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Article

What Attracts the Driver's Eye? Attention as a Function of Task and Events

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Abstract: This study explores how drivers of an automated vehicle distribute their attention as a function of environmental events and driving task instructions. Twenty participants were asked to monitor pre-recorded videos of a simulated driving trip while their eye movements were recorded using an eye-tracker. The results showed that eye movements are strongly situation-dependent, with areas of interest (windshield, mirrors, and dashboard) attracting attention when events (e.g., passing vehicles) occurred in those areas. Furthermore, the task instructions provided to participants (i.e., speed monitoring or hazard monitoring) affected their attention distribution in an interpretable manner. It is concluded that eye movements while supervising an automated vehicle are strongly 'top-down', i.e., based on an expected value. The results are discussed in the context of the development of driver availability monitoring systems.

Keywords: driving; eye-tracking; attention



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1. Introduction

Driver availability monitoring systems (DAMS) are finding their way into consumer vehicles and will soon become mandatory for newly sold cars [1]. DAMS do not only have utility in manual driving but also in automated driving [2,3]. In particular, SAE Level 2 automated driving requires drivers to focus on the driving task, which can be verified using eye- and head-tracking [4,5] and hands-on-wheel detection technology [6,7].

One point of importance in the development of DAMS is *what* the driver should look at. Lappi et al. [8] noted that a vital regularity in eye movements in driving is that drivers' "gaze is focused on task-relevant objects and locations . . . rather than the visually most salient ones . . .". Research into hazard perception shows that more experienced drivers are better able to detect and respond to hazards and precursors of hazards [9,10]. Additionally, more experienced drivers have a larger horizontal variance of gaze and are less likely to look at the road center, which may be explained by their superior skills in identifying hazards or their higher spare mental capacity [11–14]. In short, a DAMS that merely measures whether the driver looks towards the forward roadway may not be optimal as drivers acquire situational awareness by perceiving various elements of the task environment. Furthermore, safe driving involves more than looking at relevant features. For example, previous research into highway hypnosis [15,16] and the looked-but-failed-to-see phenomenon [17] showed that looking does not imply that the driver comprehends the situation.

Another factor concerns the driving task itself. It can be expected that a driver's attention distribution depends on whether the driver is driving manually or whether he or she is tasked to supervise an automated driving system. Previous research indicates that drivers of automated vehicles are less likely to glance at the forward roadway than manual drivers, which can be explained by the visual demands associated with manual lane-keeping [18–23].

When drivers supervise their automated vehicles, they still need to be situationally aware in order to be able to make an appropriate evasive maneuver after reclaiming control [24]. For example, the supervisor of the (SAE-2-level) automated vehicle may have to keep track of the speed of the vehicle and will need to be vigilant to other vehicles in the vicinity as these vehicles may have to be avoided after taking over control [25]. The extent to which drivers of automated vehicles should focus on the speedometer or hazards in the driving environment depends on the expected capabilities of the automated driving system. That is, relatively unreliable automated vehicles may require a higher level of alertness than others. In summary, there is no single definition of driving, but the goals the driver pursues may depend on the tasks the driver has. These statements resonate with classical research by Yarbus [26], which demonstrated that the task given to an observer affects eye movements to a great extent, although replication studies suggest that this finding is still contentious (see [27–30], for replication studies with mixed success).

The current study, conducted with a desktop-based eye tracker, aimed to explore how participants distribute attention while monitoring an automated car on a highway. Attentional distribution was investigated in three tasks: no extra task, an additional speed monitoring task, and an additional hazard detection task. Participants viewed the same non-interactive videos for the three tasks, allowing us to examine viewing behavior in a controlled and contextualized manner—that is, we examined how events in the environment, such as the proximity of other vehicles, affect viewing behavior. We end this work with a discussion of our findings, limitations, and recommendations for the development of DAMS.

2. Methods

2.1. Participants

Twenty students (seventeen males and three females) from the Delft University of Technology participated in the experiment. The participants had a mean age of 24.8 years ($SD = 2.1$) and were all in possession of a driver's license. They held their license for an average of 5.8 years ($SD = 3.2$). The participants' yearly driving distance was 3530 km per year ($SD = 2621$). All participants provided written informed consent before partaking in the experiment.

2.2. Experimental Setup

The experiment was performed on a 24-inch monitor with a resolution of 1920×1080 pixels (display area 531×298 mm). A head support was used to minimize participant head movements. The monitor was positioned at a distance of approximately 0.9 m from the head support; see Figure 1 for a photo of the experimental setup. Eye-tracking was performed using the SR Research EyeLink 1000 Plus eye-tracker, which recorded the right eye.



