical models to be used to design shared control algorithms across various complex domains, e.g., driving, aviation, and defense to improve safety, skillset refinement, and user experience.

References

Abbink, D. A., Carlson, T., Mulder, M., Winter, J. C. F. de, Aminravan, F., Gibo, T. L., & Boer, E. R. (2018). A Topology of Shared Control Systems—Finding Common Ground in Diversity. *IEEE Transactions on Human-Machine Systems*, *48*(5), 509–525. https://doi.org/10.1109/THMS.2018.2791570

Baek, H. J., Cho, C.-H., Cho, J., & Woo, J.-M. (2015). Reliability of Ultra-Short-Term Analysis as a Surrogate of Standard 5-Min Analysis of Heart Rate Variability. *Telemedicine and E-Health*, *21*(5), 404–414. https://doi.org/10.1089/tmj.2014.0104

Benloucif, A., Nguyen, A.-T., Sentouh, C., & Popieul, J.-C. (2019). Cooperative trajectory planning for haptic shared control between driver and automation in highway driving. *IEEE Transactions on Industrial Electronics*, *66*(12), 9846–9857.

Charles, R. L., & Nixon, J. (2019). Measuring mental workload using physiological measures: A systematic review. *Applied Ergonomics*, *74*, 221–232.

Czarnecki, K. (2018). Operational world model ontology for automated driving systems–part 2: Road users, animals, other obstacles, and environmental conditions,". *Waterloo Intelligent Systems Engineering Lab (WISE) Report, University of Waterloo.*

Guo, C., Sentouh, C., Popieul, J.-C., & Haué, J.-B. (2019). Predictive shared steering control for driver override in automated driving: A simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *61*, 326–336. https://doi.org/https://doi.org/10.1016/j.trf.2017.12.005

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In P. A. Hancock & N. B. T.-A. in P. Meshkati (Eds.), *Human Mental Workload* (Vol. 52, pp. 139–183). North-Holland. https://doi.org/https://doi.org/10.1016/S0166-4115(08)62386-9

Huang, C., Lv, C., Hang, P., Hu, Z., & Xing, Y. (2021). HumanMachine Adaptive Shared Control for Safe Driving Under Automation Degradation. *IEEE Intelligent Transportation Systems Magazine*, 2–15. https://doi.org/10.1109/MITS.2021.3065382

Huang, G., Steele, C., Zhang, X., & Pitts, B. J. (2019). Multimodal Cue Combinations: A Possible Approach to Designing In-Vehicle Takeover Requests for Semi-autonomous Driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *63*(1), 1739–1743. https://doi.org/10.1177/1071181319631053

Kaplan, S., & Prato, C. G. (2012). Braking news: link between crash severity and crash avoidance maneuvers. *Transportation Research Record*, *2280*(1), 75–88.

Li, X., Wang, W., & Roetting, M. (2018). Estimating driver's lane-change intent considering driving style and contextual traffic. *IEEE Transactions on Intelligent Transportation Systems*, *20*(9), 3258–3271.

Li, Y., Tee, K. P., Chan, W. L., Yan, R., Chua, Y., & Limbu, D. K. (2015). Continuous role adaptation for human–robot shared control. *IEEE Transactions on Robotics*, *31*(3), 672–681.

Mandal, B., Li, L., Wang, G. S., & Lin, J. (2016). Towards detection of bus driver fatigue based on robust visual analysis of eye state. *IEEE Transactions on Intelligent Transportation Systems*, *18*(3), 545–557.

Marcano, M., Díaz, S., Pérez, J., & Irigoyen, E. (2020). A Review of Shared Control for Automated Vehicles: Theory and Applications. *IEEE Transactions on Human-Machine Systems*, *50*(6), 475–491. https://doi.org/10.1109/THMS.2020.3017748

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms . In *Frontiers in Public Health* (Vol. 5). https://www.frontiersin.org/article/10.3389/fpubh.2017.00258

Tefft, B. C. (2016). *The Prevalence of Motor Vehicle Crashes Involving Road Debris, United States, 2011-2014*. https://aaafoundation.org/prevalence-motor-vehicle-crashes-involving-road-debris-united-states-2011-2014/

Terken, J. M. B., & Pfleging, B. (2020). Toward Shared Control Between Automated Vehicles and Users. *Automotive Innovation*, *3*, 53–61. internal-pdf://0761851083/1.Terken & Pfleging 2020.pdf

Thorn, E., Kimmel, S. C., & Chaka, M. (2018). *A Framework for Automated Driving System Testable Cases and Scenarios*.

Wang, W., Na, X., Cao, D., Gong, J., Xi, J., Xing, Y., & Wang, F. Y. (2020). Decision-making in driver-automation shared control: A review and perspectives. *IEEE/CAA Journal of Automatica Sinica*, *7*(5), 1289–1307. https://doi.org/10.1109/JAS.2020.1003294

Zhou, F., Yang, X. J., & de Winter, J. C. F. (2021). Using eye-tracking data to predict situation awareness in real time during takeover transitions in conditionally automated driving. *IEEE Transactions on Intelligent Transportation Systems*.