Workload Distribution Across Varying Assistance Levels in Simulated Mission Drives

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ABSTRACT

As automated assistance systems become prevalent in driving operations, understanding their impact on workload and team performance is critical. The three-car convoy in this study consisted of six participants per mission team assigned distinct roles: Lead Car Driver (n = 1), Desktop Drivers (n = 2), Lead Car Lookout (n = 1), and Desktop Lookouts (n = 2). Each role had unique task demands contributing to baseline workload differences, while all members collaborated on a shared target search and identification goal. Lookouts searched for targets while completing a shape distractor task. Drivers followed the lead car, with the Lead Car Driver accessing an overhead map. The primary objective of this project was to determine if assistance, via an object detection system (ODS) and autonomous driving, could alleviate perceived individual and team workload in a six-person team. Subjective workload measures were used to assess individual and team workload. Participants (N = 240) completed four randomized simulated driving scenarios: (1) Vehicle Automation, with all vehicles operating autonomously; (2) ODS Assistance, providing the Lead Car Lookout with visual and auditory alerts upon AI target detection; (3) Combined Assistance, integrating vehicle automation and ODS; and (4) No Assistance, with full manual control. To assess perceived individual and team workload, participants completed an updated NASA Task Load Index (NASA-TLX) and the Team Workload Questionnaire (TWLQ) post-drives. Workload scores were analyzed using mixed linear models to account for repeated drives and assess the effects of roles and assistance conditions. Results indicated that while automation significantly reduced Driver workload, Lookout workload remained unchanged and was higher overall. These findings suggest future assistance designs must prioritize a balanced workload distribution to optimize performance across all team members.

ABOUT THE AUTHORS

Johnna Stevenson, BS, is a Graduate Research Assistant at The University of Alabama's TRIP Lab, pursuing a PhD in Cognitive Psychology. She has experience in human factors research with a focus on cognitive performance and workload. She has undergraduate and graduate experience in study development, experimental design, data collection, data analysis, disseminating research findings, and she has contributed to Department of Defense and NIH-funded projects. Her interests include applied research investigating executive functioning, automation, human-AI interaction and design, and workload management.

Dr. Benjamin McManus is a Developmental Psychologist and Associate Professor at the University of Alabama Institute for Social Science Research as well as the Assistant Director in the Translational Research for Injury Prevention (TRIP) Laboratory where he manages and programs the TRIP lab's state-of-the-art driving simulator. Dr. McManus has expertise in sleep, information processing, attention, human factors, and driving safety in a variety of populations. His work has been funded by the United States Department of Transportation (USDOT) and the CDC's National Institute of Occupational Safety and Health (NIOSH).

Dr. Amanda Hudson earned her PhD in Experimental Psychology from Washington State University (WSU) in 2024. She spent over 5 years at the Sleep and Performance Research Center at WSU Spokane working with driving and shooting simulators to assess the effects of sleep loss in operational settings. Dr. Hudson now works at the Institute for Social Science Research located at The University of Alabama where she acts as the Research Program Manager for the Translational Research for Injury Prevention (TRIP) Lab. Her primary research interests include sleep and circadian rhythms and the effects of sleep deprivation on human performance and cognition.

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William Russell, BA, is a Graduate Research Assistant for The University of Alabama TRIP Lab, pursuing a PhD in Cognitive Psychology. His previous experience is in human factors research with a focus on communication and recently, AI systems. In undergraduate and now graduate school, he has assisted with study development, data collection, data analysis, and disseminating research findings and has contributed to Department of Defense and NIH-funded projects. His research interests include Human-AI teaming, cognition of driving, and leadership.

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Victor Paul is a Technical Expert at the U.S. Army GVSC's Immersive Simulation Directorate and GVSL, with 35 years of experience in ground vehicle and motion base simulation. He advises the COAT program and supports the development of crew station technologies for the Army's next generation of ground vehicles, specializing in human and hardware-in-the-loop experimentation.

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Thomas Anthony, MS, is a technology executive and entrepreneur with skills as an Analytical Research Scientist and solutions architect with expertise in Big Data Analytics, Deep Learning, and High Performance Computing (HPC). He has over 15 years of experience in HPC and Big Data system design including the largest Supercomputer in Alabama. Thomas is the Co-Founder and CIO of Analytical AI, a company that provides AI solutions to multiple federal agencies and is the Principal investigator on multiple grants, projects, and contracts for the Department of Homeland Security and Department of Defense.

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INTRODUCTION AND BACKGROUND

While prior research highlights the workload-reducing benefits of automation for individual drivers, far less is known about how such systems impact teams, particularly when task demands are unevenly distributed. This gap is especially critical in military operations, where effective coordination across distinct roles can determine mission success. Increased task demands can elevate workload and impair performance, particularly when multiple types of information must be attended to and encoded simultaneously (Cherif et al., 2018; Recarte & Nunes, 2003; Xie & Salvendy, 2000). Further, driving requires sustained attention, perceptual processing, and motor coordination (Kerruish et al., 2022; Lin et al., 2016; Pergantis et al., 2024). As environmental complexity and operational demands increase, workload intensifies and can result in performance degradation (Foy & Chapman, 2018; Khanganba & Najar, 2022; Roussou et al., 2023). When operational workload is not well regulated, drivers are more susceptible to lapses in attention, delayed responses to hazards, and poor navigation decisions, which are critical in military contexts where timing and precision are essential (Diaz-Piedra et al., 2021; Vrijkotte et al., 2016). In military teams, these challenges are compounded by the need to maintain situational awareness and coordinate effectively in dynamic and hazardous settings (Hagemann et al., 2023). Excessive workload slows reaction times, impairs decision-making, and increases the likelihood of errors, all of which can compromise mission success and team safety (Cherif et al., 2018).