Figure 1. Experimental setup. Shown from back to front is the monitor for displaying the videos, the eye-tracker camera with infrared illuminator, the keyboard used for pressing the spacebar and arrow keys, and the head support.

2.3. Stimuli

Videos were created in the Euro Truck Simulator 2, a virtual environment that offers realistically looking roads, environments, and road users (e.g., cars and trucks). The driving speed and lane position of other road users was simulated by the AI of the Euro Truck Simulator.

A total of three 120-s videos were used. In each of the pre-recorded videos, the experimenter drove the ego-vehicle by means of the keyboard. In all three videos, the ego-vehicle drove on a two-lane highway with a speed that varied between 80 and 130 km/h. The videos had a frame rate of 60 fps.

- In Video 1, the ego-vehicle overtook six vehicles and was overtaken by one vehicle. The speed of the ego-vehicle crossed the 100 km/h mark six times, and the vehicle changed lanes six times.
- In Video 2, the ego-vehicle overtook two vehicles and was overtaken by five vehicles. The speed of the ego-vehicle crossed the 100 km/h mark 13 times, and the vehicle changed lanes four times.
- In Video 3, the ego-vehicle overtook eight vehicles and was overtaken by two vehicles. The 100 km/h mark was crossed six times, and six lane changes occurred.

2.4. Experimental Task and Procedures

Participants were presented with instructions in written form on the computer monitor. It was mentioned that participants should act as if they were in a vehicle that drove itself and which they had to monitor. It was also mentioned that they should be able to take over control at any time. It was mentioned that the experiment comprised three different tasks:

1. Baseline: You do not have any secondary tasks to perform.
2. Speed Task: You should shortly press the spacebar every time the speed dial crosses the 100 km/h mark. This works two ways around, i.e., when the car is braking or accelerating. As soon as the dial is on the 100 km/h mark, you should press; as soon as the pointer has passed the mark, you should release the spacebar.
3. Hazard Task: You will have to indicate whether a car or truck is driving in the lane next to you. As long as this is the case, you have to press the arrow key. Press the right arrow key when someone is driving on your right side and the left arrow key when someone is driving on your left. When there is nothing on your left or right, you have to release the arrow key.

Although the Speed Task and Hazard Task can reliably be performed by automation technology (namely through cruise control and blind-spot monitoring systems, respectively), supervisors of automated vehicles will still need to perform these tasks in order to stay situationally aware.

Next, the participants were shown a short (13 s) example video to give them an idea of the driving environment. Then, calibration of the eye-tracker was performed. Before each trial, the task for the upcoming trial was shown on the monitor. It was repeated that the primary task was to monitor the self-driving car, to stay aware of the state of the vehicles and traffic signs, and to be able to take over steering at any time. Furthermore, before the Speed Task trial, it was mentioned that the secondary task was to press the spacebar every time the speed crossed 100 km/h. Before the Hazard Task trial, it was mentioned that the secondary task was to hold the left/right arrow key as long as a vehicle was driving next to them.

Each participant performed eighteen 120-s trials. These trials comprised three different videos and three different task instructions, as specified above. Furthermore, half of the videos contained gaze-contingent visual feedback in the form of a red outline of the front windshield, speed dial, left mirror, or right mirror (for a similar approach, see [31]). The gaze-contingent feedback was based on an algorithm that kept track of the participants' previous eye movements and accordingly aimed to guide their eye movements to relevant areas. The order of the 18 trials was randomized and different for each participant.

For this paper, results from nine of eighteen trials were used. The nine videos with gaze-contingent feedback were not analyzed because the onset and offset of the gaze-contingent feedback showed large individual differences, and preliminary analyses did not provide insights that contribute to the present paper's purpose.

2.5. Data Processing

First, data gaps (e.g., due to blinks) in the horizontal and vertical gaze coordinates were filled through linear interpolation. Next, the horizontal and vertical gaze coordinates were filtered using a median filter with a time interval of 100 ms.

The attention distribution was determined by analyzing whether a participant's gaze point fell within one of four areas of interest (AOIs): windshield, left mirror, right mirror, and dashboard (note that the rear-view mirror was not included in the animated video clips of this experiment). The AOIs for the left mirror, right mirror, and dashboard were pragmatically defined as rectangular shapes. All other gaze points were labeled as the windshield. Because of the aforementioned linear interpolation, there were no missing data—that is, for each frame, the percentage of participants looking at the left mirror, right mirror, dashboard, and windshield adds to 100%.

The number of participants who had their eyes in one of these four AOIs was counted for each time sample and moving-average-filtered with a time interval of 500 ms. Subsequently, the participants' attention to the AOIs was graphically associated with events in the scenario, such as ego-vehicle lane changes, ego-vehicle speed, and vehicle size in the mirrors.

