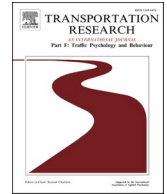




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The effects of camera perspective and augmentation on performance, situation awareness and mental workload of remote assistants of highly automated vehicles

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ABSTRACT

In real-world operations, highly automated vehicles (HAVs, SAE Level 4) face many traffic situations they cannot cope with, e.g., situations with adverse weather. Remote human support may help to resolve such situations to increase robustness of HAV operations. In this task context, human-machine interfaces (HMIs) for remote operators of HAVs often present traffic situations similar to the driver's perspective. However, this first-person view is associated with shortcomings including the occlusion of relevant objects on the road or the distortion of distance and angle perception. These shortcomings may affect the performance of the remote operator. An experimental lab study with 37 participants was carried out to investigate if three different camera perspectives affect operator performance, situation awareness, and other operator-related variables in a remote assistance task at a busy urban intersection with mixed traffic. Additionally, the interplay of camera perspectives and video augmentation by visualizing additional sensor data was investigated in an environment with and without adverse weather due to fog. Results indicated that certain performance indicators including decision time were affected by camera perspective. The positive and compensatory impact of augmentation under poor visibility conditions in adverse weather was replicated. Findings suggest that the most suitable perspective highly depends on the specific scenario. The results will help design context-sensitive HMIs for remote assistance of HAVs.

1. Introduction

Highly automated vehicles (HAVs) bear the potential to positively impact traffic safety, reliability, and availability of mobility, particularly in public transport. However, highly automated driving systems (ADS, SAE Level 4; [SAE International, 2021](#)) are still challenged by complex road environments such as urban spaces. Relying on object detection via sensors, HAV operations are often confined to certain operating conditions, known as the operational design domain (ODD). For instance, an ODD may enable highly automated driving in good weather and lighting conditions while not permitting it under adverse weather and light conditions (e.g., fog, at night). When the ODD is violated or its limit is reached, the HAV must conduct a minimum-risk maneuver (MRM) like a safe

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stop. To continue the ride, a human remote operator may guide the HAV through this challenging situation.

One way to realize HAV remote operation is *remote assistance*. In remote assistance, an operator supports the HAV on a maneuver-based level but does not perform the dynamic driving task involving steering, accelerating, and braking. The operators who perform remote assistance provide guidance based on their perception and processing of relevant information. Notably, in the European Union (EU) remote assistants must be ready at all times to support highly automated vehicles (SAE Level 4) in case they approach the limit of their ODD (*EU Implementing Regulation 2022/1426, 2022*). In the EU, the remote assistant can initiate a minimum risk maneuver, confirm maneuvers suggested by the ADS, select or modify the itinerary, and assist the passengers. However, the HAV explicitly remains responsible for performing the dynamic driving task.

To enable safe and efficient remote assistance and fulfil these legal duties, the workplace of the remote assistant should optimally support task execution. This workplace includes a human-machine interface (HMI), mitigating information exchange between the remote assistant and the assisted HAV. Despite their relevance for remote assistance, HMI design has been covered scarcely in the literature. For example, following a human-centered design process, *Kettwich, Schrank, and Oehl (2021)* designed and evaluated an HMI prototype for a workplace for remote assistance of SAE 4 shuttle buses. *Schrank, Walocha, Brandenburg, and Oehl (2024)* refined the HMI concept of *Kettwich et al. (2021)* and systematically evaluated it in an experiment with a dual-task paradigm. Other research addressed technical aspects of HMI design without focusing on human factors issues like situation awareness and operator performance (*Amador, Aramrattana, & Vinel, 2022; Andersson, Rizgary, Söderman, & Vännström, 2024; Zhao et al., 2024*). For example, *Majstorovic et al. (2022)* reviewed teleoperation concepts for automated vehicles with a focus on ADS functionalities but did not discuss the implications of the concepts for the human operator. Additional research addressed software and hardware solutions for remote operation (e.g., *DriveU.auto, 2023; Herger, 2023; T-Systems, 2023; Vay, 2022*) but did not conduct systematic research to develop and evaluate HMIs for the remote assistance of HAV.

A central component of the remote assistant's task performance is the accurate perception of the traffic situation the assisted HAV is in. The operator can assess the vehicle's traffic situation via the HMI. Current HMI concepts present traffic situations as video streams. To date, few studies systematically examined the effects of camera perspective on the remote operator, particularly regarding human factors aspects. In current HMI concepts, the video stream transmitted to the remote operator shows the driver's perspective (*Andersson et al., 2024; e.g., Nick & Deml, 2025*). However, this first-person view is associated with shortcomings, including the occlusion of relevant objects on the road or the distortion of distance and angle perception. Other camera perspectives may be beneficial in addressing these issues. For example, *Bernhard and Hecht (2021)* investigated the effect of the positions of rear-view cameras in vehicles. They found that both high and low positions lead to misestimations of distance. However, when the vehicle was visible to participants. This finding suggests that a third-person view could be beneficial for accurate distance estimation.

Table 1
Advantages and challenges of camera perspectives for remote assistance of highly automated vehicles.

Perspective	Advantages	Challenges
First-Person View (FPV)	<ul style="list-style-type: none"> Perception of the environment from the driver's perspective (<i>Boker & Lanir, 2023</i>) → Spatial presence, greater cognitive involvement (<i>Schuurink & Toet, 2010</i>) Visually realistic, graphically appealing (<i>Burigat, Chittaro, & Sioni, 2017</i>) Recognizing objects (<i>Rapp & Gena, 2014</i>) Superior in navigation and wayfinding (<i>Lamb & Hollands, 2005</i>) 	<ul style="list-style-type: none"> Scaling variance (<i>Roddick, Kendall, & Cipolla, 2019</i>) Perspective bias (<i>Roddick et al., 2019</i>) Difficulty estimating distances (<i>Roddick et al., 2019; Schuurink & Toet, 2010</i>) and movement sequences (<i>Kallinen, Salminen, Kedzior, Sääksjärvi, & Ravaja, 2007; Schuurink & Toet, 2010</i>)
Bird's Eye View (BEV)	<ul style="list-style-type: none"> Distance detection, collision avoidance (metric scaling, direct mapping of distances) (<i>Boker & Lanir, 2023; Roddick et al., 2019; Unger et al., 2023</i>) Detection of occlusions (<i>Li et al., 2024; Unger et al., 2023</i>) No perspective bias (<i>Feng, Chen, Zuo, & Asundi, 2017; Roddick et al., 2019; Unger et al., 2023</i>) Simplified representation (<i>Burigat et al., 2017; Roddick et al., 2019; Unger et al., 2023</i>) Improved fusion (<i>Unger et al., 2023</i>) Compatible 2D detection algorithms (<i>Unger et al., 2023</i>) → Decision-based tasks (<i>Roddick et al., 2019; Unger et al., 2023</i>) 	<ul style="list-style-type: none"> Object recognition (<i>Boker & Lanir, 2023</i>) Accuracy of distance detection depending on depth information (<i>Unger et al., 2023</i>) Transformation inaccuracy (<i>Unger et al., 2023</i>) Modeling the real world (<i>Unger et al., 2023</i>) Missing altitude information (<i>Unger et al., 2023</i>) Abstraction (<i>Burigat et al., 2017</i>)
Third-Person View (TPV)	<ul style="list-style-type: none"> Shorter orientation time (<i>Burigat et al., 2017, Satyavolu, Creem-Regehr, Stefanucci, & Thompson, 2014</i>) Better clarity (<i>Gawel, Lin, Koutros, Siegart, & Cadena, 2018; Schuurink & Toet, 2010</i>) Less mental stress (<i>Burigat et al., 2017</i>) Improved situation awareness (<i>Gawel et al., 2018; Schuurink & Toet, 2010</i>) Wider field of vision (<i>Gawel et al., 2018; Schuurink & Toet, 2010</i>) More efficient navigation (<i>Gawel et al., 2018</i>) Superior in tasks requiring global situation awareness (<i>Lamb & Hollands, 2005</i>) 	<ul style="list-style-type: none"> Less intuitive and close to reality (<i>Burigat et al., 2017</i>) Depending on the choice of camera angle (<i>Burigat et al., 2017</i>)

1.1. Camera perspectives

Camera-based perception is pivotal for an HAV to accurately analyze the traffic situation it is in. It affects multiple perceptual tasks, including identification of objects, depth estimation, and movement prediction (Unger et al., 2023). Additionally, the video feed of the cameras is a major source of information for the remote operator (e.g., Andersson et al., 2024). Therefore, camera perspective may have a significant impact on how the operator perceives and assesses the situation. It may affect system safety and the operator's performance, situation awareness, and workload. Studies exploring remote operation of HAVs often use a perspective similar to that of a driver's first-person view (FPV), e.g., Mutzenich, Durant, Helman, and Dalton (2021). This perspective shows what the driver sees. It does not include the driver's vehicle (ego-vehicle). Perspectives other than FPV have the potential to replace or complement the FPV. For example, infrastructure-based cameras and sensors outside the HAV may help remote operators in their assessment of the situation. Such roadside facilities are primarily installed to support the HAV in challenging road environments, such as complex intersections, but may also be used in remote assistance (DLR, 2025). Also, virtual three-dimensional representations of the road environment can be generated from sensor data, the fusion of multiple data sources, and the application of virtual sensors (Bahn, Gimm, Fischer, & Schickanz, 2024) and viewed from any desired perspective (Foxglove, 2025; Schäfer, Böker, Schmälzle, & Junghans, 2024). Table 1 lists three camera perspectives and their advantages and challenges for remotely assisted HAVs.