Automated assistance has emerged as a solution to alleviate workload, particularly in military settings. Artificial intelligence (AI) assistance and autonomous driving systems have the potential to reduce task workload by automating specific tasks (e.g., navigation, driving) and allotting more cognitive resources to higher-level tasks. By offloading routine or low-level cognitive processes, these systems can help mitigate mental fatigue and allow drivers to allocate more cognitive resources to higher-order functions like decision-making and situational awareness, both of which are critical for effective driving performance and mission success (Morales-Alvarez et al., 2020; Vrijkotte et al., 2016). Automated systems such as lane keeping assist and adaptive cruise control have been shown to reduce workload for drivers by automating routine tasks, improving safety and reducing driver fatigue (Morales-Alvarez et al., 2020; Müller et al., 2021). Although prior research has demonstrated the workload-reducing benefits of automated systems for individual drivers, less attention has been given to how such systems influence workload distribution across interdependent team roles, particularly in military scenarios where coordination and role assignments are essential. Although assistance can reduce workload, its effects may not be equally beneficial across all team members (Cuevas et al., 2007; Johnson et al., 2023). For example, in convoy scenarios, drivers may experience relief from manually operating a vehicle, but passenger lookouts may continue to experience persistent task demands that the automation does not directly assist. As automation becomes more integrated into team operations, understanding how it can support team dynamics and equal workload distribution among team members becomes more critical.

Research on human-AI teaming emphasizes the need for adaptive systems that monitor workload across the team and allocates task demands accordingly in real-time (Dubois & Ny, 2020; Heard & Adams, 2019; Heard et al., 2020). Workload is closely tied to task performance, and both over- and underload can impair effective task completion and overall performance (Dehais et al., 2020; Fiore & Wiltshire, 2016; Parasuraman & Hancock, 2000). The task demands associated with different roles can further influence how automation impacts workload and performance (Cuevas et al., 2007; Seo et al., 2023). The Distributed Cognition Framework and the Interactive Team Cognition Theory suggest that introducing automation can redistribute workload among team members, potentially enhancing or hindering team performance depending on the effectiveness of the assistance provided to meet the needs of all team members (Cooke et al., 2012; Hutchins, 2000, 2020). Distributed Cognition emphasizes that cognitive processes extend beyond individuals to encompass interactions between team members and their environmental demands (Fiore & Wiltshire, 2016; Hutchins, 2020). Interactive Team Cognition Theory builds on this by asserting that team cognition is not the sum of individual efforts, but a dynamic process shaped by real-time coordination, communication, and the interdependence of task demands across teammates (Cooke et al., 2013). In action teams, this interdependence means that changes in task demands or role responsibilities can shift workload among members, so alleviating one individual's workload does not ensure optimal workload distribution across the team (Hagemann et al., 2023; Johnson et al., 2023). Assistance design plays a critical role in shaping how workload is distributed and managed within a team, influencing both individual and team workload. In military operations, ensuring that individual and team workload management are addressed through adaptive assistance systems and training is critical for supporting mission success.

The Present Study

The current study examined the effects of different levels of automated assistance on perceived individual and team workload within a simulated networked ground vehicle mission team. Individual workload was measured using an updated version of the NASA Task Load Index (NASA-TLX) to best assess how workload was distributed across a team of individuals with unique task demands (Sellers et al., 2014). Team workload was assessed using the Team Workload Questionnaire (TWLQ), reflecting how participants coordinated target search while managing individual tasks (Sellers et al., 2014). Workload measures were completed post-drives. The unique task profiles of each crew role enabled a nuanced analysis of how vehicle automation and object detection system (ODS) assistance modulate individual and team workload. The study employed a robust design using three networked simulated vehicles to connect a six-person team within a shared simulated environment, with both the level of automated assistance and assigned team roles expected to influence workload at individual and team levels.

The overarching research question for this study was how do varying levels of automated assistance influence perceived individual and team workload across team roles with differing task demands?

- **Hypothesis 1 (H_1)**: Lookout roles will report higher overall individual and team workload than Drivers because of their continuous dual task demands.
- **Hypothesis 2 (H_2)**: The effect of automated assistance on perceived individual and team workload will be more pronounced for Drivers, and therefore they will have greater workload variation across drives, as their workload will be more directly modulated by the assistance compared to Lookouts.

METHOD

This study employed a 6 X 4 mixed factorial design with role assignment as the between-subjects factor and assistance condition as the within-subjects factor. A total of 240 participants were organized into 40 teams of six, with each team participating together. Participants were randomly assigned a role in a simulated mission team and had distinct task demands that contributed to differences in baseline workload (i.e., dual continuous task monitoring for lookouts versus maintaining a three-vehicle straight convoy for the drivers). As a team, participants completed four drives with varying levels of assistance in a randomized order. In each drive, participants were instructed to perform their individual tasks while collaborating as a team to search for designated target objects in the simulated environment (e.g. vehicles, pedestrians, bicyclists). The independent variables, assistance condition and role, were manipulated to examine their interaction on the dependent variables, perceived individual and team workload.

Participants

Participants were recruited from the local Tuscaloosa, AL community. Eligibility criteria included licensed adults aged 18–55 who were physically capable of driving, completing tasks, and responding to surveys. After providing informed consent, participants were provided with a link to schedule their appointment. Compensation was structured as follows: $200 for full study completion, $25 for partial completion (e.g., withdrawal, simulator sickness), and $250 for standby participants who filled in last-minute cancellations.

Procedure

Once the six-person team arrived for their scheduled appointment, a study overview presentation was delivered followed by a short quiz checking understanding of the team objective, role responsibilities, and assistance types. Team roles were randomly assigned. Research assistants escorted participants to their designated stations and provided instructions on how to use the technology, driving equipment, and communication headsets (Figure 1). After a group sound check, individual eye-tracking calibration was performed and verified for each participant.

A 7-minute practice drive familiarized participants with the key features they would encounter during the experimental drives (e.g., autonomous driving mode, types of target objects, scenario elements) and gave them an opportunity to interact with vehicle controls and station technology (e.g., tablet-based tasks, overhead convoy display). Participants completed the post-drive survey (NASA-TLX and TWLQ) after the practice drive to become familiar with the survey format and questions. Participants then completed the four 16-minute experimental drives with varying levels of assistance in a randomized order. After each drive, participants completed the post-drive workload survey. Participants were then debriefed and compensated for their time.