The driving simulator we used for creating the videos did not record the state of other vehicles (nor the view the ego-driver had of those vehicles). Additionally, future automated vehicles will likely rely on cameras to obtain information about surrounding traffic [32] and to replace the outside mirrors with screens [33]. Therefore, the size (~closeness) of vehicles visible in the left and right mirrors was obtained using a pre-trained YoloV4 model [34] (obtained from [35]). YoloV4 can detect 80 different object types. From these, we extracted the cars, trucks, and buses. The width of the object in the mirror that yielded the highest classification score was used as an index of vehicle size. Only objects yielding classification scores greater than 0.8 were taken into consideration, to exclude false-positive and low-quality detections (such as opposing traffic on the other side of the road).

3. Results

Figure 2 shows the heatmap for the three task conditions. It can be seen that the attention of participants was highly concentrated on either the left mirror, right mirror, the road ahead, or the speedometer. Participants also occasionally looked at the navigation display, which was ignored in the present analysis and grouped with the dashboard AOI. In summary, the heatmaps confirm that the use of four AOIs (windshield, left mirror, right mirror, dashboard) is appropriate.

Figure 3 shows the attention distribution across the four AOIs for Videos 1, 2, and 3 in the Baseline condition, i.e., without a secondary task. It is noticeable that the attention distribution strongly fluctuated with elapsed time. In an attempt to elucidate the causes of these fluctuations, Figures 4–7 show the moments in Video 3 when a maximal proportion of participants focused their attention on the windshield ($t = 94.1$ s), left mirror ($t = 24.8$ s), right mirror ($t = 84.0$ s), and dashboard ($t = 17.0$ s), respectively.