Table 1 reveals that FPV is characterized by spatial presence and high cognitive involvement (Kallinen et al., 2007; Schuurink & Toet, 2010). Participants consider it visually realistic and aesthetically appealing (Burigat et al., 2017). FPV shortens the time to find objects compared to other perspectives (Rapp & Gena, 2014). Also, it showed better performance in navigation and wayfinding tasks operationalized by task completion time (Lamb & Hollands, 2005). However, the non-orthogonal camera angle in FPV distorts the size of objects, leading to a perspective bias and poor distance estimations (Roddick et al., 2019).

The Bird's Eye View (BEV) refers to the bird-like perspective on a situation, usually orthogonal to the ground and often centered on the most relevant object in the situation, mostly the ego-vehicle. The major advantage of this perspective is the isogonal representation of the situation, i.e., angles are not distorted, and thus no perspective bias occurs (Feng et al., 2017). This allows for a direct mapping of distances and metric scaling, positively contributing to distance estimation (Boker & Lanir, 2023). Occlusion of objects does not occur in BEV (Li et al., 2024). It can be used for simplified representations and yields positive results when combined with other sensor data (Roddick et al., 2019). Further, BEV is compatible with two-dimensional detection algorithms to support decision-making. Shortcomings of BEV include poor object recognition due to large object distances and views from unfamiliar angles (Boker & Lanir, 2023). When camera images are post-hoc transformed into BEV, inaccuracies may occur. Also, when the situation is viewed from above, height information is missing. This may limit the accuracy of distance detection, which depends on the provided depth information (Unger et al., 2023). Finally, images viewed from BEV may appear abstract, particularly to inexperienced viewers (Burigat et al., 2017).

The Third-Person View (TPV) is the perspective from above and behind the ego-vehicle, showing the vehicle itself and the environment around it. On the one hand, TPV is associated with shorter orientation times (Satyavolu et al., 2014), improved clarity (Schuurink & Toet, 2010), less mental stress (Burigat et al., 2017), enhanced situation awareness, and a wider field of vision (Gawel et al., 2018). It was found to be more efficient in navigation tasks and superior in tasks that require global situation awareness than FPV (Lamb & Hollands, 2005). On the other hand, participants found TPV to be less intuitive and less close to reality. Additionally, the configuration of the camera angle is important as it may result in relevant objects being concealed or unclear, lowering usability (Burigat et al., 2017).

In summary, each perspective has its distinct advantages and challenges (see Table 1). To date, different camera perspectives have not yet been systematically compared regarding their effect on safety, performance, and operator-related variables such as situation awareness and workload.

Therefore, the objective of the paper is to determine whether BEV or TPV positively affect operator performance, situation awareness, and other user-related variables compared to FPV in a remote assistance scenario with adverse weather conditions. Additionally, the interplay of camera perspectives with an augmentation of visualized sensor data will be examined. Augmentation refers to the highlighting of relevant road users with three-dimensional bounding boxes based on visualized sensor data and is described in more detail in the following section. To answer these questions, we conducted an experimental study in a simulated environment.

1.2. Augmented HMI and adverse weather

In current HMI concepts for HAV remote operation, the video feed from the assisted supervised HAV is the dominant source of information for the remote operator (Andersson et al., 2024; e.g., Nick & Deml, 2025). It affects the operator's situation awareness and performance. Video-based systems may work well under conditions with good visibility and high bandwidth. However, optimal conditions may be rather the exception than the rule in real-world operations of HAVs, depending on the geographical and climatic context of the operational area. Weather effects such as precipitation, lightning and fog may pose special challenges to HAV sensors, including restricted visibility (Vargas, Alswiss, Toker, Razdan, & Santos, 2021). Dannheim, Icking, Mader, and Sallis (2014) showed that fog affects operator perception negatively by reducing image contrast and making pattern edge recognition more difficult. It may even become impossible for remote operators to assess a traffic situation based on the video feed alone because of adverse weather conditions. Also, not all relevant road users may be identified in foggy situations based on video data alone. Thus, including testing conditions that examine adverse weather effects is essential in order to deploy HAVs in real-world operations, including the application of remote operation technology.

In spite of the practical relevance of investigating suboptimal weather conditions in simulated driving tasks, these conditions are not adequately represented in existing research. This is particularly true for the remote operation of vehicles. For example, [Boker and Lanir \(2023\)](#) investigated the effect of a bird's-eye view on situation awareness in simulated remote driving scenarios. However, all scenarios appeared to have had optimal weather conditions, with blue skies and bright daylight present and no adverse weather conditions noticeable. Thus, a need arises to test the effect of camera perspectives under adverse weather conditions.

In addition to investigating their effect on performance and situation awareness, approaches to mitigate the potentially negative impact of adverse weather on these measures need to be researched. The development of augmented HMIs that support perception may be helpful to ensure robust operations of HAVs even under adverse weather conditions, such as fog, also in conjunction with remote operation. HAVs are often equipped with a variety of sensors, including radar, sonar, LiDAR, and ultrasonic sensors ([Sarker et al., 2020](#)). [Schrank, Wendorff, and Oehl \(2024\)](#) proposed to utilize this sensor data as an additional source of information for remote operators. In an online user study, [Schrank et al. \(2024b\)](#) visualized LiDAR point clouds of real-world driving footage by applying object segmentation and classification algorithms to colour-code the LiDAR points by object class, e.g., other vehicles and pedestrians. In conditions with low visibility, the colour-coded LiDAR overlay led to an increase in objective situation awareness. The authors concluded that visualizing sensor data may improve operator situation awareness in situations of low visibility.

Again, situations with low visibility of objects may occur due to low bandwidth, low-light environments, adverse weather conditions, low contrast, blocked sensors, etc. ([Zhang, Guo, Ma, Liu, & Zhang, 2021](#)). These situations may lead to poor object recognition, which may increase accident rates. In a recent study, [Schrank, Wilbrink, Brandenburg, and Oehl \(2025\)](#) again proposed using additional sensor data to support the operator's perception of relevant objects when visibility is poor. In the concept of [Schrank et al. \(2025\)](#), the sensor data is visualized by highlighting road users with three-dimensional bounding boxes, which are laid over the video stream. To avoid visual clutter, an adaptive approach was used that highlighted only those road users relevant to the traffic situation, a complex left turn. The results of an experimental study revealed that the augmented HMI effectively supported participants in their remote assistance task of giving clearance to a complex left-turn maneuver. The bounding boxes reduced collisions, improved situation awareness, and received higher usability ratings from the operators, particularly in foggy situations at moderate levels of cognitive workload ([Schrank et al., 2025](#)). These findings suggest that augmentation is effective in enhancing operator situation awareness and performance in situations with poor visibility.

1.3. Research question and hypotheses

As no research exists on the effect of camera perspectives in remote operation under adverse weather, the present study examines whether the alternative camera perspectives third-person view (TPV) and bird's-eye view (BEV) are better suited to support remote operators in their task of assisting HAVs compared to first-person view (FPV), and how the adverse weather condition of fog influences these effects. In addition, we want to examine whether the previously demonstrated effects of bounding box augmentation and fog from the study by [Schrank et al. \(2025\)](#) can be replicated. The following hypotheses are posed:

H1. Operator Performance – It is hypothesized that augmentation will have a positive impact on operator performance, i.e., decision time, minimum distance to oncoming vehicles, and collision rate, while fog will decrease operator performance. An interaction effect between augmentation is expected as well, with augmentation compensating for the negative impact of fog. For camera perspectives, it is assumed that TPV and BEV will result in better performance than FPV.

H2. Situation Awareness (SA) – It is assumed that augmentation will have a positive impact on SA, while fog will decrease SA. An interaction effect between augmentation is expected as well, with augmentation compensating for the negative impact of fog. For camera perspectives, it is assumed that TPV and BEV will result in better SA than FPV.

H3. Mental Workload – We expect augmentation to lower mental workload, while fog will increase it. An interaction effect between augmentation is expected as well, with augmentation compensating for the negative impact of fog. For camera perspectives, it is assumed that TPV and BEV will result in a lower workload than FPV.

H4. Usability – It is hypothesized that augmentation will have a positive impact on usability ratings, with fog affecting them negatively. An interaction effect between augmentation is expected as well, with augmentation compensating for the negative impact of fog. For camera perspectives, it is assumed that TPV and BEV will result in higher usability ratings than FPV.

2. Method

2.1. Sample

Participants were recruited via postings in the research institute's participant database and circulating email invitations to local universities. The analysis includes data from $N = 37$ participants (9 female). Participants were between 20 and 55 years old ($M = 31.20$; $SD = 7.70$). They had possessed a passenger car driver's license for at least two years and steered a vehicle at least 5000 km within the last twelve months. The participants showed a high affinity for technology ($M = 4.45$, $SD = 2.68$; 1 = "not true at all", 5 = "completely true"; [Franke, Attig, & Wessel, 2019](#)) and a positive attitude towards automated vehicles ($M = 4.16$, $SD = 0.93$; 1 = "not at all", 5 = "very strong"). Attitudes towards digital games were slightly positive ($M = 3.47$, $SD = 3.16$; 1 = "do not agree at all", 5 = "strongly agree"; [Chang, Kuo, & Liu, 2014](#)) and self-reported driving behavior was predominantly defensive ($M = 1.82$, $SD = 1.80$; 0 = "never", 5 = "very often"; [Reason, Manstead, Stradling, Baxter, & Campbell, 1990](#)). Detailed information on the methods applied and

data collected can be found in [Table A1](#) in the Appendix. Participation was voluntary. Participants received 20 Euros as compensation upon the completion of the study. The study was conducted in accordance with the Declaration of Helsinki and approved by the ethics committee of the institute serving as the institutional review board (decision no. 34/24).