Assistance

The four 16-minute experimental mission drives followed a straight route (18,600 meters):

1. No Assistance: Team members completed their tasks without automated assistance.
2. Vehicle Automation (VA): The vehicles (n = 3) were fully autonomous (i.e., did not require drivers to operate), but drivers were instructed to maintain attention to "take back control" if needed.
3. Object Detection System (ODS): The Lead Car Lookout had access to an ODS tablet that provided visual and auditory alerts if the current assigned target was detected by the system in the front- or rear-view camera.
4. Combined Assistance (VA + ODS): Both Vehicle Automation and the ODS were engaged.

These different assistance types were chosen to best examine how differences in provided assistance affect individual and team workload in a simulated ground vehicle mission team:

- Vehicle Automation was integrated to support drivers and allow for attentional resources to be reallocated to target search and identification.
- Object Detection technology was integrated to support the team's primary target search task and offload workload for the Lead Car Lookout who was leading the target search effort.
- The Combined Assistance condition was chosen to systematically reduce workload by addressing individual task demands across team roles through both forms of support.

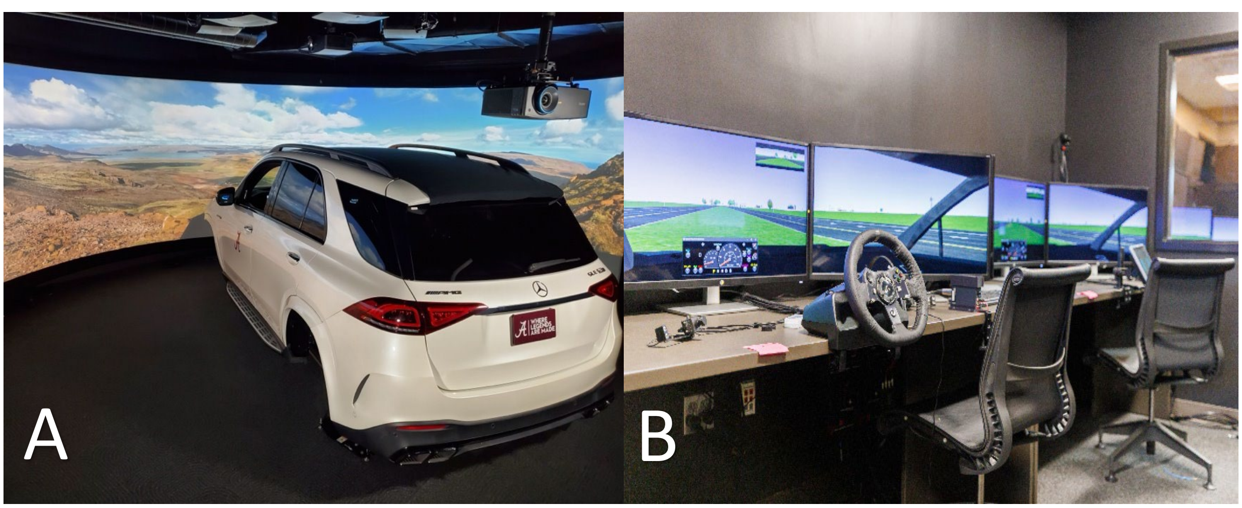

Figure 1. RDS-2000 full-cab simulator with 225-degree projection screen for Lead Car Driver and Lookout **(A)**; RDS-100 desktop simulators for Desktop Drivers and Lookout roles **(B)**.

Roles

Participants retained their randomly assigned roles throughout the appointment. Each six-member team was split into driver-lookout pairings across three simulators (i.e., one full-cab and two desktop simulators; Figure 1) in a networked driving simulation. All roles were responsible for monitoring the environment for target objects and coordinating to support the overall mission while completing their individual tasks:

1. Lead Car Driver (*n* = 1): Participants in this role operated the first vehicle in the three-car convoy using the full-cab simulator (Figure 1A). They were responsible for leading the team at a speed of 45 miles per hour (mph) and maintaining an organized straight convoy. The Lead Car Driver had access to an overhead top-down view of the environment displayed on a tablet to support their efforts to maintain convoy organization and assist in the target search task.
2. Desktop Drivers (*n* = 2): Desktop drivers were responsible for operating the desktop simulators, the second and third car (Figure 1B), and maintaining a following distance of 100 feet from the vehicle immediately ahead.
3. Lead Car Lookout (*n* = 1): Lead Car Lookouts were passengers in the lead car and primarily responsible for leading the target search effort. In addition to performing their continuous dual task demands (Figure 2B), Lead Car Lookouts were provided with the ODS interface and were instructed to tap the target object on the tablet whenever it was identified in the environment. Lead Car Lookouts interacted with the ODS tablet in each drive by double-confirming the target object, even when the ODS was not actively engaged (Figure 2A).
4. Desktop Lookouts (*n* = 2): The lookouts in the desktop simulators were passengers in the second and third car. All lookouts (*n* = 3) were responsible for completing their left and right-side dual tasks on their workstation tablet. The tasks included a shape distractor task to mirror continuous monitoring (left side) and a target identification task, which provided an image of the current assigned target (right side) (Figure 2B).

The lookout workstation tablet and Lead Car Lookout's ODS tablet are displayed in Figure 2. All lookouts were responsible for completing their workstation dual tasks. The left-side task was a shape distractor task designed to simulate the continuous monitoring and vigilance demands typical in military operations. Participants monitored a set of cycling images and were instructed to determine when a shape image matched a descriptive text cue displayed at the top of the screen (e.g., "orange hexagon"). Upon detecting a match, participants tapped "object identified". The text cue periodically changed, assigning a new target shape to monitor. This task was ongoing throughout all four drives (Figure 2B, left side), and required sustained attention and visual discrimination while participants simultaneously searched for target objects, thereby increasing cognitive load and mimicking continuous monitoring demands.

