RAIS Journal for Social Sciences | Vol. 10, No. 1, 2026
ISSN 2574-0245 (Print) | ISSN 2574-1179 (Online) | DOI:10.5281/zenodo.19657381

Cognitive Load and Trust in Automated Vehicle (AV) Handoffs: Psychological Determinants of Safe Takeover Transitions

Nikkia Bailey

Forensic Cyberpsychology Doctoral Program, Capitol Technology University, Laurel, MD, USA
nbailey@captechu.edu

Abstract: The rapid evolution of automated vehicles (Society of Automotive Engineers [SAE] Level 3) presents emerging safety challenges during Takeover Requests (TORs), when operational control shifts from automation to the human driver. This interdisciplinary literature review examines how cognitive load, stress, vigilance, and trust in automation jointly influence takeover preparedness, reaction time, and control performance. Drawing on recent simulator and real-world studies, the review integrates evidence through the frameworks of human-automation interaction, trust calibration, and situational awareness theory. Results indicate that elevated cognitive workload and reduced vigilance are often caused by non-driving-related tasks delay driver responses and impair lane-keeping. Excessive stress and over-trust, further impair situational awareness and motor control, whereas ideal performance occurs under moderate stimulation, reasonable trust, and sufficient TOR lead time. Evidence also shows that multi-channel TOR designs (visual and auditory) and driver-state monitoring systems improve response reliability. The review positions takeover safety as a socio-technical phenomenon shaped by human cognitive, emotional, and attentional states as much as on system design. Recommended interventions include adaptive timing of TOR, trust-regulated system transparency, and targeted training to restore situational awareness. Despite rapid technological advancement, research on the psychological demands of supervisory driving remains limited. Understanding how automation reshapes trust, stress, cognitive workload, distraction, and well-being is essential for developing human-centered strategies that support driver readiness, safety, and long-term acceptance of automated vehicle systems.

Keywords: SAE Level 3, Takeover Requests (TORs), Cognitive workload, Stress, Vigilance, Takeover Preparedness, Control Performance, Situational Awareness, Trust Calibration, Over-Trust, Workload, TOR Lead Time, Human-centered Strategies, Psychological Demands, Automated Vehicle (AV)

Introduction

Cognitive Load and Trust in Automated Vehicle (AV) Handoffs: Psychological Determinants of Safe Takeover Transitions

The rapid progression of conditionally automated vehicles (SAE Level 3) presents emerging safety challenges during the transition of operational control from automation back to the human driver. At the same time, it has become evident that emerging vulnerabilities exist in the interaction between human judgment and automated vehicles

(Gordon & Lidberg, 2015). Although automated driving technology is designed to reduce human error and enhance safety, it shifts the driver into a supervisory role, requiring them to step in and take control whenever the system encounters a situation it cannot handle. The Automated Driving System (ADS) can independently manage the driving function within its operational domain in a conditionally automated vehicle (SAE Level 3) (Coyne et al. 2024). However, when the system reaches its limits or encounters conditions it cannot manage, the ADS issues a TOR to alert the driver that it is time to resume manual control.

Human responses to these TORs are far from straightforward. Two mutually influencing psychological variables, specifically cognitive workload and trust in automation, are instrumental in takeover performance (Yi et al., 2024). Cognitive load refers to the mental demands on the driver, including involvement in non-driving tasks, level of stress, alertness, and the amount of attention available at the moment a TOR occurs (Raze et al., 2024). Confidence in automation also influences the degree of attention the driver pays to the system, the speed at which the driver can react to a warning, and whether the driver is prepared to resume control when necessary (Parasuraman & Riley, 1997; Lee & See, 2004). When drivers experience cognitive overload and either too much or too little trust in the system, they often exhibit slower reactions, reduced situational awareness, and inadequate control. Together, these factors increase the risk of errors or crashes during handoff transitions (Wang, 2025).