2.2. Experimental design

The study was conducted in a $3 \times 2 \times 2$ within-subject design with the independent variables camera perspective (first-person (FPV) vs. third-person (TPV) vs. bird's-eye view (BEV)), augmentation (with vs. without), and fog (with vs. without). Each participant completed all twelve scenarios twice, resulting in 24 trials per participant. The order of trials was counterbalanced. Thus, each participant underwent the same conditions but in a different order. [Fig. 1](#) provides screenshots from selected scenarios. [Fig. A1](#) in the Appendix shows a comprehensive set of screenshots from all conditions.

2.3. Operator tasks and scenario

Participants were asked to assist an HAV in a complex left-turn scenario at an urban intersection with two lanes per direction (adopted from [Schrank et al., 2025](#)). In regular operations, the HAV would make the decision to turn left based on information from the traffic light that is transmitted via vehicle-to-infrastructure (V2I) technology. This was not possible in the scenario due to signal failure. Therefore, the HAV needed external support from the participant who was assigned the role of a remote assistant during the study. Once the HAV requested support and came to a halt at the intersection, the participant's tasks were to observe the oncoming road users (pedestrians, cyclists, vehicles) who had the right of way, identify an adequate gap for turning left, and trigger the implementation of the left turn by pressing a button at an assigned input panel, as illustrated in [Fig. 2](#). The speed of oncoming road users was 5, 16.9, and 40 km/h for pedestrians, cyclists, and vehicles, respectively. The cyclist speed reflects the average value for urban cycle traffic according to [Poliziani, Rupi, Schweizer, Saracco, and Capuano \(2022\)](#).

2.4. Experimental setup

The simulated environment was created in the Unreal Engine (version 5.4.4), executed in real time, and presented on a 49-in. Dell monitor (5120×1440 px, 329 ratio). Participants issued left-turn clearances via a Stream Deck input panel. Additionally, questionnaire data were collected separately via a Microsoft Surface tablet ($13''$, 1920×1280 px, 3,2 ratio). [Table 2](#) presents detailed information on the camera perspectives used in the study, including viewing angle, height, and field of vision. Visibility under fog conditions was 25 m. We used the Unreal module "ExponentialHeightFog" to create the fog with default settings except for the following parameters (Unreal [Engine, 2026](#)): Fog Density was set to 0.01, Fog Height Falloff to 0.2, Fog Max Opacity to 1.0, and Start Distance to 2000. We activated the Volumetric Fog option, setting Scattering Distribution to 0.2, Extinction Scale to 1.0, and View Distance to 6000. [Fig. 3](#) shows the positioning of the virtual cameras in each perspective condition as well as the reference points used for measuring distances and visibility lines.

In each scenario, participants were tasked with finding a gap in the stream of road users in order to perform a safe left turn. [Fig. 4](#) illustrates the temporal stream of oncoming vehicles and potential gaps to initiate the left-turn maneuver. In each trial, three different gaps in the stream of oncoming vehicles were implemented and administered in a loop, i.e., after the third gap, the first gap reappeared. The gaps differed by duration with regard to their suitability for conducting a left-turn maneuver. Gaps were considered passable if an immediate initiation of the maneuver by clicking the button on the input pad sufficed to turn left without colliding with another road user. The duration of gaps was determined in a pre-study. This approach was adopted from [Schrank et al. \(2025\)](#) and is based on research on real-world data on turning behavior at urban intersections ([Quante, Theisen, Junghans, & Schießl, 2021](#)) and cognitive modeling of turning decisions ([Zgonnikov, Abbink, & Markkula, 2022](#)). The number of vehicles before the first gap and between all subsequent gaps was randomized across a range of five to twelve vehicles per lane. Following from this, the sequence of oncoming road users in each trial was: 5–12 vehicles, gap 1, 5–12 vehicles, gap 2, 5–12 vehicles, gap 3, 5–12 vehicles, gap 1, and so on. In addition to oncoming vehicles, oncoming cyclists and pedestrians, moving both ways, i.e., in the same and the opposite direction of the HAV, crossed the intersection in random intervals while vehicles were oncoming. During gaps in the vehicle stream, cyclists and pedestrians did not cross the intersection.

2.4.1. Objective measures

[Table 3](#) lists four objective measures that were collected to evaluate operator task performance.

2.4.2. Subjective measures

To measure the participant ratings of subjective variables, six self-report questionnaires were administered, see [Table 4](#). These questionnaires assessed each participant's affinity to technology, attitude towards computer games, driver behavior, mental workload, situation awareness, as well as usability and user experience ratings of the investigated HMI features.

2.5. Experimental procedure

Participants were first briefed on the study objectives and provided informed consent, a non-disclosure agreement, and a data protection declaration. Subsequently, they completed a sociodemographic questionnaire, the ATI, CGAS, and DBQ ([Table 4](#)).



(caption on next page)

Fig. 1. Screenshots from video clips used in the study. (a) first-person view without augmentation and fog, (b) bird's-eye view, without augmentation and fog, (c) third-person view, without augmentation and fog, and (d) first-person view, with augmentation and fog. For a complete set of screenshots from all conditions, see Fig. A1 in the Appendix.

Participants were instructed to imagine working as a remote assistant for a highly automated vehicle (HAV) operating as a shuttle bus. Images of the HAV “U-Shift” (DLR, 2022) and a prototypical workplace for remote assistance (Schrank, Walocha, et al., 2024) were shown, and the setup and features of the workplace were explained.

After the window blinds in the laboratory were closed and artificial light sources were turned off, participants were seated in front of the participant screen (see section 2.4 “Experimental Setup”), where the experimenter described the task in detail, introduced participants to the input device, and presented one video clip per camera perspective, some of which were presented with fog and/or augmentation. Participants then underwent a test run (FPV, no augmentation, no fog) to familiarize themselves with the setup. An optional five-minute break concluded the familiarization phase.



Fig. 2. Participant initiating the left turn at the intersection by pressing one of two available confirmation buttons (green checkmarks on top left and right corner) on the Stream Deck input panel. The top right checkmark is covered by the participant's thumb. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2

Parameters of camera perspectives measured when the highly automated vehicle (HAV) comes to a complete stop at the intersection and the participant is required to initiate the left turn. Note that only pedestrians will move both ways, i.e., in the same direction of HAV as well as opposed to it, while other vehicles and cyclists are oncoming traffic only, i.e., move in the direction opposed to the HAV. For an illustration of reference points, see Fig. 3.

Parameter	Operationalization	First-Person View (FPV)	Bird's-Eye View (BEV)	Third-Person View (TPV)
Viewing angle	–	110°	110°	110°
Height above ground	–	3.2 m	7 m	30 m
Distance to HAV front	Distance between the camera and the HAV's front; distances are indicated in the travel direction of the HAV. Positive values: cameras located ahead of the HAV; negative values: cameras located behind the HAV	–1.6 m	–12 m	26.7 m
Distance to left HAV side	Horizontal distance of the camera to the center of the left side of the HAV. Positive values: location left of the left vehicle side, i.e., on the lanes of the oncoming traffic; negative values: location towards the right-hand side of the left vehicle side	–1 m	–1 m	4.95 m
Camera tilt	–	13.6°	30°	90°
Rotation of camera view	BEV: rotated 90° clockwise around the z axis, with the z axis located perpendicular to street level	0°	0°	90°
Visibility of oncoming road users	Distance from the HAV reference point to the point where other road users become visible. Positive values: other road users will be spotted when they appear ahead of the HAV; negative values: road users will already be noticed when they are still behind the HAV	116 m	116 m	69.5 m
Visibility of pedestrians	See “Visibility of oncoming road users”	7.7 m	–2 m	–15.8 m