The right-side task was the target object identification task. Lookouts were presented with a static image of the current target object and used it to discuss object details with the team. Once the team located the target object in the simulated environment, lookouts selected "target identified" (Figure 2B, right side) after personally confirming they had seen the target object. Lead Car Lookouts were responsible for tapping the target object on the ODS tablet as a double confirmation. The ODS displayed a real-time camera view of the front and rear views of the lead vehicle using mounted cameras directed toward the projected screens. During the ODS and Combined Assistance drives, the ODS tablet provided visual (i.e., highlighted bounding boxes) and auditory alerts (i.e., front and rear sounds) to the Lead Car Lookout when the target was detected in either view (Figure 2A).

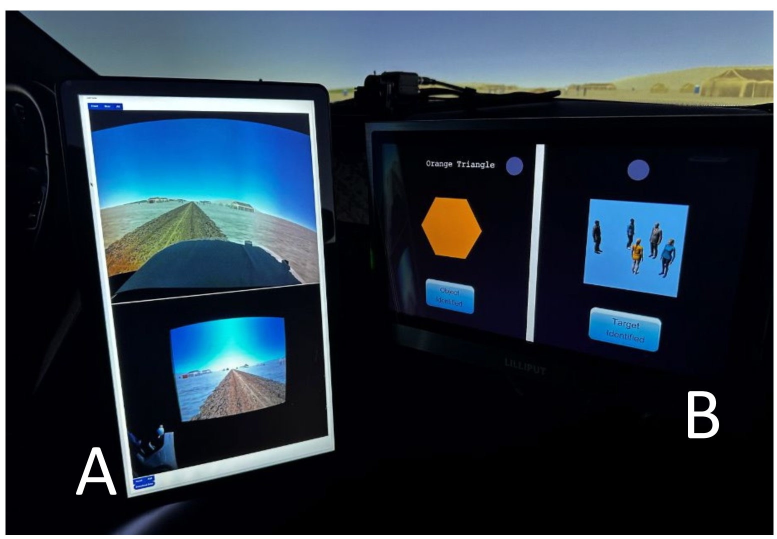

Figure 2. ODS front- (top) and rear- view (bottom) of simulated environment for the Lead Car Lookout **(A)**; Lookouts dual task workstation tablet consisting of shape distractor task (left) and target identification task (right) **(B)**.

Measures

An updated version of the NASA-TLX was used in this study to better assess individual workload demands; it was developed by the author of the TWLQ (Sellers et al., 2014) specifically for evaluating individual task workload. The updated NASA-TLX has been validated and is a preferable measure of task workload compared to the original (Hart, 2006; Helton et al., 2022). The updated version of the NASA-TLX includes four of the original dimensions with two newer validated dimensions: Emotion Demand and Performance Monitor Demand, with factor loadings of .46 and .63 respectively (Sellers et al., 2014). The final individual workload dimensions measured from the NASA-TLX were: Mental demand, Physical demand, Temporal demand, Effort, Performance Monitor Demand, and Emotion Demand on a scale of 0–100.

Team workload was measured using the Team Workload Questionnaire (TWLQ), which was modeled after the updated NASA-TLX (Hart, 2006; Helton et al., 2022; Marques et al., 2015; Sellers et al., 2014). Team workload dimensions measured from the TWLQ were Communication Demand, Coordination Demand, Team Support, Time Share Demand, Team Emotion Demand, and Team Performance Monitor Demand on a scale of 0–100. This study used all six items of the TWLQ for a single team workload score (Greenlee et al., 2019; Pirta-Dreimane et al., 2024; Sellers et al., 2014). For the specific items of the updated NASA-TLX and TWLQ, refer to the author of the TWLQ (Sellers et al., 2014).

The NASA-TLX and TWLQ were scored by taking the unweighted raw average of their respective dimensions (i.e., summing values of each dimension score and dividing by six, for a total score from 0–100)(Nygren, 1991; Virtanen et al., 2022). The NASA-TLX has been used in various fields such as aviation, occupational health, military, and driving research (Grier, 2015; Hart, 2006; Helton et al., 2022). It was selected to best assess subjective individual workload in this project because of its established psychometric properties, including high inter-rater reliability (ICC = .71–.81)(Devos et al., 2020). Regardless of the recent modifications to two dimensions of the NASA-TLX, its core structure remains widely validated, and the improvements to the NASA-TLX have increased its suitability for assessing workload (Sellers et al., 2014). Likewise, despite the TWLQ being a newly introduced measure, it has undergone psychometric validity testing, ensuring its ability to measure individual and team workload and predict task performance (Sellers et al., 2015). The task workload factor of the TWLQ (i.e., the updated NASA-TLX referenced in this study) demonstrated high internal consistency ($\alpha = .78$). Similarly, the team workload and team-task balancing subscales showed strong internal consistency ($\alpha = .74$ and $\alpha = .69$, respectively) supporting the reliability of the overall team workload measure used in this study (Sellers, 2013). In addition, internal consistency for both individual and team workload was assessed within this sample. Individual workload dimensions showed high internal consistency across all assistance conditions ($\alpha = .80$–$.84$); Team workload dimensions also demonstrated strong internal consistency ($\alpha = .77$–$.80$). Additionally, individual and team workload scores were highly correlated across assistance conditions ($r = .69$–$.73$, $p < .0001$), indicating consistent perceptions of workload at both individual and team levels.

Data Analysis

Data were screened to ensure completion and compliance. Non-compliance was identified by average raw scores that were either < 2 or equal to 100, indicating dimension responses that were 100 or less than 2 on all scales of the NASA-TLX and TWLQ. Participants completed four post-drive NASA-TLX and TWLQ surveys, resulting in a total of 960 observations per dependent variable (i.e., individual workload score, team workload score, respective dimension scores). Sixteen observations were excluded from analysis: two due to missing survey responses resulting from appointment incompletion (i.e., one participant only completed two drives), and fourteen due to non-compliance on a post-drive workload survey.