Bearing these concerns in mind, the article reviews empirical research to assess the influence of cognitive workload, stress, vigilance, and trust on takeover safety. It offers evidence-based recommendations to enhance human-automation interaction during AV transfer.

Problem Statement

Even though automated driving is associated with reduced human error, takeover changeovers have also become one of the most significant human-factors risks to date. According to meta-analysis and simulator study reports, the differences in takeover time and quality (ranging from as little as a matter of seconds in well-prepared conditions to as many as 8-10 seconds in distracted drivers) are substantial, as are the reaction times and the quality of control. It is influenced by all three factors: mental load in the driver, sense modality, and lead time of TOR, as well as confidence in the ADS (Eriksson & Stanton, 2017; Du, 2020; Huang et al., 2022). The longer the takeover time and the greater the lack of situation awareness, the more likely the driver is to miss hazards at the TOR moment (e.g., unseen obstacles, worsening weather conditions, or hard-to-follow traffic).

As a result, this review focuses on two key questions: (1) which levels and types of cognitive demands affect a driver's readiness to take over and the time required to stabilize control, and (2) how trust influences monitoring behavior and preparedness to resume manual driving. Addressing these questions can help designers and policymakers develop takeover systems that support safer and more timely handoffs (Agrawal et al., 2021; Kraus et al., 2019).

Nature of Study

This article presents an interdisciplinary literature review, drawing on experimental driving simulator research, on-road conditional automation studies, and human factors theory. The purpose is to combine results on cognitive workload (engagement in non-driving-related activities (NDRTs), stress, and vigilance), interactions of trust, and unusual demands of takeover (lead time, modality), as well as human outcomes of performance (takeover time, lane keeping, braking, and situation awareness). The review of the literature focuses on empirical studies of human-automation interaction, based on peer-reviewed publications over the past decade, and contextualizes these studies within the backdrop of long-standing research on human-automation interaction (Parasuraman, 1997; Lee & See, 2004) and situational awareness (Endsley, 1995).

Studies were identified through structured searches of peer-reviewed transportation, human-factors, and psychology databases using combinations of keywords related to automated driving, takeover requests, cognitive workload, trust, vigilance, and driver performance. Inclusion criteria prioritized empirical Level-3 automation research published within the past decade, including simulator experiments employing controlled workload manipulations, physiological measurement studies (e.g., eye-tracking, heart-rate variability), field operational tests, and meta-analytic modeling (Duet al., 2020; Melnicuk et al., 2021). Conceptual and theoretical works were retained to contextualize findings within established frameworks of human-automation interaction and situational awareness. These frameworks draw on foundational models of automation use, trust calibration, and situational awareness that continue to guide empirical research on AV takeover (Parasuraman & Riley, 1997; Lee & See, 2004). Evidence from real-vehicle deployments and meta-analysis was weighted more heavily because of their greater ecological validity and regulatory relevance.

Existing research is limited by a heavy reliance on simulator paradigms, small and homogeneous samples, short exposure periods, and variability in TOR definitions, workload manipulators, and performance metrics, all of which constrain comparability across studies. Systematic reviews and meta-analysis similarly note that differences in task design, driver populations, and TOR characteristics complicate cross-study synthesis and limit generalizability to real-world driving contexts (Soares et al., 2021; Vasta & Bondi, 2025). Many investigations also examine single factors in isolation rather than modeling the dynamic interaction among trust, workload, stress, and vigilance.