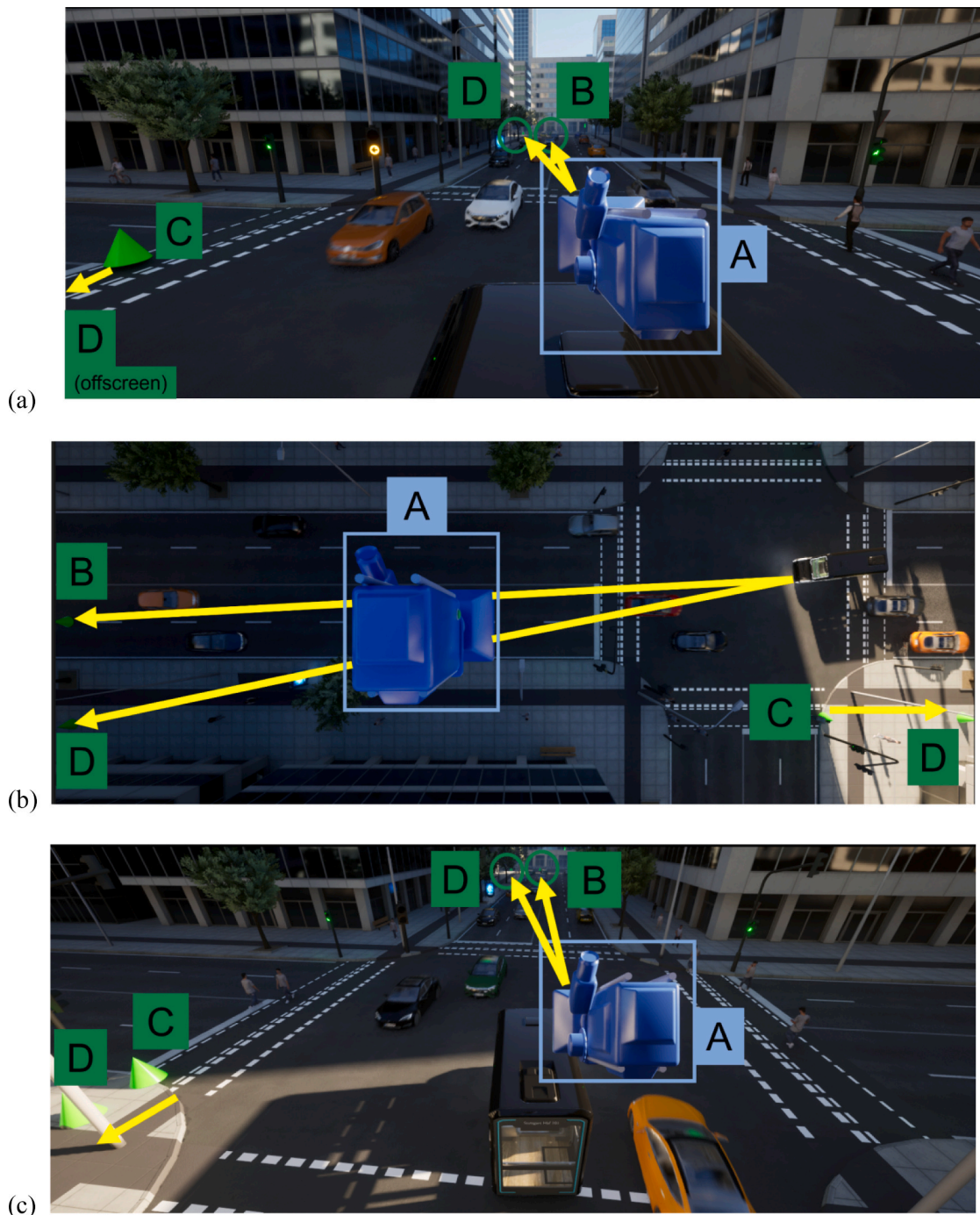


Fig. 3. Screenshots of camera perspectives, including the location of the virtual camera (A). Yellow arrows indicate the maximum visibility distance of other road users (vehicles, cyclists, pedestrians). Green cones (B–D) indicate reference points. B indicates the furthest point from which oncoming vehicles are visible. C is the measuring point indicating the intersection between the paths of the HAV and pedestrians moving in parallel to the HAV. D marks the earliest points where pedestrians (both with or towards the HAV) can be spotted. (a) First-person view (FPV), (b) bird's-eye view (BEV), (c) third-person view (TPV). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In the subsequent data collection phase, participants completed 12 experimental conditions with two trials each, presented directly after each other, resulting in a total of 24 trials (see [section 2.2](#) “Experimental Design”). Each trial took about 1–2 min, depending on the decision time and the occurrence of suitable gaps to initiate the left-turn maneuver. After each condition, participants completed

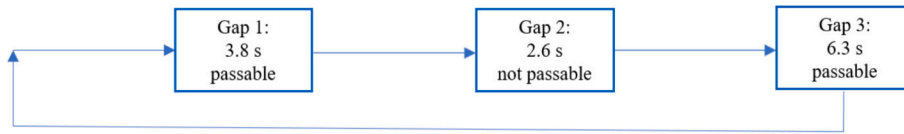


Fig. 4. Illustration of gaps in the stream of oncoming vehicles to be yielded to.

Table 3
Objective indicators to measure safety and performance used in the study.

Measure	Description
Decision time	Time interval in seconds from a complete stop of the HAV until the turn button is pushed by the participants. Longer time intervals are an indicator for lower task performance.
Distance to the nearest road user	Length measured in meters from the front right corner of the ego vehicle to the middle of the front of oncoming road users. A higher distance is considered safer.
Collision rate	Percentage of trials in which the ego vehicle collided with other road users (vehicles, cyclists, pedestrians) during left turns. It serves as a safety indicator; lower rates reflect higher safety.

Table 4
Overview of questionnaires used in the study. Scale poles shown in the table partly represent example illustrations for clarification and may not reflect the full range of scale descriptors used in the questionnaires. DBQ: Short version by Parker et al., 1995; German version by Glaser & Waschulewski, 2005.

Questionnaire	Construct	Items	Scale	Scale Poles
ATI (Franke et al., 2019)	Affinity for technology	9 items	6-point Likert scale	1 = Completely disagree; 6 = Completely agree
CGAS (Chang et al., 2014)	Attitude towards computer games	17 items in 3 subscales: Cognition, Affection, Behavior	5-point Likert scale	1 = Strongly disagree; 5 = Strongly agree
DBQ (Reason et al., 1990)	Driver behavior	Short version: 24 items	6-point Likert scale	1 = Never; 6 = Very frequently
NASA-TLX (Hart & Staveland, 1988)	Workload	Subscale Mental Demand	21-point scale	1 = Low; 21 = High
SART (Taylor, 1990)	Situation awareness	10 items in 3 subscales: Attentional Demand, Attentional Supply, Understanding	7-point Likert scale (Computed as: Understanding – (Demand – Supply); Range: -14 to +46)	1 = Entirely stable; 7 = Entirely unstable
UEQ (Laugwitz, Held, & Schrepp, 2008)	Usability, user experience	3 subscales for usability: Perspicuity, Stimulation, Novelty	7-point semantic differential (Range of sum scores: 4 to 28)	1 = Obstructive; 7 = Supportive

the NASA-TLX Mental Demand item, UEQ scales on usability, and the SART questionnaire before the next condition started without a break. All participants were able to complete all trials without a time-out. Finally, participants were debriefed and invited to give qualitative feedback. The session lasted approximately 1.5–2 h per participant.

2.6. Analysis

We used repeated-measures analyses of variances (RM-ANOVA; conducted in RStudio 2024.09.0) to determine the influence of the independent variables camera perspective, fog and augmentation on the dependent variables performance, situation awareness, mental workload, and usability ratings. For each hypothesis, a separate two-way RM-ANOVA was computed, treating the hypothesis-relevant independent variables as within-subject factors. Prior to performing inferential statistical analyses, checks on the violation of normality and homogeneity assumptions were conducted using the Shapiro-Wilk test and Mauchly’s test of sphericity, respectively. For analyses that violated the assumption of normality, RM-ANOVAs were computed. Nevertheless, as this statistical test tends to be robust against violations of the normality assumption, particularly in sample sizes of 30 and more (Berkovits, Hancock, & Nevitt, 2000; Kherad-Pajouh & Renaud, 2015). Descriptive statistics are reported in Table A2 in the Appendix. Effect sizes (η^2) are interpreted based on Cohen’s (1988) guidelines, where 0.01 indicates a small, 0.06 a medium, and 0.14 a large effect. The significance level was set to $\alpha = 0.05$. Where applicable, post-hoc comparisons were conducted as Bonferroni-corrected pair-wise *t*-tests. In accordance with theoretical considerations reflected in the hypotheses and in order to streamline the analysis, only the main and two-way interaction effects are reported.

3. Results

3.1. Operator performance (H1)

3.1.1. Decision time

Regarding the decision time, the line graph in Fig. 5 visualizes the significant main effect of augmentation, $F(1,36) = 12.44, p < .01, \eta^2 = 0.02$. Longer decision times were observed in conditions with augmentation compared to conditions without augmentation, which is contrary to our expectations. The effect of camera perspective was also significant, $F(2,72) = 3.55, p = .034, \eta^2 < 0.01$. Post-hoc tests showed a significant difference between BEV and TPV, with BEV leading to faster decision times than TPV ($p = .021$). No significant effect emerged for fog ($p = .334$), and no significant interaction effects were identified. Main and interaction effects are reported in Table 5.

3.1.2. Minimum distance to oncoming vehicles

Fig. 6 presents the effects of camera perspective and augmentation on the minimum distance to oncoming vehicles. Significant main effects were found for augmentation ($F(1, 36) = 18.41, p < .001, \eta^2 = 0.06$) and fog ($F(1, 36) = 23.18, p < .001, \eta^2 = 0.03$), indicating shorter distances under fog and greater distances with augmentation. No significant effect was observed for camera perspective ($p = .575$). Main and interaction effects are reported in Table 6.

3.1.3. Collision rate

Fig. 7 visualizes the significant main effects of fog ($F(1,36) = 53.48, p < .001, \eta^2 = 0.06$) and augmentation ($F(1,36) = 18.95, p < .001, \eta^2 = 0.05$) on collision rate. Collisions were more frequent under fog and less frequent with augmentation. No significant effect emerged for camera perspective ($p = .062$). Table 7 summarizes the main and interaction effects.

3.2. Situation awareness (H2)

Fig. 8 visualizes the main effects of fog ($F(1,36) = 86.73, p < .001, \eta^2 = 0.21$), augmentation ($F(1,36) = 132.80, p < .001, \eta^2 = 0.17$), and camera perspective on situation awareness. Fog reduced SART scores, while augmentation increased them. Camera perspective did not yield a significant main effect ($p = .254$). Details on main and interaction effects can be found in Table 8.

3.3. Mental workload (H3)

Fig. 9 illustrates the main effects of fog ($F(1,36) = 40, p < .001, \eta^2 = 0.14$), augmentation ($F(1,36) = 29.37, p < .001, \eta^2 = 0.05$), and camera perspective on mental workload. Fog increased and augmentation decreased workload. No significant effect was found for camera perspective ($p = .374$). Table 9 summarizes main and interaction effects.