Descriptive statistics for participant demographics, individual workload, and team workload were conducted. Least squares means (LSmeans) were used to estimate and compare descriptive statistics of workload scores between Roles and across Assistance conditions, accounting for covariates in the model. A series of 6 (Roles) X 4 (Assistance conditions) mixed linear models were used to analyze differences in workload scores across assistance conditions and between roles. Separate models were run for each dependent variable: total individual workload score, total team workload score, and each workload dimension for both individual and team workload, resulting in a total of 14 models. Follow-up analyses were run to examine these differences specifically between stratified subgroups of Drivers ($n = 3$) and Lookouts ($n = 3$) using Tukey adjustments for multiple comparisons. For all models, the fixed effects included assistance condition ($n = 4$), role (i.e., 1–6 or Driver vs. Lookout), and their interaction. Assistance condition order

(1–4) was included as a fixed covariate to control for potential order effects. Random intercepts were modeled for each participant to account for the repeated measures, and assistance condition order was also modeled as a random effect to account for slope variability within subjects. An unstructured covariance structure was used for all random effects, selected based on comparisons of model fit indices (i.e., AIC and BIC).

RESULTS

Overall, the sample (N = 240) was young (M_{age} = 24.83 years, SD = 8.05 years, [18–54]), predominantly Caucasian (61%), Female (55%), and native English speakers (85%). Most participants reported experience working with a team (81%) and a small proportion reported previous experience with driving (14%) and military/combat games (22%). Only n = 3 participants reported prior military service, and all identified as former enlisted rank and were no longer active duty.

Individual Workload

For individual workload, there were significant main effects of assistance condition (F (3, 448) = 28.48, p < .001) and role assignment (F (5, 448) = 6.73, p < .001). A significant interaction between assistance and role was observed (F (15, 448) = 6.25, p < .001), indicating that the effect of assistance on individual workload varied by Role. Follow-up analyses examining Driver and Lookout subgroups revealed that this interaction was driven by Drivers, who reported significantly lower individual workload than Lookouts (F (3, 460) = 26.96, p < .001). Drivers perceived individual workload was significantly less than that of Lookouts in all conditions except the No Assistance condition. These differences were more pronounced during the automated drives (VA M_{diff} = -16.41; Combined Assistance M_{diff} = -15.36), whereas Lookouts' workload scores remained consistent across all assistance conditions (Figure 3, left).

To better understand the components contributing to individual workload, each NASA-TLX dimension was analyzed separately. Mental Demand revealed significant main effects of assistance condition (F (3, 448) = 4.92, p = .002) and role assignment (F (5, 448) = 5.6, p < .001). A significant Assistance X Role interaction (F (15, 448) = 2.14, p = .008) indicated that Mental Demand across the drives was dependent on participant role. This moderation was supported by a significant interaction between assistance and Driver vs. Lookout subgroups (F (3, 460) = 7.3, p < .001), where again Drivers reported significantly less Mental Demand than Lookouts across the assistance conditions, but at a greater magnitude when automation was engaged (VA M_{diff} = -17.65; Combined Assistance M_{diff} = -16.05); Lookouts' Mental Demand was relatively stable across drives. Physical Demand revealed a significant main effect of Assistance condition (F (3, 448) = 23.71, p < .001) and a significant Assistance X Role interaction, (F (15, 448) = 6.87, p < .001) revealing that the effect of assistance on Physical Demand was moderated by role assignment. The difference in Physical Demand across assistance conditions was evident in Driver and Lookout subgroup analyses (F (3, 460) = 29.43, p < .001), where Drivers reported significantly less Physical Demand only in the automated drives (VA M_{diff} = -10.29; Combined Assistance M_{diff} = -8.65), but the Physical Demand for Lookouts remained the same regardless of assistance condition. Temporal Demand had a significant main effect of assistance (F (3, 448) = 3.51, p = .015) and role assignment (F (5, 448) = 8.58, p < .001), but no significant interaction, suggesting only an additive effect of Driver and Lookout subgroups. This is supported by Drivers reporting significantly lower Temporal Demand *(F* (1, 460) = 40.88, p < .001) to the same degree across all assistance conditions compared to Lookouts. Temporal Demand was significantly higher in the ODS drive compared to the Vehicle Automation drive (F (1,460) = 8.53, p = .019), but no other assistance condition comparisons showed significant differences for Temporal Demand. Effort revealed a significant main effect of assistance (F (3, 448) = 8.29, p < .001) and role assignment (F (5, 448) = 9.10, p < .001). Further, a significant interaction between assistance and role assignment (F (15, 448) = 2.71, p < .001) indicated a multiplicative effect, which is supported by analyses between Drivers and Lookouts (F (3, 460) = 8.76, p < .001); Drivers reported significantly less Effort in all assistance conditions, especially in the automated and ODS conditions (VA M_{diff} = -21.56; Combined Assistance M_{diff} = -19.01; ODS M_{diff} = -14.86). Emotion Demand findings only yielded a significant main effect of role assignment (F (5, 448) = 3.45, p = .005), and subgroup analyses indicated that Drivers reported significantly less Emotion Demand than Lookouts (F (1, 460) = 16.48, p < .001). Lastly, Performance Monitor Demand exhibited a significant main effect of assistance (F (3, 448) = 30.77, p < .001) and a marginal effect of role assignment (F (5, 448) = 2.09, p = .065). A significant Assistance X Role interaction (F (15, 448) = 8.46, p < .001) was followed up with subgroup analyses, which showed that Drivers reported significantly lower Performance Monitor Demand than Lookouts (F (3, 460) = 34.3, p < .001), but only during the automated drives (VA M_{diff} = -5.48; Combined Assistance M_{diff} = -6.27). Table 1 summarizes the mean differences between Driver and Lookout subgroups across each assistance level for all individual workload dimensions.