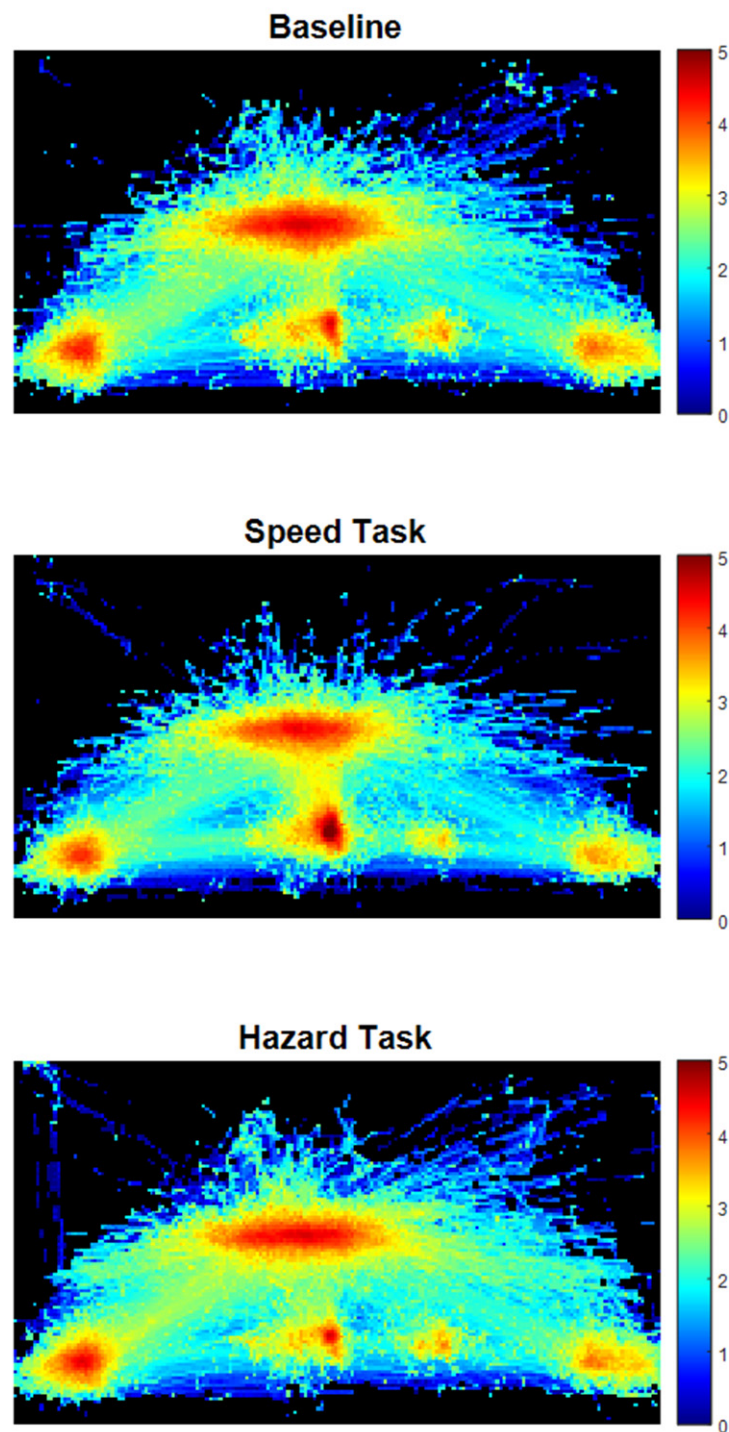


Figure 2. Heatmap of gaze points for the three videos aggregated for the Baseline Task (**top**), Speed Task (**middle**), and Hazard Task (**bottom**). The heatmap was divided into 10×10 -pixel squares and normalized. The colors are on a base-10 logarithmic scale. For example, a dark red color (value = 5) means there was 100 times more attention to that region than a yellow color (value = 3).

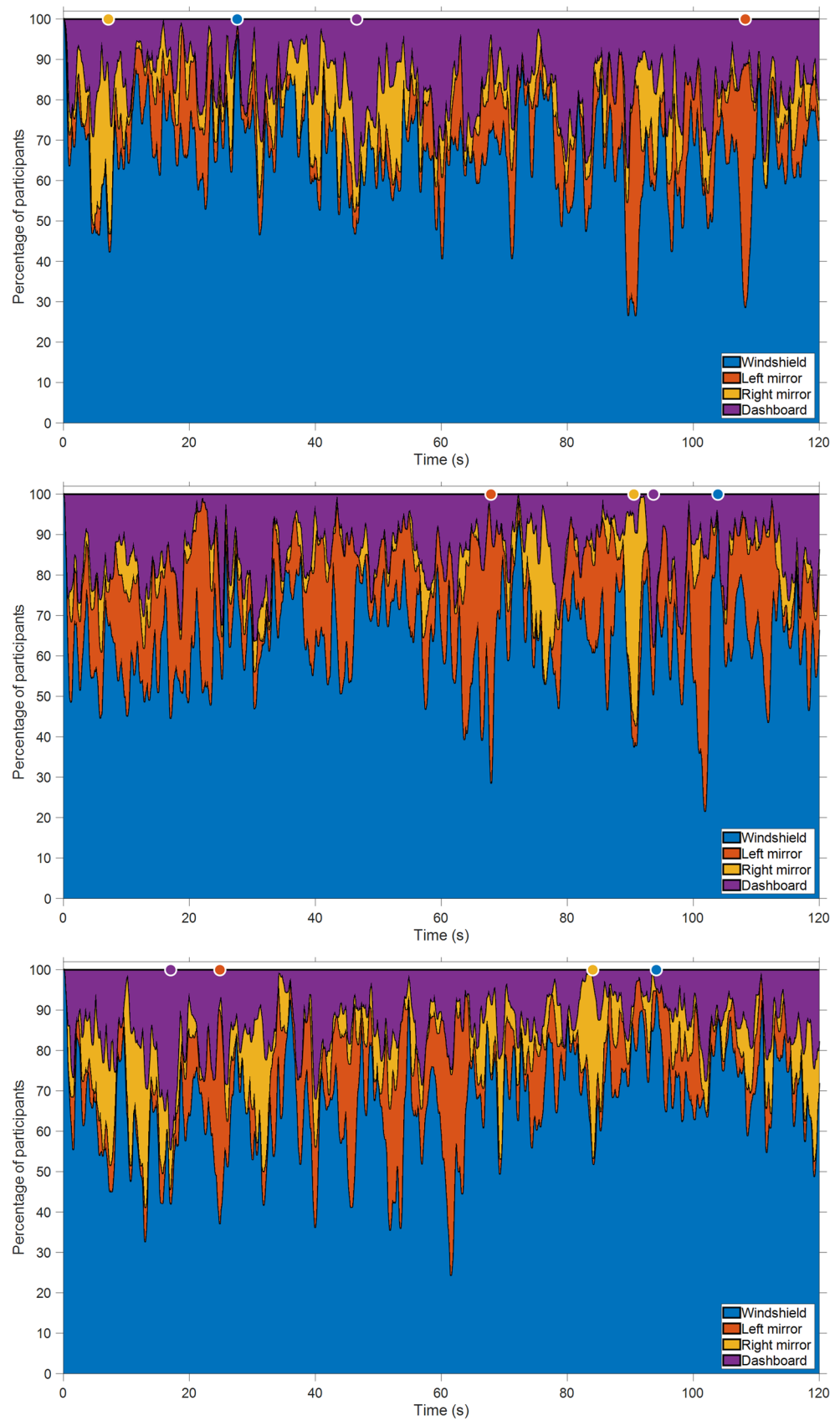


Figure 3. Attention distribution across four areas of interest (AOIs) for Video 1 (top), Video 2 (middle), and Video 3 (bottom) in the Baseline task. The colored circular markers at the top of each figure represent the moments where the maximal number of participants glanced at the AOI.