3.4. Usability (H4)

Fig. 10 shows that fog ($F(1,36) = 88.77, p < .001, \eta^2 = 0.10$) and augmentation ($F(1,36) = 10.91, p < .001, \eta^2 = 0.08$) had significant main effects on usability, with fog impairing and augmentation enhancing usability. No significant main effect was

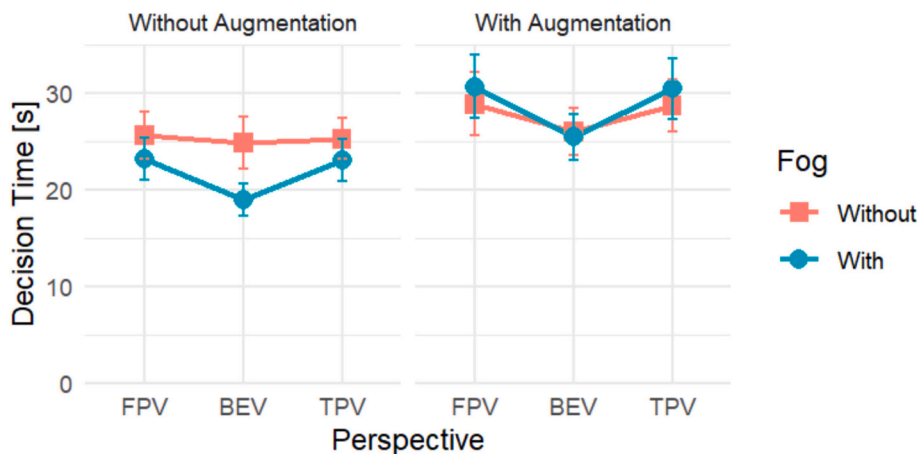


Fig. 5. Mean decision times (in seconds) by camera perspective; error bars indicate standard errors of the mean. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5

Summary of main and interaction effects from the repeated-measures ANOVA on decision time. df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	0.96	0.334	<0.01
Augmentation	1	36	12.44	0.001	0.02
Perspective	2	72	3.55	0.034	< 0.01
Fog \times Augmentation	1	36	3.23	0.081	< 0.01
Fog \times Perspective	2	72	0.96	0.389	< 0.01
Augmentation \times Perspective	2	72	0.29	0.748	< 0.01

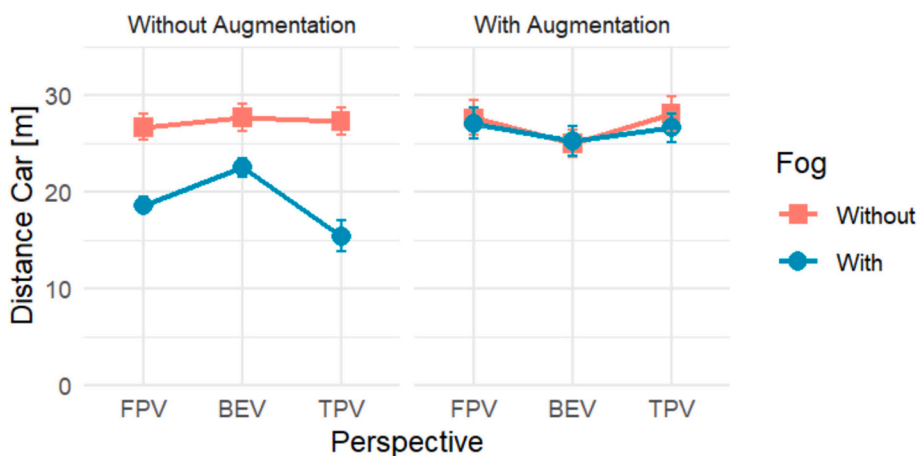


Fig. 6. Means and error bars of distance in meters of the ego-vehicle to the closest oncoming vehicle at the start of the left-turn maneuver. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6

Summary of main and interaction effects from the repeated-measures ANOVA regarding **minimum distance to oncoming vehicles**. df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	18.41	< 0.001	0.06
Augmentation	1	36	23.18	< 0.001	0.03
Perspective	2	72	0.56	0.575	< 0.01
Fog \times Augmentation	1	36	40.04	< 0.001	0.04
Fog \times Perspective	2	72	3.43	0.041	< 0.01
Augmentation \times Perspective	2	72	7.60	0.001	0.02

observed for camera perspective ($p = .198$). Details on main and interaction effects can be found in [Table 10](#).

4. Discussion

This study investigated the effects of camera perspective, adverse weather conditions, and augmentation on operator performance, situation awareness, mental workload, and usability ratings in a remote assistance task. The compensatory effect of the augmentation, a visualization of sensor data highlighting relevant road users, for poor visibility in adverse weather conditions from [Schrank et al. \(2025\)](#) was replicated. When the augmentation was shown, operator performance and situation awareness reached levels similar in the conditions with fog as in the conditions without fog. While camera perspective did not show a main effect on the outcome measures, it revealed an interplay of camera perspectives with two other independent variables: First, the interaction between perspective and augmentation yielded a significant effect for most outcome variables. In some operator performance variables, including distance to other road users, the augmentation was able to make up for the detrimental effect of certain camera perspectives, particularly the third-person view. Second, an interaction effect between perspective and fog emerged. This effect indicated that the efficacy of camera perspectives also depends on the visibility of the traffic environment.

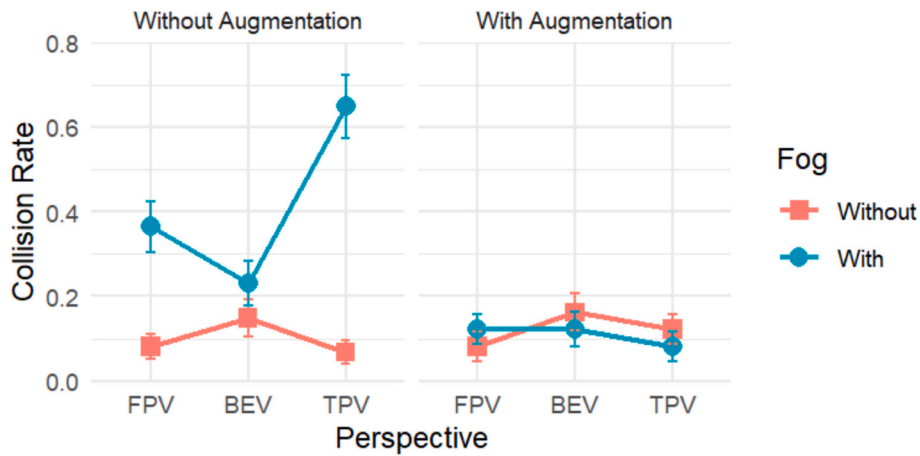


Fig. 7. Means and error bars of collision rate (percentage averaged across all road user types) by camera perspective, augmentation and fog. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7

Summary of main and interaction effects from the repeated-measures ANOVA on collision rate (percentage averaged across all road user types). df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	53.48	< 0.001	0.06
Augmentation	1	36	18.95	< 0.001	0.05
Perspective	2	72	2.88	0.063	< 0.01
Fog × Augmentation	1	36	48.47	< 0.001	0.07
Fog × Perspective	2	72	11.81	< 0.001	0.03
Augmentation × Perspective	2	72	6.50	0.003	0.02

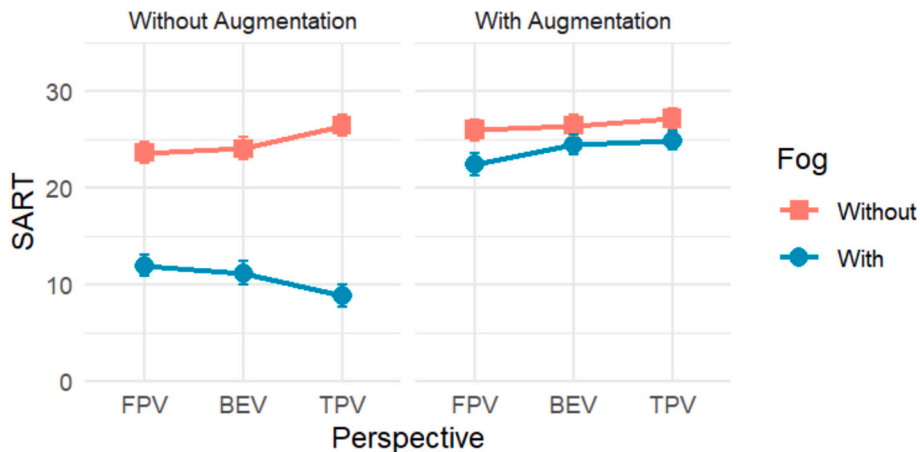


Fig. 8. Means and error bars of situation awareness scores by camera perspective, augmentation, and fog based on a scale ranging from -14 to +46. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.1. Discussion by hypotheses

Regarding operator performance (H1), camera perspective had a significant impact on the time participants spent making the decision to initiate the left turn. This effect is driven by a faster decision when the road environment is presented in a bird's-eye view (BEV) compared to a third-person view (TPV). This finding is in line with previous research underscoring BEV's advantages in gauging

Table 8

Summary of main and interaction effects from the repeated-measures ANOVA on situation awareness. df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	86.73	< 0.001	0.21
Augmentation	1	36	132.80	< 0.001	0.17
Perspective	2	72	1.40	0.254	<0.01
Fog \times Augmentation	1	36	143.30	< 0.001	0.10
Fog \times Perspective	2	72	5.35	0.007	<0.01
Augmentation \times Perspective	2	72	6.50	0.003	0.02