Team Workload

For team workload, there was a significant main effect of assistance condition (F (3, 448) = 27.3, p < .001) and a significant Assistance X Role assignment interaction (F (15, 448) = 2.80, p < .001). This interaction was examined further in follow-up analyses between Drivers and Lookouts (F (3, 460) = 11.79, p < .001), revealing the finding that Drivers reported significantly less team workload only during the automated drives (VA M_{diff} = -8.69; Combined Assistance M_{diff} = -8.29). Notably, the Lookouts' team workload remained high and relatively stable across all assistance conditions, while Drivers' workload decreased when autonomous driving was engaged (Figure 3, right).

To explore the underlying factors of team workload, analyses were conducted on each dimension of the TWLQ individually. Communication Demand did not significantly differ between roles or assistance conditions, indicating no detectable differences in perceived Communication Demands among team members or across conditions. Coordination Demand revealed a significant main effect of assistance (F (3, 448) = 19.46, p < .001) and a significant Assistance X Role interaction (F (15, 448) = 3.70, p < .001). Follow-up analyses comparing Driver and Lookout subgroups indicated that Drivers reported significantly less Coordination Demand than Lookouts only during the automated drives (F (3, 460) = 14.10, p < .001; VA M_{diff} = -11.8; Combined Assistance M_{diff} = -12.51). In contrast, no significant differences between Drivers and Lookouts were found in the ODS or No Assistance conditions. Team Support did not yield any significant differences between roles or assistance conditions, indicating no detectable differences in perceived support across team members or conditions. Time Share Demand revealed a significant main effect of assistance (F (3, 448) = 12.36, p < .001) and role assignment (F (5, 448) = 7.26, p < .001). No interaction was detected, indicating an additive effect of assistance and role assignment. However, a subgroup analysis between Drivers and Lookouts yielded a significant Assistance X Role interaction, with Drivers reporting significantly less Time Share Demand than Lookouts, particularly in the automated drives (F (3, 460) = 4.81, p = .003; VA M_{diff} = -19.71; Combined Assistance M_{diff} = -19.76). Team Emotion Demand demonstrated a significant main effect of assistance (F (3, 448) = 3.88, p = .009), with Emotion Demand being greater in non-automated conditions (i.e., ODS and No Assistance). Lastly, Team Performance Monitor Demand only revealed a significant main effect of assistance (F (3, 448) = 15.74, p < .001), indicating that Team Performance Monitor Demand was significantly greater in the non-automated drives for all roles. Table 1 summarizes the mean differences between Driver and Lookout subgroups across each assistance level for all team workload dimensions.

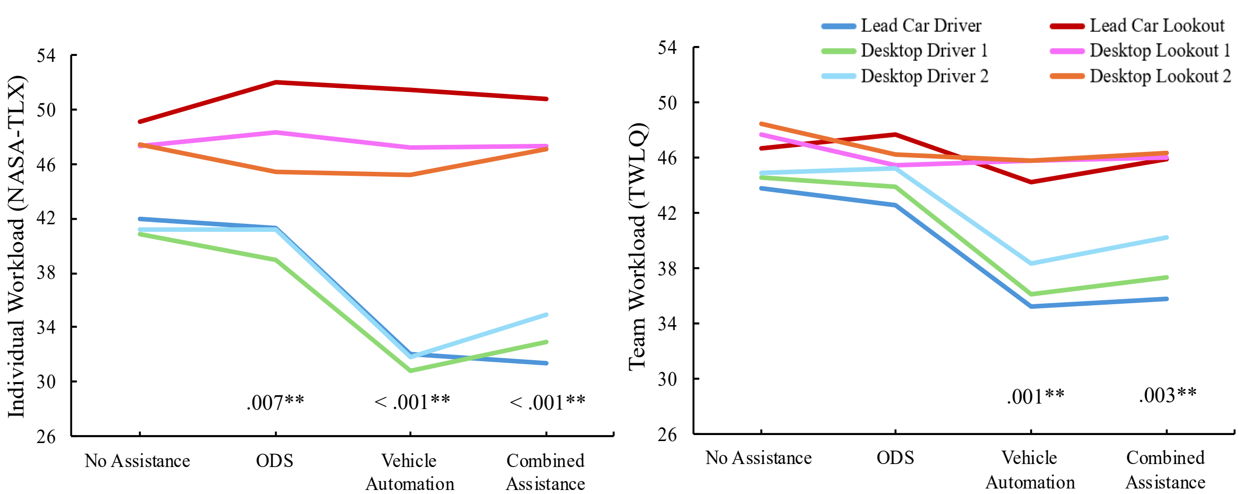

Figure 3. Individual and team workload scores (0–100) by role and assistance condition. The left panel displays least-squares mean (LSmean) individual workload scores measured by the updated NASA-TLX. The right panel shows LSmean team workload scores measured by the TWLQ. ** indicates a statistically significant mean difference (p < .01) between Driver (cool colored) and Lookout (warm colored) subgroups within each assistance condition.

Table 1. *Summary of least square mean (LSmean) difference comparisons of NASA-TLX and TWLQ workload dimensions between Driver (n = 3) and Lookout (n = 3) subgroups.*