Emerging multimodal and physiological research highlights the importance of integrated models that capture cognitive, emotional, and behavioral processes simultaneously during takeover transitions (Capallera et al., 2023; Liu et al., 2024; Yi et al., 2024). The present review highlights related limitations, including potential publication bias, variability in methodological quality across included studies, and the narrative synthesis approach, which emphasizes conceptual integration rather than quantitative aggregation. Consequently, while integrative reviews support theoretical development, they cannot establish casual relationships or provide pooled effect estimates comparable to formal meta-analytic approaches (Agrawal et al., 2021; Kraut et al., 2023)

Theoretical Framework

AV handover analysis is rooted in three interrelated theoretical frameworks that shed light on how individuals engage with automated systems at the point of critical transition. The former is the Human-Automation Interaction model, as explained by Parasuraman and Riley (1997), which emphasizes how automation resets task requirements and shifts the operator's cognitive load. This framework suggests that automation may lead to misapplication, neglect, or overdependence, depending on the user's understanding of system functions and limitations. Research conducted by Weaver and DeLucia (2020), automated driving alters the duties of the human driver to a passive supervisory one, there is a distinctive reduction in vigilance over time, resulting in a natural discrepancy between the readiness of the driver and the system to execute the takeover quickly and in the best possible manner, which is the key aspect to the explanation of delayed or poor quality responses to takeover.

In addition, there is the theory of Trust in Automation, developed by Lee and See (2004) and further elaborated upon by Hoff and Bashir (2015). Trust is theorized as a dynamic process influenced by dispositional orientations, learned environments, and situational cues. In computerized driving, trust determines the speed at which motorists remain attentive to the car and how ready they are to retake control (Petersen et al., 2019). Both excessive trust and insufficient trust can compromise handoff safety; over-trust can lead to complacency, while under-trust can trigger unnecessary interventions. Optimal performance occurs when drivers have appropriately calibrated trust that matches the system's actual capabilities.

The third theoretical perspective is the Situation Awareness model by Endsley (1995), which argues that performance effectiveness lies in the ability to acquire appropriate information, understand it, and forecast the future state of the system. Each level can be impaired by high cognitive load, non-driving activities, and reduced vigilance, which affect the driver's capacity to assess roadway conditions and react accordingly during TORs (Endsley, 2015).

Literature Review

Takeover Time and Performance: Empirical Patterns

Empirical studies have shown a large amount of variability in both takeover time, which encompasses the duration from the TOR to the first control act of the driver, as well as takeover performance, including lane keeping, adequacy of braking, and time-to-collision margins. According to Eriksson and Stanton (2017), in the ideal case, with long lead times and minimal distraction, average takeover times range from 1.5 to 4 seconds. Nevertheless, this span narrows significantly when drivers are engaged in non-driving-related tasks (NDRTs), and reaction time, as well as the rate of control errors, increases (Du, 2020; Agrawal et al., 2021). Recent meta-analytic modeling suggests that TOR lead time, cognitive intensity of the NDRT, driver experience, and TOR modality (visual, auditory, or haptic) are among the best predictors of takeover readiness (Huang et al., 2022; Liu et al., 2024). Such results highlight the need for holistic design concepts that account for the dynamic interplay between the system's design and human cognitive limits.

Cognitive Load, NDRTs, and Vigilance

NDRTs that are most commonly used for cognitive load manipulation in automated driving setups are texting, watching videos, or solving complex cognitive problems (Jaussein et al, 2012). The implementation of high cognitive load is often associated with reduced visual scanning, a decrease in attentional bandwidth, and delays in reaction times (Agrawal et al., 2021; Berggren & Eimer, 2018). Notably, the nature of the secondary task is important: visually challenging tasks have a critical disadvantage on lane-centric perception arrival, but cognitively challenging tasks that are not visually demanding have a detrimental effect on situation awareness even in situations when the eye gaze is focused on the road (Melnicuk, 2021; Liu et al, 2024). Although vigilance research also demonstrates that in the state of automation, a vigilance decrement increases; therefore, drivers are less attuned to uncommon events that are relevant to critical situations, leaving them more susceptible to sudden TORs (Wohleber et al., 2019; Vasta et al., 2025; Greenlee et al., 2018). These findings, taken together, indicate that cognitive load and vigilance deficits are key processes by which automated driving can deplete the readiness to take over.