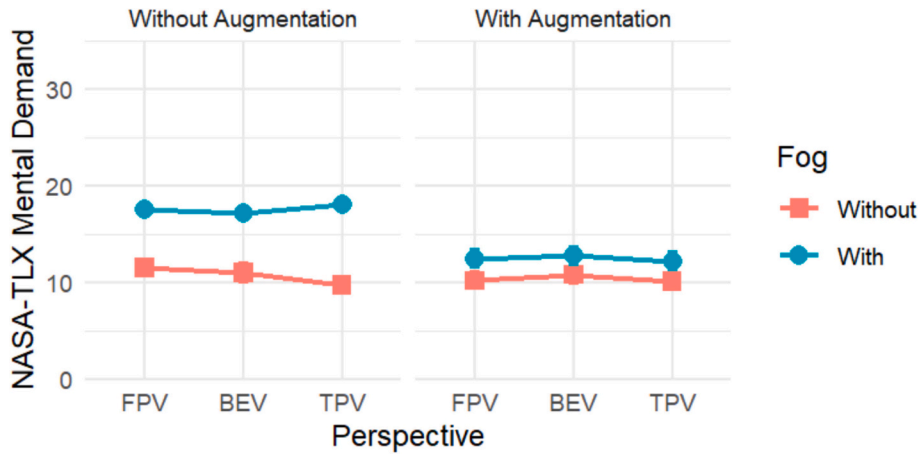


Fig. 9. Means and error bars of mental workload by camera perspective, augmentation and fog, based on a scale ranging from 1 to 21. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 9

Summary of main and interaction effects from the repeated-measures ANOVA on mental workload. df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	40.00	<0.001	0.14
Augmentation	1	36	29.37	< 0.001	0.05
Perspective	2	72	1.00	0.374	< 0.01
Fog \times Augmentation	1	36	42.05	< 0.001	0.04
Fog \times Perspective	2	72	2.61	0.081	< 0.01
Augmentation \times Perspective	2	72	1.72	0.187	< 0.01

distance and avoiding collisions thanks to metric scaling (Boker & Lanir, 2023; Roddick et al., 2019; Unger et al., 2023). While FPV and TPV distort angles and distances, the BEV provides an isogonal representation of the road environment. It has to be noted, however, that the effect size is relatively small, necessitating further research to ascertain the use of camera views in practical HMI design. Also, a shorter decision time does not necessarily indicate better performance or a successful decision because participants may respond quickly but with an unsafe choice. Interestingly, augmentation led to significantly longer decision times, which is not in line with the hypothesis. It may be an indicator for a more careful behavior when initiating the turn: Participants might turn only once they are sure to have detected all relevant road users they have to yield to, rather than initiating the turn prematurely, succumbing to a higher collision risk. By taking more time for making the decision to initiate a turn, safety may be increased. This interpretation is supported up by a lower collision rate when the augmentation is on. The augmentation makes complex left turns safer but comes at the cost of speed indicated by decision time, suggesting a speed-accuracy tradeoff (Heitz, 2014). An alternative explanation is that the presentation of information using bounding boxes in the augmentation condition may require more cognitive processing. In Multiple Resource Theory, cognitive processes may compete for the same cognitive resources, particularly when they origin in the same modality (Wickens, 2002). As both the video feed and the bounding boxes are visual stimuli, they compete for the same cognitive resources at the stages of perception and cognition; their cognitive processing may be slowed down. In order to explore this question more deeply, eye-tracking could be used in future research to compare fixations between augmented and non-augmented conditions.

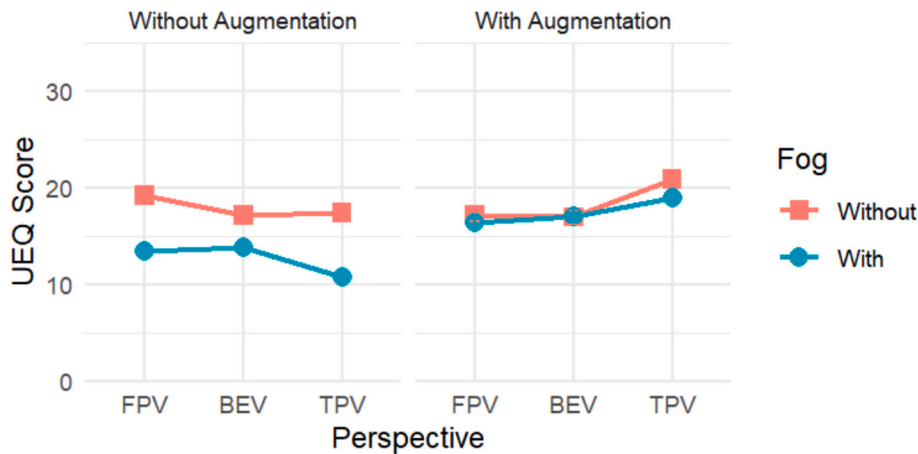


Fig. 10. Means and error bars of UEQ score measuring usability by camera perspective, augmentation, and fog, ranging from 4 to 28. The x-axis labels indicate the perspectives: FPV = first-person view, BEV = bird's-eye view, TPV = third-person view. Red line with squares: conditions without fog. Green line with circles: conditions with fog. Left panel: conditions without augmentation. Right panel: conditions with augmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 10

Summary of main and interaction effects from the repeated-measures ANOVA on usability. df_{Num} indicates degrees of freedom numerator. df_{Den} indicates degrees of freedom denominator.

Effects	df_{Num}	df_{Den}	F	p	η^2
Fog	1	36	88.77	< 0.001	0.10
Augmentation	1	36	10.91	0.002	0.08
Perspective	2	72	1.66	0.198	< 0.01
Fog \times Augmentation	1	36	30.73	< 0.001	0.05
Fog \times Perspective	2	72	14.13	< 0.001	0.01
Augmentation \times Perspective	2	72	27.10	< 0.001	0.06

The measure of *distance to the closest oncoming vehicle* can be interpreted as a safety margin around the assisted HAV. When fog was present, the distance to other vehicles was shorter. When the augmentation was active, it was longer. Thus, augmentation seemed to increase traffic safety. All three two-way interactions on distance reached the level of significance, including the interaction effect of augmentation and fog found by Schrank et al. (2025), underscoring the compensatory effect of the augmentation on distance under foggy conditions. In addition, interaction effects of perspective and fog, as well as perspective and augmentation, were found: While TPV was inferior in the foggy conditions without augmentation, it performed equally well to the other perspectives when the augmentation was on. This finding implies that the augmentation may also have a compensatory effect on unfavorable camera perspectives by diverting attention from the relevant stimuli. The SEEV model by Wickens, Goh, Helleberg, Horrey, and Talleur (2003) explains how the bottom-up factors salience (S) and effort (E) and the top-down factors expectancy (E) and value (V) affect the allocation of visual attention to objects. Augmentation seems to increase the probability for relevant stimuli to be attended to by increasing salience, the extent to which these stimuli stand out from their surroundings. Increased salience can therefore be considered a result of the augmented bounding boxes around oncoming road users, with repercussions on performance indicators such as distance.

For the metric *collision rate*, similar patterns of effects as for distance were yielded. While fog and augmentation had a significant impact on collision rate, perspective did not affect collisions. More collisions occurred in foggy conditions, fewer with augmentation. As with distance, all two-way interactions reached the level of significance. The interactions between augmentation and fog, as well as between augmentation and perspective, suggest a compensatory role of augmentation for adverse weather and unfavorable perspectives, respectively, also regarding collision. Thus, augmentations are indicative of pushing safety by reducing collisions for both contextual factors like weather conditions and system-inherent factors, including camera configuration.

Regarding *situation awareness* (SA, H2), similar effects as in the performance indicators were observed: Fog decreased and augmentation increased SA. Camera perspective did not affect SA, meaning the perspectives established a comparable degree of SA in the operator. Much like in the performance measures, all two-way interactions yielded significance: No difference was observed between fog and no-fog conditions and between different perspectives when the augmentation was on. These findings again suggest the twofold compensatory dynamics of augmentation on poor visibility due to contextual and system-inherent factors. They extend the study by Schrank et al. (2025) by showing that inadequate system design, such as selecting less suitable camera perspectives, can be compensated for by applying augmentations. These appear to improve recognition of relevant stimuli and subsequent decision-making in both regards. The findings regarding augmented sensor data and SA also align with research by Colley, Eder, Rixen, and Rukzio (2021). They investigated the effects of visualized and semantically segmented sensor data recorded by autonomous vehicles. When

presented comparably to augmented reality, the visualized data improved SA.

In terms of *mental workload* (H3), augmentation was able to lower workload while fog increased it significantly. In line with the hypothesis, the workload-lowering effect of augmentation was particularly prominent in foggy conditions, which is underlined by the significant interaction between fog and augmentation. This finding is similar to Schrank et al. (2025). No significant differences were observed regarding perspective, indicating that different camera perspectives did not affect workload.

Finally, similar effects were observed for *usability* (H4), with fog decreasing and augmentation enhancing usability. Again, all two-way interactions were returned as significant. Without augmentation, participants rated usability inferior when fog obstructed the participants' view of the intersection and when observing the scenario from the TPV. However, as soon as the augmentation was on, the usability levels of conditions with fog matched those without fog. Similar to the previous variables, the augmentation levelled out lower usability ratings for foggy and unfavorable perspectives. This result implies that the augmentation supports usability in the given remote assistance task, not only under adverse weather conditions but also with regard to improper camera perspectives. Thus, shortcomings in interface designs are offset by improving salience via sensor data augmentation.

4.2. Global discussion

To conclude, across hypotheses and dependent variables, three overarching patterns were observed. First, while the main effect of augmentation could be demonstrated for many outcome variables and replicated the findings from Schrank et al. (2025), the main effect of camera perspective on the investigated camera perspectives remained very limited. Only the performance metric decision time showed to be significantly impacted by camera perspective. In particular, BEV showed superior to TEP in making decisions. However, the effect size was small, and no advantage of BEV regarding the accuracy of decisions, such as operationalized by collision rate, was measured.