	Drivers (LSmean)	Lookouts (LSmean)	LSMean Difference	*t* (460)	*p*	95% CI LCI, UCI
Mental Demand						
Combined Assistance	48.11	64.16	-16.05	-5.05	<.001**	-25.73, -6.37
No Assistance	52.25	63.58	-11.33	-3.56	<.001**	-21.03, -1.64
Object Detection System (ODS)	53.15	62.99	-9.84	-3.11	.041*	-19.45, -.22
Vehicle Automation (VA)	46.13	63.69	-17.56	-5.59	<.001	-27.12, -7.99
Physical Demand						
Combined Assistance	15.77	24.42	-8.65	-3.07	.046*	-17.22, -.07
No Assistance	28.35	23.71	4.65	1.65	.722	-3.94, 13.23
Object Detection System (ODS)	26.23	24.36	1.87	0.67	.997	-6.64, 10.37
Vehicle Automation (VA)	14.58	24.88	-10.29	-3.72	.005**	-18.72, -1.86
Temporal Demand						
Combined Assistance	36.04	53.46	-17.42	-5.7	<.001**	-26.72, -8.12
No Assistance	37.96	54.52	-16.56	-5.42	<.001**	25.87, -7.25
Object Detection System (ODS)	38.78	54.99	-16.21	-5.35	<.001**	-25.43, -6.98
Vehicle Automation (VA)	34.18	52.98	-18.79	-6.24	<.001**	-27.97, -9.63
Effort						
Combined Assistance	41.05	60.06	-19.01	-6.4	<.001**	-28.04, -9.97
No Assistance	50.1	60.16	-10.06	-3.39	.017*	-19.11, -1.01
Object Detection System (ODS)	46.23	61.09	-14.86	-5.05	<.001**	23.82, -5.91
Vehicle Automation (VA)	39.36	60.92	-21.56	-7.37	<.001**	-30.46, -12.65
Emotion Demand						
Combined Assistance	18	30.41	-12.41	-3.7	.006**	-22.62, -2.21
No Assistance	20.07	30.52	-10.44	-3.12	.040*	-20.64, -.24
Object Detection System (ODS)	19.68	30.97	-11.29	-3.38	.017*	-21.47, -1.11
Vehicle Automation (VA)	15.86	29.34	-13.48	-4.02	.002**	-23.7, -3.28
Performance Monitor Demand						
Combined Assistance	38.82	58.84	-20.02	-6.27	<.001**	-29.74, -10.3
No Assistance	58.46	56.12	2.34	0.73	.996	-7.37, 12.05
Object Detection System (ODS)	58.11	57.5	0.6	0.19	1.000	-9.09, 10.3
Vehicle Automation (VA)	38.66	56.21	-17.55	-5.48	<.001**	-27.3, -7.79
Communication Demand						
Combined Assistance	66.22	68.31	-2.09	-0.7	.997	-11.16, 6.96
No Assistance	69.46	69.84	-0.38	-0.13	1.000	-9.45, 8.69
Object Detection System (ODS)	69.85	67.77	2.07	0.7	.997	-6.9, 11.06
Vehicle Automation (VA)	66.35	68.83	-2.48	-0.85	.990	-11.38, 6.43
Coordination Demand						
Combined Assistance	46.7	59.21	-12.51	-3.63	.008**	-23.01, -2.01
No Assistance	60.08	60.11	-0.03	-0.01	1.000	-10.53, 10.46
Object Detection System (ODS)	59.99	57.64	2.35	0.69	.997	-8.09, 12.8
Vehicle Automation (VA)	44.8	56.6	-11.8	-3.44	.015*	-22.24, -1.36
Team Support						
Combined Assistance	27.32	33.99	-6.67	-2.4	.246	-15.15, 1.8
No Assistance	29.42	33.71	-4.28	-1.54	.787	12.76, 4.2
Object Detection System (ODS)	30.27	33.97	-3.7	-1.34	.883	-12.1, 4.71
Vehicle Automation (VA)	25.49	33.12	-7.63	-2.78	.102	-15.98, .72
Time Share Demand						
Combined Assistance	26.07	45.83	-19.76	-6.1	<.001**	-29.62, -9.9
No Assistance	36.79	48.96	-12.17	-3.76	.005**	-22.03, -2.31
Object Detection System (ODS)	34.67	47	-12.33	-3.84	.004**	-22.11, -2.55
Vehicle Automation (VA)	25.96	45.86	-19.71	-6.22	<.001**	-29.65, -10.17
Team Emotion Demand						
Combined Assistance	17.67	23.63	-5.97	-2.16	.379	-14.4, 2.44
No Assistance	20.01	24.13	-4.11	-1.49	.814	-12.53, 4.31
Object Detection System (ODS)	19.33	24.15	-4.82	-1.76	.646	-13.19, 3.53
Vehicle Automation (VA)	16	22.87	-6.87	-2.52	.191	-15.19, 1.44
Team Performance Monitor Demand						
Combined Assistance	42.22	46.02	-3.79	-1.12	.953	-14.17, 6.57
No Assistance	49.95	49.33	0.62	0.18	1.000	-9.76, 11

Object Detection System (ODS)	48.51	48.69	-0.19	-0.05	1.000	-10.51, 10.13
Vehicle Automation (VA)	40.17	44.53	-4.34	-1.28	.905	-14.66, 5.97

Note. Tukey adjusted p-values were used. $^*p < .05$, $^{**}p < .01$, 95% CI = Confidence Interval (Lower, Upper).

DISCUSSION

These findings demonstrate that automation reduces perceived workload unevenly across team roles, with Drivers experiencing greater benefits from assistance systems than Lookouts. For individual and team workload measures, significant assistance by role interactions revealed that Drivers reported lower workload, particularly in automated conditions, while Lookouts consistently reported high workload regardless of assistance condition. These results highlight an important design consideration: current assistance systems tend to prioritize driver support while neglecting non-driving roles, such as Lookouts, who often manage dual tasks involving continuous monitoring and frequent task switching, ultimately compromising both team performance and equity in human-automation teaming.