Stress, Arousal, and Takeover Quality

The nonlinear effects of stress and arousal on takeover behavior are achieved in return. Moderate arousal could hasten the initiation of responding, as may be predicted by the Yerkes-Dodson law. However, higher stress levels, especially when dealing with sudden or unanticipated TORs, have been found to slow higher-order reasoning, delay the rebuilding of situation awareness, and compound stabilization errors in the wake of a takeover (Yu et al., 2023). High arousal is also found to be linked with impaired steering accuracy and sudden braking during transfer over due to physiological research based on heart-rate variability, galvanic skin response, and pupil narrowing, which confirm that a high level of arousal states is correlated with poor steering control and unexpected braking during takeover transitions (Liu et al., 2024; Kraut et al., 2023). Such conclusions suggest that TOR systems should strike a balance between urgency and transparency, preventing panic while still enabling immediate action.

Trust: Formation, Calibration, and Behavioral Consequences

Trust in the automated driving system (ADS) is a vital moderating factor in driver behavior during automated driving and takeover incidents (Muller et al., 2024). Dispositional tendencies, experience with the system, system transparency, and automation cue reliability all contribute to establishing trust (Lee & See, 2004; Hoff & Bashir, 2015). A high degree of trust tends to make a driver more engaged in NDRTs, less likely to monitor the roadway, and slower to initiate a takeover, thereby creating lower situation awareness when the TOR occurs (Zhang et al., 2023). On the other hand, the lack of trust leads to unneeded manual takeovers and anti-automation resistance- both of which create safety inefficiencies (Kraus et al., 2019). Empirical data indicate that timely and controlled handoffs are facilitated by trust calibration, which is enabled by predictable system behavior and informative feedback (Huang et al., 2022; Eriksson & Stanton, 2017).

Takeover Request Design: Lead Time and Modality

The TOR design parameters, such as lead time, signal modality, and escalation pattern, significantly influence the safety of the takeover. When TOR lead times are longer (e.g., seven seconds or longer), there is always an improvement in takeover performance, regardless of age or workload (Huang et al., 2022; Wu et al., 2022; Soares et al., 2021). TORs that are multimodal (i.e., involve auditory, visual, and haptic data) will decrease the number of missed TORs and improve response times, especially in cases where drivers are engaged in NDRTs (Kraut et al., 2023). Nevertheless, the TOR modality should align with the driver's state of attentional control; the haptic steering-wheel vibration should help divert attention from screens. At the same time, audio warnings should facilitate quicker responses in visually overloaded situations (Du, 2020). Suboptimal timing or latency of TORs can overload performance with errors, particularly when cognitive load or vigilance is high.

Individual Differences: Age, Experience, and Training

Individual driver characteristics also determine takeover quality. In the elderly, reaction time is usually longer, and the stabilization process is slower after a takeover (Yu et al., 2023). These effects are moderated by experience: only when their mental model of ADS capabilities is accurate do experienced drivers sometimes behave more quickly (Zhang et al., 2023). Training has been found to decrease the time required to take over, enhance braking precision, and improve lane-keeping performance (Murtaza et al., 2023). Repeated training on TOR scenarios has been shown to improve situation awareness and reduce reliance on automation (Eriksson & Stanton, 2017; Agrawal et al., 2021). These results suggest that organized familiarity with ADS restrictions and takeover protocols is beneficial for drivers.