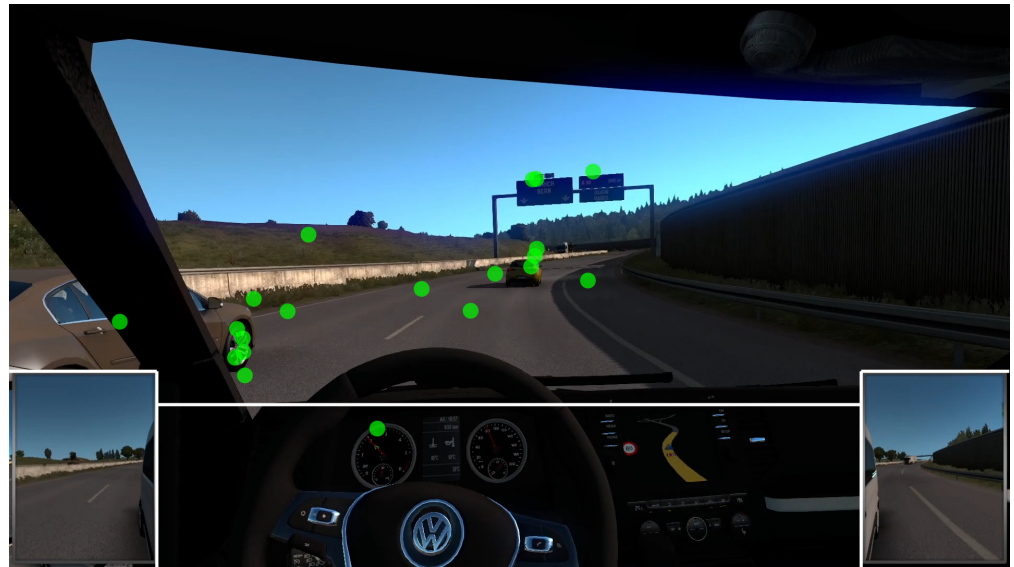


Figure 4. Moment in Video 3 where most participants attended to the windshield (Baseline Task). The green markers represent the gaze coordinates of individual participants. White lines are drawn around the AOIs.



Figure 5. Moment in Video 3 where most participants attended to the left mirror (Baseline Task). The green markers represent the gaze coordinates of individual participants. White lines are drawn around the AOIs.



Figure 6. Moment in Video 3 where most participants attended to the right mirror (Baseline Task). The green markers represent the gaze coordinates of individual participants. White lines are drawn around the AOIs.



Figure 7. Moment in Video 3 where most participants attended to the dashboard (Baseline Task). The green markers represent the gaze coordinates of individual participants. White lines are drawn around the AOIs.

- The windshield attracted attention when events (e.g., car in front, curve, road signs) were happening in that AOI (Figure 4).
- The left mirror attracted attention right before a lane change to the left lane and while a vehicle was visible in the left mirror (Figure 5). The participants may have anticipated that a lane change was about to happen based on the proximity of other vehicles as well as the turn indicator usage visible on the dashboard.
- The right mirror attracted attention right before changing lanes to the right after having overtaken another vehicle (Figure 6).
- Finally, the speedometer attracted attention in otherwise uneventful conditions while the road was relatively empty (Figure 7).

Figure 8 illustrates that vehicles in the mirror attracted attention—that is, when another vehicle was driving in the left lane to overtake the ego-vehicle, participants were increasingly likely to focus on the left mirror as this vehicle got closer.