For individual workload, analysis of NASA-TLX dimensions revealed consistent patterns indicating that current assistance systems primarily reduce workload for Drivers, while offering little support for Lookouts. Mental Demand varied significantly by both assistance condition and role, with a notable interaction indicating that Drivers experienced the greatest reduction in cognitive load during automated drives, whereas Lookouts reported consistently high Mental Demand across all conditions. A similar pattern emerged for Physical Demand, where only Drivers experienced relief under automation, while Lookouts' physical effort remained unchanged. This finding was expected, as automation relieved Drivers from manual vehicle operation, whereas Lookouts, whose tasks were unrelated, received no direct physical benefit from the autonomous driving. Temporal Demand was also lower for Drivers overall, but this effect was additive, indicating that Drivers consistently felt less rushed than Lookouts, regardless of assistance condition. This heightened Temporal Demand for Lookouts likely reflects the continuous monitoring and task switching required of their role, generating persistent time pressure. Effort ratings mirrored these trends, with significant reductions for Drivers under all assistance conditions, especially in the ODS and fully automated drives, while Lookouts again saw no benefit, highlighting the nature of their increased task workload. Emotion Demand was higher for Lookouts across the board, suggesting that supporting roles may have involved more emotional regulation, likely due to their increased need to manage their tasks effectively. Emotion Demand differences were amplified in automated drives, likely reflecting increased burden on Lookouts to coordinate and maintain situational awareness in response to reduced driver engagement. Finally, Performance Monitor Demand decreased for Drivers only in automated drives, while remaining steady for Lookouts, indicating that Drivers had reduced involvement with the target search task when the vehicles were autonomous. Collectively, these findings suggest that although assistance systems are effective at offloading individual workload components for Drivers, they may unintentionally neglect the needs of Lookouts. This imbalance emphasizes the need for more equitable workload distribution and highlights the importance of designing assistance systems that actively support all team members by dynamically reallocating tasks through adaptive task-sharing mechanisms (e.g., AI-driven systems that monitor workload in real time and adjust task assignments based on team members' workload)(Heard & Adams, 2019; Heard et al., 2020; Jo et al., 2024).

Team workload results mirrored the imbalanced findings observed with individual workload. Drivers reported lower team workload in only the automated conditions, driven by reduced Coordination Demand and Time Share Demand dimensions. However, Lookouts' team workload remained high and stable across all assistance conditions, indicating that automation did not alleviate their responsibilities related to team coordination, communication, and maintaining situational awareness while simultaneously completing their dual tasks. This imbalance highlights that although automation may reduce certain workload dimensions for Drivers, it inadvertently shifts more burden onto the Lookouts, who are already managing complex, attention-demanding tasks. The increased responsibility placed on Lookouts may exacerbate the task and team workload they experience, further underscoring the need for more equitable task allocation when teams are augmented by assistance. Interestingly, Communication and Team Support Demands did not differ by role or assistance, implying that communication and mutual support needs were perceived as consistent across the drives for all team members. Additionally, Team Emotion Demand and Team Performance Monitor Demand were elevated in non-automated drives for all roles, likely reflecting heightened stress and greater responsibility for overseeing team progress in the target search task when autonomous support was unavailable, and all members had to independently perform their tasks while also meeting team objectives. These results highlight the importance of designing assistance systems that dynamically balance support across roles, ensuring that no team member, particularly those in continuous monitoring or task-switching positions, is left with a disproportionate share of the workload as task demands shift.

These findings have key implications. First, AI assistance should not be uniformly applied but dynamically tailored to the shifting workload of different team members. For example, assistance could be enhanced with technology that tracks physiological indicators (e.g., heart rate variability or eye tracking) to detect elevated workload and then redirect non-critical monitoring tasks or environment scanning responsibilities across teammates (Diaz-Piedra et al., 2021; Heard & Adams, 2019; Heard et al., 2020; Jo et al., 2024). Real-time workload monitoring could enable systems to offload high-demand tasks, such as sustained vigilance or performance monitoring, especially for roles like lookouts, who remain cognitively overloaded even during automation support (Cherif et al., 2018; Jo et al., 2024). Second, the clear distinction of responsibilities within teams assisted by automation is essential. Drivers' responsibilities noticeably shifted under automation, yielding decreased workload, while lookouts' responsibilities remained elevated and consistent. Training must therefore focus on helping human operators understand their shifting task demands under varying assistance conditions, to ensure workload is properly distributed and support systems are effectively used. As a result, designing training protocols that highlight how tasks will shift between roles under different assistance levels is critical (Tucholski, 2022). Without such training, operators may fail to adapt to shifting expectations and be inadequately supported, limiting the effectiveness of assistance systems (Tucholski, 2022; Zhao et al., 2025).

In summary, these findings suggest that achieving effective workload reduction in human-AI assisted teams requires more than the application of static automation. Rather, it calls for the integration of adaptive, workload-sensitive support systems capable of detecting operator overload in real time and dynamically reallocating tasks as needed. Such systems should also be complemented by training that prepares operators to anticipate and manage changes in their responsibilities arising from external contingencies (e.g., mission demands, automation capabilities, environmental conditions, or workload imbalance). In absence of these adaptive supports and training, automation may inadvertently intensify workload disparities, especially for roles that may not be directly supported by automation.

Limitations and Future Directions

This study provided important insights into workload distribution in human-AI/automated assisted teams, but several limitations and opportunities for future research should be noted. The controlled simulated environment in this study limits the generalizability of the findings to real-world conditions. For instance, the visual perspectives of team members varied across different car positions in the convoy, which may have affected attitudes towards their tasks. The structure of the straight three-vehicle convoy may not align with other military protocols (e.g., V-formation convoy). Moreover, role assignments were fixed, unlike real-world scenarios where roles may be more fluid and shift dynamically depending on mission objectives or external factors. The controlled environment did not account for variations in terrain, lighting, or navigational uncertainty, all of which could impact workload in real-world scenarios. Additionally, the absence of realistic risk factors (e.g., driving "under fire" or avoiding road hazards) may have reduced the level of stress or seriousness experienced by participants, limiting the ecological validity of the findings. Finally, the use of a convenient sample that was mostly non-military raises concerns about the external validity of the results, as the findings may not fully reflect the experiences of trained military personnel. It is important to note that the findings in this study were based on subjective self-reports, which may introduce response biases.

Without adaptive, role-sensitive support systems, automation may inadvertently shift workload rather than alleviate it, undermining mission performance. These findings emphasize that assistance systems should not be designed as one-size-fits-all solutions; instead, they must monitor team member workload in real time and dynamically reassign tasks to maintain operational balance. Further, training protocols should equip operators with a clear understanding of how assistance affects role expectations across changing mission conditions. Future research should examine how trust in AI and automation evolves through repeated exposures to varying levels of assistance, as this could offer deeper insights into the nature of trust in assistance systems and its impact on team performance. Future studies should address these limitations by incorporating more realistic and varied conditions to better capture the complexities of human-automation collaboration in dynamic, high-risk settings.

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