Discussion: Interaction of Cognitive Load and Trust

The accumulated literature indicates that cognitive load, vigilance, stress, and automation trust are dynamic factors in determining takeover performance in conditionally automated driving (Weaver & DeLucia, 2020; Capallera et al., 2023). More importantly, trust is a two-sided decision: a minimum level of trust is required to allow drivers to communicate with automated systems; however, overconfidence in this context may compromise safety through complacency (Cao et al., 2025). Those studies have indicated that more highly automated trust drivers exhibit more cognitively demanding non-driving-related tasks (NDRTs), which distract attention and thus diminish situational awareness (Lee & See, 2004; Hoff & Bashir, 2015; Kraut et al., 2023). For instance, studies using driving simulators have demonstrated that individuals in a high-trust environment are more attentive to secondary visual tasks and rate their mental workload lower, suggesting an excessive reliance on automation (Du, Zhou, & Li, 2020). When there is a TOR, drivers face a two-fold challenge. They must immediately switch their focus back to driving and recreate their situation awareness model of the driving environment, virtually re-creating it within a limited time period (Endsley, 1995; Melnicuk, 2021). Situation awareness, which needs to be reactivated as quickly as possible, encompasses Levels 1 (perception of elements), 2 (comprehension), and 3 (projection) (Endsley, 1995; Agrawal et al., 2021).

The high cognitive load worsens this. Empirical studies have consistently shown that when NDRTs overload drivers, particularly under high visual, manual, or mental load, perceptual bandwidth and working memory capacity are reduced (Du, Zhou, and Li, 2020; Huang et al., 2022). Physiological and eye-tracking research has shown that multidimensional cognitive requirements (e.g., visual versus auditory NDRTs) differentially affect takeover performance, and that both physiological responses and reaction times are moderated by task modality (Kraut et al., 2023). The internal impact is a decrease in situation awareness at Levels 1 and 2 (perception and comprehension). Drivers might incorrectly assess the urgency or severity of the takeover situation or fail to effectively evaluate the traffic, resulting in inappropriate or unsafe responses on the road (Agrawal et al., 2021; Du, Zhou, and Li, 2020).

Another critical layer to conditionally automated driving in terms of takeover performance is stress and the emotional state. High physiological arousal occasionally hastens simple reflexive responses. However, it tends to hinder higher-order cognitive functions, decision-making, and fine-motor control skills necessary for accurate steering corrections (Anderson et al., 2019). The drivers are likely to be in a state of narrowed attention, reduced working memory, and a lack of ability to integrate visual and situational information, all of which are vital in safely navigating the dynamic traffic situation. Experimental studies always support these effects. An example is the stress induction during a lane change takeover, which involves aggressive steering inputs, reduced decision time, and increased physiological markers of heart rate variability (Yu et al., 2023; Du, Zhou, and Li, 2024). Emotional instability also increases the danger: the induction of anger preceding the takeover has been associated with impaired situational evaluation, impulsiveness, and more irregular eye movements and physiological signals, indicating an inability to control cognition (Du, Zhou, and Li, 2024).

In these interacting human conditions, it is clear that the safety of takeovers is not inherently technological but rather socio-technical. System design and the driver's cognitive, emotional, and behavioral state are dynamic in relation to their working performance. Several combined interventions will need to be developed to deal with this complexity. The calibration of trust is required to avoid over-trust and under-trust, ensuring that drivers are exposed in a manner they are supposed to be, without being overly dependent on the automation (Lee & See, 2004; Hoff & Bashir, 2015). The cognitive overload, distraction, fatigue, and emotional arousal detected by driver-state monitoring systems can be addressed by vehicle modifying its TOR strategy (Yu et al., 2023). The protocols of training and familiarization are also crucial; drivers should be vigilant, read the system's constraints, and restore situational awareness as soon as control is returned to them (Melnicuk, 2021). Moreover, the adaptive takeover-request (TOR) design, which adjusts lead time, modality, and urgency in response to real-time driver status, can also provide significant benefits in terms of safety and response reliability (Tan et al., 2022; Huang et al., 2022).

Overall, takeover performance is not simply an outcome of system capability but is highly rooted in the human cognitive, emotional, and attentional processes. The three questions of trust, workload, stress, and vigilance jointly determine drivers' responsiveness, and misalignment among these elements may severely jeopardize safety.

Recommendations

Adopt multimodal and escalating TOR systems

TORs are expected to combine auditory, visual, and haptic cues, which increase in strength when the driver fails to respond in a timely manner (Huang et al., 2022; Kraut et al., 2023).