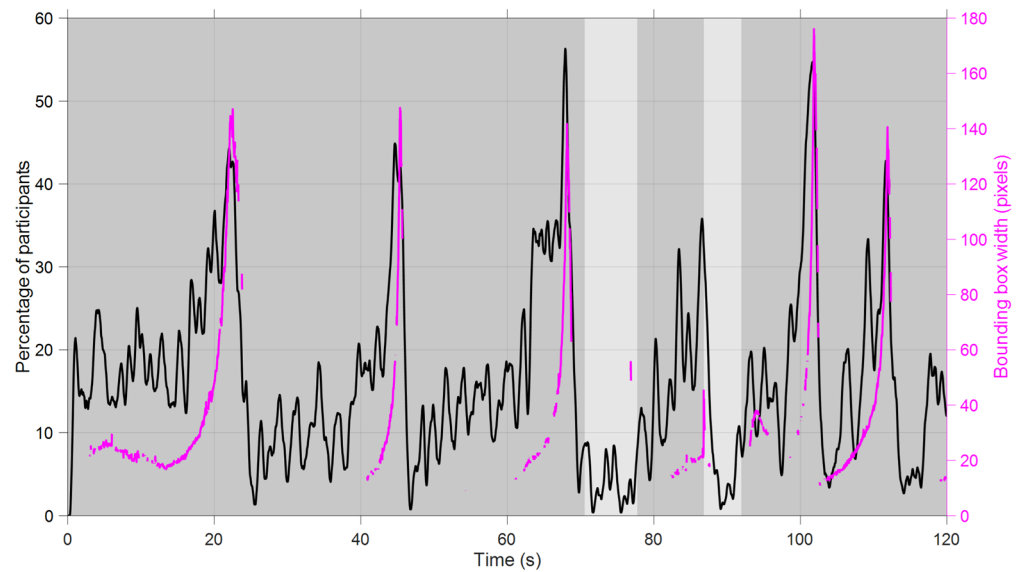


Figure 8. Left axis (black): Percentage of participants with their eyes on the left mirror (Video 2; three tasks averaged). Right axis (magenta): Width of the bounding box of the detected vehicle in the left mirror. The shaded background indicates whether the ego-vehicle was driving on the right lane (dark gray) or left lane (light gray).

The effects of the three task-instruction conditions are shown in Table 1. The Speed Task caused attention to be focused on the dashboard (~40% vs. ~14% in the Baseline Task). In the Hazard Task, attention was directed away from the dashboard and towards the left mirror (13–21% vs. 10–17% in the Baseline Task).

Table 1. Attention distribution to the four Areas of Interest (AOIs) for the nine trials.

Video Number	Task	Windshield (% of Time)	Left Mirror (% of Time)	Right Mirror (% of Time)	Dashboard (% of Time)
1	Baseline	67	10	8	15
2	Baseline	65	17	5	14
3	Baseline	68	11	8	13
1	Speed Task	50	8	5	37
2	Speed Task	43	12	3	43
3	Speed Task	46	8	5	42
1	Hazard Task	67	13	8	11
2	Hazard Task	62	21	5	12
3	Hazard Task	72	13	8	7

The focus on the dashboard during the Speed Task fluctuated over time, with the peaks in attention to the dashboard corresponding to moments when the speed was close to 100 km/h (Figures 9 and 10). In the same vein, in the Hazard Task, participants were relatively likely to attend to the mirrors when objects were visible in those mirrors (see Figure 11 for an illustration). Thus, this again shows that attention distribution is a function of the situation and task.

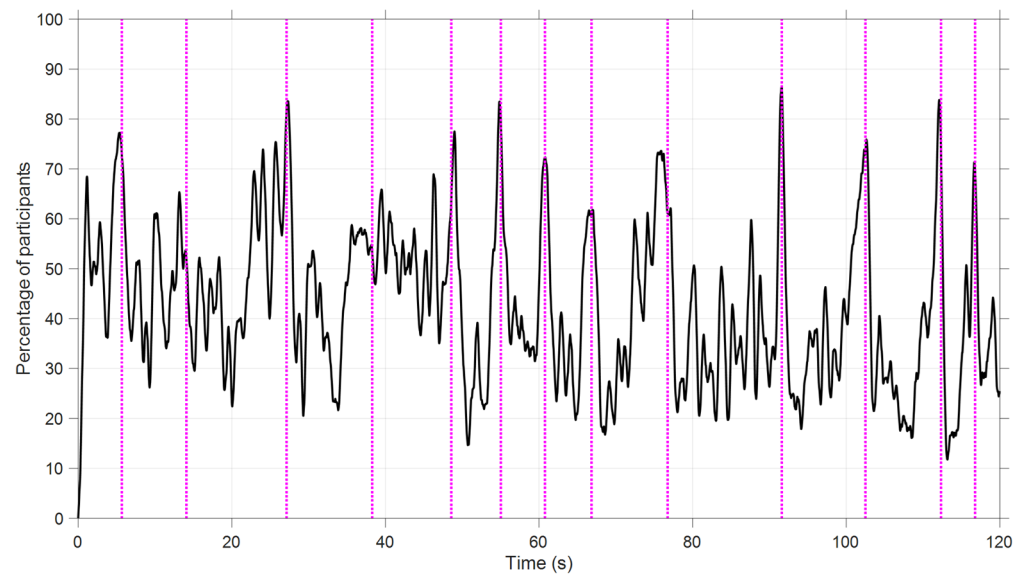


Figure 9. Percentage of participants with their eyes on the dashboard (Video 2, Speed Task). The dotted vertical lines represent the moments of 100 km/h threshold crossings.