Second, results support the notion of a dual compensatory role of augmentation for both fog and perspective. The compensation of augmentation for the adverse weather effect of fog from Schrank et al. (2025) could be replicated. In addition, it was found that augmentation could also compensate for inappropriate camera perspectives. This finding bears implications for HMI design: Augmentation might be able to at least partially offset the negative impact of a less favorable or less familiar perspective. It provides an interesting way of introducing new views that conventional drivers are less familiar with, such as a bird's-eye view, without risking a drop in safety and performance.

Third, the study found evidence for a speed-accuracy trade-off between decision time and safety: the quicker participants made the decision to turn, the more collisions with other road users were measured. This result indicated that quick decisions in remote assistance come at the cost of safety. Thus, it is imperative to provide remote assistance for as much time as needed to safely complete their task. Avoid assigning time-critical tasks to the remote operator and not posing time limits for processing tasks is therefore highly advisable.

Taken together, the findings support the hypotheses regarding augmentation and fog as well as their interaction, replicating the compensatory effect of augmentation on fog. The investigated camera perspectives did not make a difference for performance, SA, workload, and usability. Hence, perspective does not seem matter for these variables as long as relevant objects are visible. The angle and distance distortions in FPV and TPV that were expected to have a negative impact did not have that effect. In cases where certain perspectives did affect the outcome negatively, augmentations helped level out the deficits.

4.3. Practical implications for HMI design and future research

The results of the present study have some implications for future research and HMI design. First, the camera view depends heavily on the operator's task and scenario. The task of identifying gaps for a complex left turn relies on the correct assessment of distance and speed of the other road users. Performing this task requires an accurate perception of the road users' behavior and, based on this, a valid interpolation of their current state to the future state at the moment of crossing the oncoming traffic. The camera perspective chosen bears advantages or disadvantages, respectively, for supporting or hindering the fulfilment of these task requirements (see also Table 1). The first-person view is advantageous, particularly for experienced drivers, since it is similar to the driver's perspective. However, it presents distances in a distorted way and is associated with occlusions, posing difficulties in estimating how far an oncoming road user is away or in detecting relevant objects concealed behind other objects. It may therefore have a negative effect on gap selection. Regarding the bird's-eye view, its advantage is the accurate representation of distances and the detection of occlusions. However, it is unusual for drivers, which may pose difficulties regarding the abstraction of the traffic space and object recognition from an uncommon angle and potentially high altitude. Thus, specific training might be required for this perspective. The third-person view unites some aspects from both first-person and bird's-eye views: While it provides an overview from above like the bird's-eye view and minimizes occlusions, distances and angles are distorted and might lead to misestimations in the selection of suitable gaps.

Even though the investigated perspectives did not yield a significant main effect on outcome variables, attention shall be given to the complex interaction effects found both between perspective and augmentation and between perspective and fog. These findings implicate that the use of camera perspectives is highly dependent on the context, including visibility of the traffic situation, as well as on the HMI that is used together with the respective perspectives. Thus, the selection of camera calls for a nuanced and human-centered approach that takes both the context of use and the concrete HMI design into account.

For example, a complex urban scenario as examined in this study poses very different requirements from a highway scenario where interactions with other road users tend to be less frequent and immediate. In line with research by [Boker and Lanir \(2023\)](#), particularly the BEV should be used cautiously as it was associated with lower performance and SA in our study. Thus, the camera perspective has to be chosen based on the task and scenario. An adaptive approach could be useful in dynamically selecting a suitable perspective. Second, increasing the salience of stimuli to make them more visible and therefore more likely to detect has positive repercussions on safety, operator performance, and human factors aspects, including SA and workload. Using salience-enhancing HMI elements such as augmented bounding boxes as overlays is advisable for remote operation HMIs. The examined augmentation concept has been shown to affect the investigated outcome variables positively in general. In particular, it displayed compensatory properties in less favorable conditions, be they caused by factors external to the system, such as poor visibility due to adverse weather conditions, or internal, such as the selection of unsuitable camera perspectives. How augmentations can be modified for a specific use case and task and how they can be integrated into a holistic concept for a workstation and operator workflow is subject to future research. Third, the effect of the HMI elements augmentation and perspective on the outcome has to be carefully analyzed as it is multifaceted and complex. For example, augmentation led to improved performance and higher safety, as larger distances to oncoming road users and collision rates indicate. However, decision time was longer compared to non-augmented conditions, which can be considered an indicator of lower performance. Also, camera perspective shortened decision times significantly. This effect is driven by quicker decisions made in BEV compared to TPV. At the same time, safety and performance measured by distance to others and collision rate were not affected. Thus, the effect of HMI elements may vary by measure. When designing an HMI, the measures to assess the HMI have to be carefully selected in light of the objectives of the system and tasks to be completed with it. Vital outcome variables such as safety may need to be prioritized over less important ones, e.g., efficiency.

4.4. Limitations

The study comes with several limitations. First, the potential of using different camera perspectives heavily depends on the task. While for some tasks, using a BEV or TPV may be beneficial or even inevitable, others might perform better with the common FPV. A careful consideration of the operator task is pivotal to using the potential of various perspectives. Generalizing results to other tasks and situations in which, for instance, BEV may prove more helpful than in this study, is not simply possible. It is advisable to conduct a task analysis prior to deciding on a camera perspective ([Koskinen, Schrank, Lehtonen, & Oehl, 2024](#)). We therefore advocate for testing a multitude of perspectives in various situations to ascertain their potential.

Second, this study considered each camera perspective in a distinct experimental condition without combining multiple perspectives in one condition. While this approach is part of a sound experimental design and necessary to isolate distinct effects of perspective, it does not account for the potential benefits that combining multiple views may have. Additional potential for improvement may come from the use of dynamic views that might alternate across phases of a task or between tasks. E.g., an HMI could display FPV in regular operations to ensure global SA while switching to BEV in situations where angles and distances matter. Thus, combinations or alternations of multiple views shall be investigated in future research.

Third, the study was conducted in a simulated environment. Therefore, the transferability of results from the laboratory environment to the real world has to be reviewed critically. One issue might be reckless behavior as participants might have turned even when they felt it was not safe because no immediate negative impact of their decisions became apparent. Thus, real-world driving studies are required to highlight the true impact of decisions and increase ecological validity.

Fourth, even though the age of participants ranged from 20 to 55 years, the sample consisted predominantly of young and technology-affine drivers. While this composition might limit the transferability of results to other groups, such as older and less technology-savvy populations, it provides a suitable kick-off point for research on adaptive HMIs for remote operation. If the effects we hypothesized would not have become evident under the conditions in this study, they are not likely to occur in individuals with progressed age or lower spatial cognition, either. The next step will be to investigate if the found main effect of augmentation and interaction effect of augmentation and fog persist also in other samples that might not be as likely to show this effect, as those mentioned above. Additionally, investigating augmentation and camera perspective in professional remote operators is an objective for future research. As of now, barely any professional remote operators are available as study participants, particularly not with a standardized set of skills, qualifications, and tasks.

Finally, as the participants experienced every condition only twice. Changes in behavior because of learning or other intermediate and long-term effects of training and experience are not accounted for. For example, experienced users may benefit more from BEV once they acquired a more accurate mental model representing the road environment from above. A training study or a novice-expert setup may help identify the potential of perspectives in trained samples. Insights from empirical studies will provide information for guidelines to the creation of person-adaptive HMIs.

4.5. Conclusions and future research

The present study is one of the first that systematically investigated the impact of different camera perspectives and HMI augmentation in situations with adverse weather conditions. While a general compensatory effect of the augmentation on operator performance, safety, SA, and workload was found in conditions of adverse weather and less favorable camera perspectives, camera

perspectives did not significantly impact these measures in general. Thus, as long as the relevant elements of a situation are visible, distortions in angles and distance are compensated for by a sample of experienced drivers. Whether unexperienced drivers and professional staff in certain use cases, e.g., remotely operated trucks or warehouse vehicles such as forklifts, might benefit from particular camera perspectives in specific tasks, is yet to be investigated. At any rate, the augmentation concept we presented here was shown to make up for loss in operator performance and SA as well as decrease workload for both internal and external factors.

In order to select the ideal camera perspective, it is worthwhile to investigate if adapting the presented perspective to the situation and the task as well as the operator state is advisable. Hence, this study can be seen as a starting point for further research on features for displaying information about the road environment and the supervised HAV. If any given feature proves useful for supporting the remote operator in their task, it could be incorporated into a holistic framework for adaptive HMIs for HAV remote operation. This way, the framework would be underscored empirically and may open the way to safer, smoother, and more reliable remote operation of HAVs.

CRedit authorship contribution statement

Andreas Schrank: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Anneke-Sophie Kaas:** Writing – original draft, Formal analysis. **Stefan Brandenburg:** Writing – review & editing, Supervision. **Michael Oehl:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1

Sample characteristics. CI = 95% confidence interval, LL = lower limit, UL = upper limit. AV = automated vehicles. ATI = Affinity for Technology Interaction. CGAS = Computer Game Attitude Scale. DB = Driver Behavior.