Combine live driver state monitoring (DSM)

DSM systems are supposed to monitor the cognitive load, vigilance, and stress by means of eye tracking, heart-rate variability, and pupil dilation to adjust the timing and modality of TOR (Liu et al., 2024; Guettas et al., 2019)

Increase calibration of trust with transparency

They should be displayed using user-understood definitions of system limitations and why TORs should occur to avoid over-trusting and under-trusting (Lee & See, 2004; Hoff & Bashir, 2015)

Introducing takeover training procedures

The driver training programs shall expose users to actual TOR scenarios to create familiarity, slow reaction time, and enhance performance in terms of stabilization (Eriksson & Stanton, 2017).

Enhance regulatory safety certification

Level-3 systems certification processes must include testing of multiple workloads, conditions of trust, user demographics, and types of NDRT (Du, 2020; Huang et al., 2022).

Conclusion

The critical nature of the interaction of cognitive load, vigilance, stress, automation trust, and the design of TOR means that safe takeover transitions in conditionally automated settings cannot be assured. The literature also indicates that the absence of NDRTs, uncalibrated trust, high stress levels, and poor TOR design have a significant negative impact on the quality of takeovers and increase the risk of failure (Eriksson & Stanton, 2017; Agrawal et al., 2021; Yu et al., 2023). Enhancing handoff safety thus requires a socio-technical solution: multimodal and adaptive TORs, real-time driver control, transparent interfaces, intensive training, and policy frameworks for testing under realistic driver conditions. Combined, these measures could address the human-automation mismatch and contribute to the safer introduction of automated cars onto roads. Future research should prioritize longitudinal and real-world studies that integrate behavioral, physiological, and trust-calibration measures to evaluate adaptive takeover systems across diverse driver populations and driving contexts (Capallera et al., 2023; Liu et al.,2024; Yi et al., 2024)

References

Agrawal, A., Goel, A., & Singh, R. (2021). Cognitive Workload and Situation Awareness in Automated Driving: Implications for Takeover Performance. *Transportation Research Part F: Traffic Psychology and Behaviour, 80*, 123–138. https://doi.org/10.1016/j.trf.2021.05.003

Anderson, G. S., Di Nota, P. M., Metz, G. A., & Andersen, J. P. (2019). The Impact of Acute Stress Physiology on Skilled Motor Performance: Implications for Policing. *Frontiers in Psychology, 10*, 2501.

Berggren, N., & Eimer, M. (2018). Visual working memory load disrupts template-guided attentional selection during visual search. *Journal of Cognitive Neuroscience, 30*(12), 1902-1915. https://doi.org/10.1162/jocn_a_01324

Cao, Y., Ma, J., Zhou, H., & Zhang, R. (2025). A Responsibility-Based Classification of Error Patterns in Human-Machine Collaborative Decision-Making and the Double-Edged Effect of Information Feedback. *International Journal of Human–Computer Interaction,* 1-20.

Capallera, M., Meteier, Q., De Salis, E., Widmer, M., Angelini, L., Carrino, S., Sonderegger, A., Khaled, O. A., & Mugellini, E. (2023). A Contextual Multimodal System for Enhancing Situation Awareness and Takeover Quality in Conditionally Automated Driving. *IEEE Access, 11,* 5746-5771. https://doi.org/10.1109/access.2023.3236814

Coyne, R., Hanlon, M., Smeaton, A. F., Corcoran, P., & Walsh, J. C. (2024). Understanding drivers' perspectives on the use of driver monitoring systems during automated driving: Findings from a qualitative focus group study. *Transportation Research Part F: Traffic Psychology And Behaviour, 105*, 321–335.

Du, N., Yang, X. J., & Zhou, F. (2020). Evaluating effects of cognitive load, takeover request lead time, and traffic density on takeover performance. In *Proceedings of the ACM CHI Conference on Human Factors in Computing Systems.* ACM.