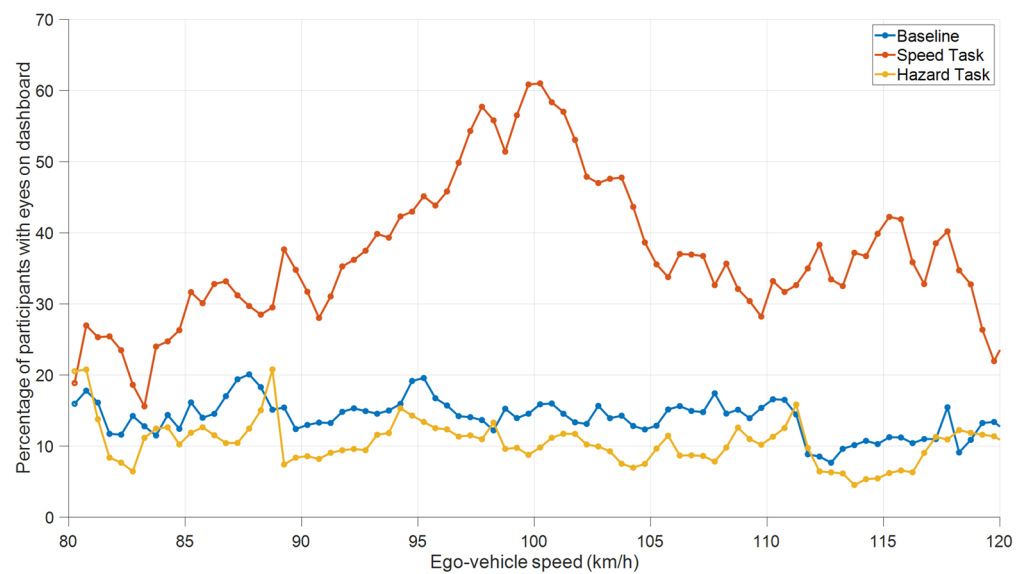


Figure 10. Percentage of participants with their eyes on the dashboard as a function of vehicle speed in the Baseline Task, Speed Task, and Hazard Task (Videos 1–3 combined, first 5 s of each video excluded).

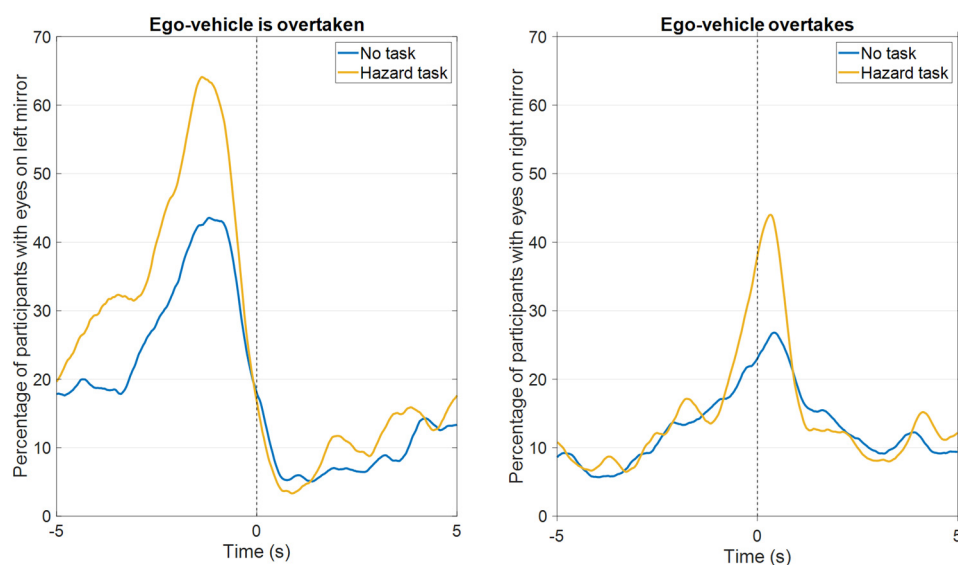


Figure 11. Percentage of participants with their eyes on the left mirror when another vehicle overtook the ego-vehicle in the left lane (left panel) and with their eyes on the right mirror when the ego-vehicle overtook another vehicle in the right lane (right panel) (Videos 1–3 combined, 8 and 15 overtakes, respectively). The vertical line at $t = 0$ s represents the first moment when part of the overtaking car became visible in the left side window (**left panel**) or the last moment when part of the overtaken car was visible in the front window (**right panel**).

4. Discussion

This study examined participants' viewing behavior when presented with videos depicting a simulated automated car. The use of videos enabled us to evaluate participants' viewing behavior for three different task instructions under identical traffic conditions for all participants.