Main Category	Variables	Statistical Results
Demographics	Age	$M = 31.16$, $SD = 7.68$, Min. = 20, Max. = 49, CI (LL) = 28.60, CI (UL) = 33.72
Previous Study Participation	Gender	Female: 9 (24.3%), male: 28 (75.7%)
	Previous participation in remote operation studies	Yes: 21 (56.8%), no: 16 (43.2%)
Car Usage	Participation in vehicle-related studies at institution facilitating the study	Yes: 13 (35.1%); no: 24 (64.9%)
	Frequency	Daily: 14; several times a week: 21, weekly: 1, monthly: 1
Interest in Technology	Car mileage in last twelve months	$M = 13,805$ km, $SD = 7810$ km
	Technology affinity (ATI scale, 0–5; 0 = very low, 5 = very high affinity)	$M = 4.07$, $SD = 1.40$
Additional Scales	AV interest (from 0 to 5; 0 = no interest, 5 = very strong interest)	$M = 4.16$, $SD = 0.93$
	Gaming interest & usage (CGAS scale, 0–5; 0 = very low, 5 = very high)	$M = 3.47$, $SD = 3.16$
	Risk behavior in traffic (DB scale, 0–5; 0 = very low, 5 = very high)	$M = 1.82$, $SD = 1.80$

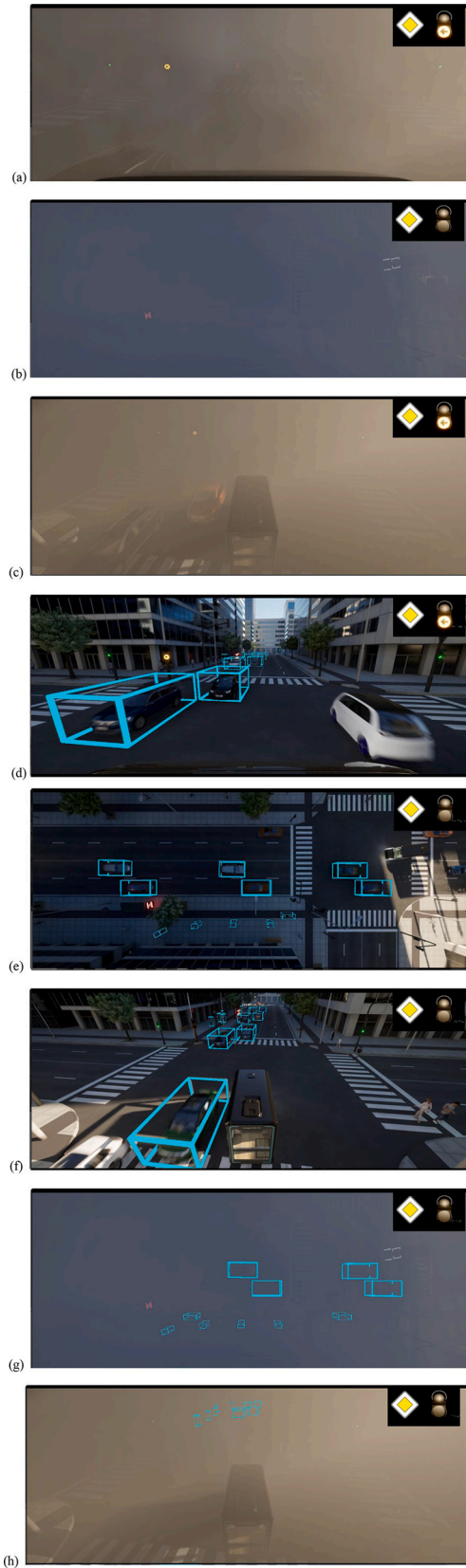


Fig. A1. Screenshots from videoclips for all conditions used in the study. (a) First-person view, without augmentation and with fog, (b) bird's-eye view, without augmentation and with fog, (c) third-person view, without augmentation and with fog, (d) first-person view, with augmentation and without fog, (e) bird's-eye-view, with augmentation and without fog, (f) third-person view, with augmentation and without fog, (g) bird's-eye view, with augmentation and with fog, (h) third-person view, with augmentation and with fog.

Table A2

Descriptive analyses of significant study findings. Augment. = Augmentation. CI = 95% confidence interval, LL = lower limit, UL = upper limit.

Variables	Fog	Augment.	Perspective	M	SD	Min.	Max.	CI (LL)	CI (UL)
Decision Time	/	Off	/	23.45	13.59	7.42	71.08	21.67	25.27
Decision Time	/	On	/	28.33	17.46	7.67	94.18	26.02	30.64
Decision Time	/	/	BEV	23.79	14.31	7.42	71.08	21.47	26.12
Decision Time	/	/	TPV	26.85	15.58	7.67	84.03	24.31	29.38
Distance Car	Off	/	/	27.04	9.27	7.96	52.17	25.81	28.27
Distance Car	On	/	/	22.57	9.27	- 0.47	48.22	21.34	23.79
Distance Car	/	Off	/	23.03	9.08	- 0.47	50.83	21.825	24.23
Distance Car	/	On	/	26.58	9.66	10.02	52.17	25.30	27.86
Distance Car	On	Off	/	18.83	7.75	-0.47	42.59	17.37	20.29
Distance Car	On	On	/	26.30	9.19	10.67	48.22	24.57	28.03
Distance Car	On	Off	TPV	15.38	9.71	- 0.47	42.59	12.14	18.62
Distance Car	On	Off	BEV	22.50	5.86	13.13	42.44	20.55	24.46
Distance Car	On	Off	FPV	18.61	5.35	9.09	33.10	16.83	20.40
Distance Car	On	On	TPV	26.57	8.69	12.45	48.22	23.68	29.47
Distance Car	On	On	BEV	25.28	9.34	10.67	47.93	22.16	28.39
Distance Car	On	On	FPV	27.05	9.67	12.86	47.32	23.82	30.28
Collision Rate	Off	/	/	0.11	0.22	0	1.0	0.08	0.14
Collision Rate	On	/	/	0.26	0.37	0	1.5	0.21	0.31
Collision Rate	/	Off	/	0.26	0.37	0	1.5	0.21	0.31
Collision Rate	/	On	/	0.12	0.23	0	1.0	0.08	0.15
Collision Rate	On	Off	/	0.41	0.42	0	1.5	0.34	0.49
Collision Rate	On	On	/	0.11	0.23	0	1.0	0.07	0.15
Collision Rate	On	Off	TPV	0.65	0.45	0	1.5	0.50	0.80
Collision Rate	On	Off	BEV	0.23	0.32	0	1.0	0.12	0.34
Collision Rate	On	Off	FPV	0.36	0.37	0	1.5	0.24	0.49
Collision Rate	On	On	TPV	0.12	0.22	0	0.5	0.05	0.19
Collision Rate	On	On	BEV	0.12	0.25	0	1.0	0.04	0.20
Collision Rate	On	On	FPV	0.12	0.21	0	0.5	0.05	0.19
Situation Awareness	Off	/	/	25.60	6.60	7	42	24.73	26.48
Situation Awareness	On	/	/	17.26	9.48	- 5	37	16.01	18.52
Situation Awareness	/	Off	/	17.66	9.87	- 5	42	16.35	18.96
Situation Awareness	/	On	/	25.21	6.50	0	42	24.35	26.07
Situation Awareness	On	Off	/	10.63	7.12	- 5	29	9.29	11.97
Situation Awareness	On	On	/	23.89	6.40	0	37	22.69	25.10
Situation Awareness	On	Off	TPV	8.78	6.91	- 5	26	6.48	11.09
Situation Awareness	On	Off	BEV	11.16	7.59	- 4	29	8.63	13.69
Situation Awareness	On	Off	FPV	11.95	6.62	- 1	24	9.74	14.15
Situation Awareness	On	On	TPV	24.86	5.96	11	36	22.88	26.85
Situation Awareness	On	On	BEV	24.43	6.19	10	36	22.37	26.50
Situation Awareness	On	On	FPV	22.38	6.91	0	37	20.07	24.68
Situation Awareness	Off	/	TPV	26.80	6.13	15	42	25.38	28.22
Situation Awareness	Off	/	BEV	25.23	6.77	9	37	23.66	26.80
Situation Awareness	Off	/	FPV	24.78	6.78	7	42	23.21	26.36
Mental Workload	Off	/	/	10.53	5.51	1	21	9.80	11.26
Mental Workload	On	/	/	15.01	5.71	1	21	14.25	15.76
Mental Workload	/	Off	/	14.14	6.13	1	21	13.33	14.95
Mental Workload	/	On	/	11.40	5.64	1	21	10.66	12.15
Mental Workload	On	Off	/	17.55	4.50	3	21	16.70	18.40
Mental Workload	On	On	/	12.47	5.67	1	21	11.40	13.53
Usability	Off	/	/	18.12	4.17	7	28	17.57	18.67
Usability	On	/	/	15.07	4.76	4	28	14.44	15.70
Usability	/	Off	/	15.28	4.89	4	28	14.63	15.93
Usability	/	On	/	17.91	4.17	10	28	17.36	18.47
Usability	On	Off	/	12.66	4.14	4	19	11.88	13.44
Usability	On	On	/	17.49	4.09	10	28	16.72	18.26
Usability	On	Off	TPV	10.70	2.49	4	14	9.87	11.53
Usability	On	Off	BEV	13.81	4.31	4	19	12.37	15.25
Usability	On	Off	FPV	13.46	4.65	4	19	11.91	15.01
Usability	On	On	TPV	18.97	3.57	13	28	17.78	20.16
Usability	On	On	BEV	17.05	4.12	11	28	15.68	18.43
Usability	On	On	FPV	16.43	4.21	10	28	15.03	17.84
Usability	Off	/	TPV	19.14	3.70	12	28	18.28	19.99
Usability	Off	/	BEV	17.05	4.70	7	28	15.97	18.14
Usability	Off	/	FPV	18.18	3.83	12	28	17.29	19.06

Data availability

Data will be made available on request.

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