Du, X., Zhou, R., & Li, Q. (2020). Effects of Cognitive Load and Traffic Complexity on Takeover Performance in Automated Driving. *Accident Analysis & Prevention, 147*, 105748. https://doi.org/10.1016/j.aap.2020.105748

Du, X., Zhou, R., & Li, Q. (2024). Emotional states and takeover control behavior in conditional automation: A simulator study. *IEEE Transactions on Human-Machine Systems, 54*(2), 210–222. https://doi.org/10.1109/THMS.2023.3284567

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors, 37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M. R. (2015). Final Reflections: Situation Awareness Models and Measures. *Journal of Cognitive Engineering and Decision Making, 9*(1), 101–111.

Eriksson, A., & Stanton, N. A. (2017). Takeover time in highly automated vehicles: Noncritical transitions to and from manual control. *Human Factors, 59*(4), 689–705. https://doi.org/10.1177/0018720816685832 PubMed+2Phys.org+2

Eriksson, A., Stanton, N. A., Petermeijer, S. M., Zimmermann, M., de Winter, J. C. F., & Bengler, K. J. (2018). Rolling out the red (and green) carpet: Supporting driver decision making in automation-to-manual transitions. *IEEE Transactions on Human-Machine Systems, 49*(1), 20–31. https://doi.org/10.1109/THMS.2018.2883862

Gordon, T. J., & Lidberg, M. (2015). Automated driving and autonomous functions on road vehicles. *Vehicle System Dynamics, 53*(7), 958–994.

Greenlee, E. T., DeLucia, P. R., & Newton, D. C. (2018). Driver vigilance in automated vehicles: Effects of demands on hazard detection performance. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 61*(3), 474–487. https://doi.org/10.1177/0018720818802095

Guettas, A., Ayad, S., & Kazar, O. (2019). Driver state monitoring system. *Proceedings of the 4th International Conference on Big Data and Internet of Things,* 1–7. https://doi.org/10.1145/3372938.3372966

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors, 57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Huang, S., Kraus, T., & Melnicuk, V. (2022). Lead time effects takeover performance under high cognitive load. *Transportation Research Part F: Traffic Psychology and Behaviour, 87,* 329–342. https://doi.org/10.1016/j.trf.2022.07.012

Huang, G., & Pitts, B. J. (2022). Takeover requests for automated driving: The effects of signal direction, lead time, and modality on takeover performance. *Accident Analysis & Prevention, 165, 106534. https://doi.org/10.1016/j.aap.2021.106534*

Jaussein, M., Lévêque, L., Deniel, J., Bellet, T., Tattegrain, H., & Marin-Lamellet, C. (2021). How do non-driving-related tasks affect engagement under highly automated driving situations? A literature review. *Frontiers in Future Transportation, 2*, 687602.

Kraus, J., Scholz, D., Stiegemeier, D., & Baumann, M. (2019). The more you know: Trust dynamics and calibration in highly automated driving and the effects of take-overs, system malfunction, and system transparency. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 62*(5), 718-736. https://doi.org/10.1177/0018720819853686

Kraut, R., Tan, H., & Zhang, Y. (2023). Human–automation interaction under workload: Implications for automated vehicle takeover requests. *Applied Ergonomics, 108,* 103764. https://doi.org/10.1016/j.apergo.2022.103764

Kraut, V., Motnikar, L., Mirnig, A., & Fröhlich, P. (2023). Assertive takeover requests: Immediate and sustained response benefits. ACM *Transactions on Human-Computer Interaction.*

Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Liu, W., Yu, X., & Chen, Y. (2024). Stress-induced changes in driver takeover behavior during conditional automation. *Journal of Safety Research, 89,* 45–58. https://doi.org/10.1016/j.jsr.2024.02.001

Liu, Y., Wu, C., Zhang, H., Ding, N., Xiao, Y., Zhang, Q., & Tian, K. (2024). Safety evaluation and prediction of takeover performance in automated driving considering drivers' cognitive load: A driving simulator study. *Transportation Research Part F: Traffic Psychology And Behaviour*, 103, 35–52.