The results indicated that viewing behavior in driving is strongly top-down. More precisely, top-down attention refers to attention that is governed by task-related expectancies and the value of task components (i.e., expected value), as opposed to bottom-up attention, which is governed by salient stimuli and head/eye-movement effort [36]. In particular, the task given to drivers determined their attention distribution (speedometer, hazards), and the drivers' eyes were directed towards task-relevant elements (e.g., overtaking cars) in a highly time-varying manner.

A relatively novel aspect of our work is that it focused on eye movements in relation to tasks and events in the environment. In comparison, research about eye movements in driving seems most developed in regard to curve driving on relatively uneventful roads (see [37] for a review). For example, there is research that reports that on curved roads, drivers focus on the tangent point [38,39], a future path [40,41], or the vanishing point [42]. That said, there is a growing body of research that examines eye movements in relation to the driving context [43] and specific driving events, such as overtaking and lane-changing [44,45], approaching road crossings and roundabouts [46], processing feedback and advice on the dashboard [47], responding to warnings [48,49], and reclaiming control from an automated vehicle (e.g., [50–52]). Especially noteworthy is research by Kircher and Ahlstrom [53], which provide similar figures as our Figure 11 but obtained in real traffic with the help of manual annotations of driving maneuvers. The participants' eye movements in our study seemed aimed at *predicting* the behaviors of other road users, a finding consistent with earlier hazard perception research (e.g., [54]). For example, viewing behavior was forward-facing when events occurred that could be relevant to the driver, such as vehicles approaching or possibly planning to perform a lateral maneuver.

The present study also revealed indications of task prioritization. For example, participants were more inclined to look at less critical elements such as the speedometer when

no hazards were present in the vicinity. In the Speed Task, participants looked at the speedometer considerably more often than in the Baseline task, but still in a functional manner—that is, attention seemed to be focused on the speedometer when there was a high probability that the threshold speed would be exceeded. This latter finding is in line with Senders’s [55] notion of conditional sampling and with Eisma et al. [56], who observed similar results when participants had to detect threshold crossings while watching an instrument panel of moving dials.

The current study revealed a congruence between environmental events and attention distribution. Future research could use more formal models, such as the Salience, Effort, Expectancy, Value (SEEV) model, which has been used before in various transportation research studies. Horrey et al. [57], for example, studied the SEEV model in a driving simulator, where participants had to maintain lane position while performing an in-vehicle technology task. Their results showed a high correlation between predicted and observed percentage dwell time. Other studies also showed high correlations between SEEV-predictive and observed dwell time percentages in various types of human–machine interaction tasks [58–63].

A limitation of this work is the small horizontal field of view of 30 degrees, which prevents the use of peripheral vision—an important component of driving [64,65]. In comparison, the human visual field is about 200 degrees [66], meaning that drivers could infer moving objects from, e.g., the side windows [67]. The participants also could not turn their heads—something that drivers normally do [68]. At the same time, there is ample research that claims valid results for movie clips. For example, there are studies on hazard perception (with and without eye-tracking) that use a small field of view and provide discriminative validity between beginner and expert drivers [69,70]. Additionally, our findings for lane changes resemble the findings of an on-road study by Kircher and Ahlstrom [53]. More classically, Hughes and Cole [71] claimed that “visual information presented by the movie film is sufficient to generate attentive processes characteristic of driving” (p. 377).

The use of short 2-min highway-driving trips only and the lack of a rear-view mirror are other limitations of the present study. Additionally, the participants were young engineering students, who can be expected to have fast response times and strong visual-spatial ability [72,73]. The current work could be replicated with older drivers. Finally, no sound, motion, or tactile cues were produced during the experiment. Future research into predicting eye movements in driving should be conducted in real vehicles (e.g., [43,74]).

What do the current findings mean for the development of DAMS? One interpretation of the results is that drivers’ attention should be distributed. For example, a DAMS could assess whether drivers look in the left or right mirrors when another car is passing or when they pass another car. This observation corresponds to earlier work on a gaze-based DAMS that was built on the assumption “that glances to the mirror and the speedometer are necessary for safe driving” [75] (p. 967). However, their DAMS was not contextualized; that is, it did not consider whether meaningful objects were present in the front view or mirrors. The present results may hold promise for object recognition in combination with eye-tracking. It is expected that future cars and trucks will be equipped with camera systems as a replacement for exterior mirrors in cars and trucks [76]. Object recognition on these camera images (such as using YoloV4 in this study) may prove useful input for DAMS.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Human Research Ethics Committee of the Delft University of Technology (approval number 1479, 22 March 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Raw data, videos, and a MATLAB script that reproduces all figures can be found at <https://doi.org/10.4121/20254071> (accessed on 8 May 2022).

Conflicts of Interest: The authors declare no conflict of interest.

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