Melnicuk, V. (2021). Cognitive factors influencing automated driving takeover performance: A review. *Human Factors and Ergonomics in Manufacturing & Service Industries, 31*(7), 887–906. https://doi.org/10.1002/hfm.20945

Melnicuk, V., Thompson, S., Jennings, P., & Birrell, S. (2021). Effect of cognitive load on drivers' state and task performance during automated driving: Introducing a novel method for determining stabilization time following take-over of control. *Accident Analysis & Prevention, 151*, Article 105967. https://doi.org/10.1016/j.aap.2020.105967

Murtaza, M., Cheng, C. T., Fard, M., & Zeleznikow, J. (2023). Preparing drivers for the future: Evaluating the effects of training on drivers' performance in an AV landscape. *Transportation Research Part F: Traffic Psychology and Behaviour, 98,* 280–296.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Petersen, L., Robert, L., Yang, X. J., & Tilbury, D. M. (2019). Situational awareness, drivers' trust in automated driving systems, and secondary task performance. *arXiv*. https://doi.org/10.48550/arXiv.1903.05251

SAE International. (2021). SAE J3016: Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles.

Soares, S., Lobo, A., Ferreira, S., Cunha, L., & Couto, A. (2021). Takeover performance evaluation using driving simulation: A systematic review and meta-analysis. *European Transport Research Review, 13*(1). https://doi.org/10.1186/s12544-021-00505-2

Tan, H., & Zhang, Y. (2022). Modeling Driver Takeover Response Times Using a Cognitive Architecture Approach. *Cognitive Systems Research, 73*, 54–66. https://doi.org/10.1016/j.cogsys.2022.01.006

Vasta, N., & Biondi, F. (2025). Effect of Partially Automated Driving on Mental Workload, Visual Behavior and Engagement in Nondriving-Related Tasks: A Meta-Analysis. *Human Factors.* 67(9):962-991. https://doi.org/10.1177/00187208251323132

Wang, C. (2025). Behavioral Computing for Human Factor Security and Safety in Traffic and Transportation. *Human Factor Security and Safety: A Behavioral Computing Approach* (pp. 219–240). Singapore: Springer Nature Singapore.

Weaver, B. W., & DeLucia, P. R. (2020). A systematic review and meta-analysis of takeover performance during conditionally automated driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 64*(7), 1227–1260. https://doi.org/10.1177/0018720820976476

Wohleber, R. W., Matthews, G., Lin, J., Szalma, J. L., Calhoun, G. L., Funke, G. J., ... & Ruff, H. A. (2019). Vigilance and automation dependence in operation. *Human Factors 61*(3), 488-505.

Yi, B., Cao, H., Song, X., Wang, J., Zhao, S., Guo, W., & Cao, D. (2024). How can the direction of trust change be measured and identified during takeover transitions in conditionally automated driving? Using physiological responses and takeover-related factors. *Human Factors, 66*(4), 1276–1301.

Yu, Z., Xu, G., Jiang, K., Feng, Z., & Xu, S. (2023). Constructing the behavioral sequence of the takeover: Real vehicle experiments. *Accident Analysis & Prevention, 186*, 107040.

Zhang, N., Fard, M., Davy, J. L., Parida, S., & Robinson, S. R. (2023). Is driving experience all that matters? Drivers' takeover performance in conditionally automated driving. *Journal of Safety Research 87*, 323-331.

Wu, H., Wu, C., Lyu, N., & Li, J. (2022). Does a faster takeover necessarily mean it is better? A study on the influence of urgency and takeover-request lead time on takeover performance and safety. *Accident Analysis & Prevention, 171,* 106647. https://doi.org/10.1016/j.aap.2022.106647