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Eye movements of cyclists when interacting with automated vehicles: What can static images tell us? [1]

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Abstract.
The transition period towards large-scale or full automated driving will pose specific challenges. One of the challenges concerns the interaction of automated vehicles with vulnerable road users. So far, most studies into this type of interactions took the perspective of the car. The current study, however, takes the perspective of the vulnerable road user. More specifically, it explores how cyclists perceive and expect automated vehicles to 'behave' and how cyclists would react. Expectations are important determinants of traffic behaviour. Incorrect expectations could lead to overly trustful or hesitant behaviour and subsequent unsafe interactions. Recently, Hagenzieker and colleagues (2017) conducted a photo experiment in which regular cyclists had to judge photos of traffic situations where they encountered manually-driven cars and automated cars (recognisable by either a sticker on the side of the car or a roof name plate on top of the car). Participants judged 30 photos twice, in random order. In that study a subset of nine participants were equipped with an eye tracker in order to study their eye movements while judging the photos. This study further examined these eye tracking data, comparing time-to-first-fixation, dwell time from the start of the first fixation, and total number of revisits in interactions with automated and with manually-driven cars. Results indicate no differences in time-to-first-fixation nor in the number of revisits between situations with automated cars and traditional cars. Dwell times revealed an effect of familiarity, showing that cyclists spent more time looking at cars during the first round of photos compared to the second round. In particular, they spent more time looking at automated cars which were identifiable by a sticker on the side. The results are discussed and suggestions for future research are given.

Keywords: cyclists, automated driving, eye tracking, interaction, external features, behaviour

1. Introduction

Partially and fully automated vehicles gradually enter our roadway system. The expectations about the impact of vehicle automation on the efficiency of the road transport system, including road safety, often run high. However, before we reach a full automated traffic system, a transition period is inevitable, posing specific challenges. One of the challenges during this transition period, and the topic of the current paper, is how cyclists interact with automated vehicles.

Research on the interaction of (partially) automated vehicles and vulnerable road users has been limited. Vissers et al. [1] provide an overview of the literature in this area. They conclude that research generally takes the perspective of the vehicle, e.g. focusing on the technology for detecting and recognizing pedestrians and cyclists, and more recently also on the communication of the automated vehicle towards pedestrians and cyclists. One issue that is particularly underrepresented in research, as indicated by Vissers and colleagues, is research that takes the perspective of the cyclists and pedestrians. How do they expect automated or partially automated vehicles to behave? How do they expect these vehicles to respond to them, and how would this affect their behaviour and interaction with the vehicle? And, last but not least, how do they know whether it is a fully automated vehicle, a partially automated vehicle or a 'traditional' manually driven vehicle?

This type of knowledge is essential for predicting pedestrians' and cyclists' behaviour so that an automated vehicle can accurately adjust its response when necessary and ensure a safe interaction. The few studies that assessed the behaviour of pedestrians while interacting with automated vehicles point at a rather cautious attitude (see Vissers et al., [1], for an overview).

A recent study [2] specifically focused on the expectations of cyclists towards automated vehicles and their (self-reported) behaviour in interactions. Cyclists form a specific challenge in the transition toward an automated traffic system, especially in countries with a large share of cyclists such as the Netherlands. The reason is that both the potential number and variety of encounters are much larger than for pedestrians. This small and exploratory study investigated the expectations and behavioural intentions of cyclists when interacting with automated vehicles and with manually driven vehicles. Participants were regular cyclists who had to judge

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photos of traffic situations where a cyclist had to interact with either an automated car or a manually driven car. Automated cars were identifiable by either a roof name plate on top of the car or a sticker on the side of the car, both saying “self-driving”. Figure 1 is an example of an interaction situation from the perspective of a cyclist with the three types of cars. Participants went through a total of 30 photos twice (in different, random order); the first time, participants had not been instructed how to differentiate between automated and manual vehicles; the second time they had.

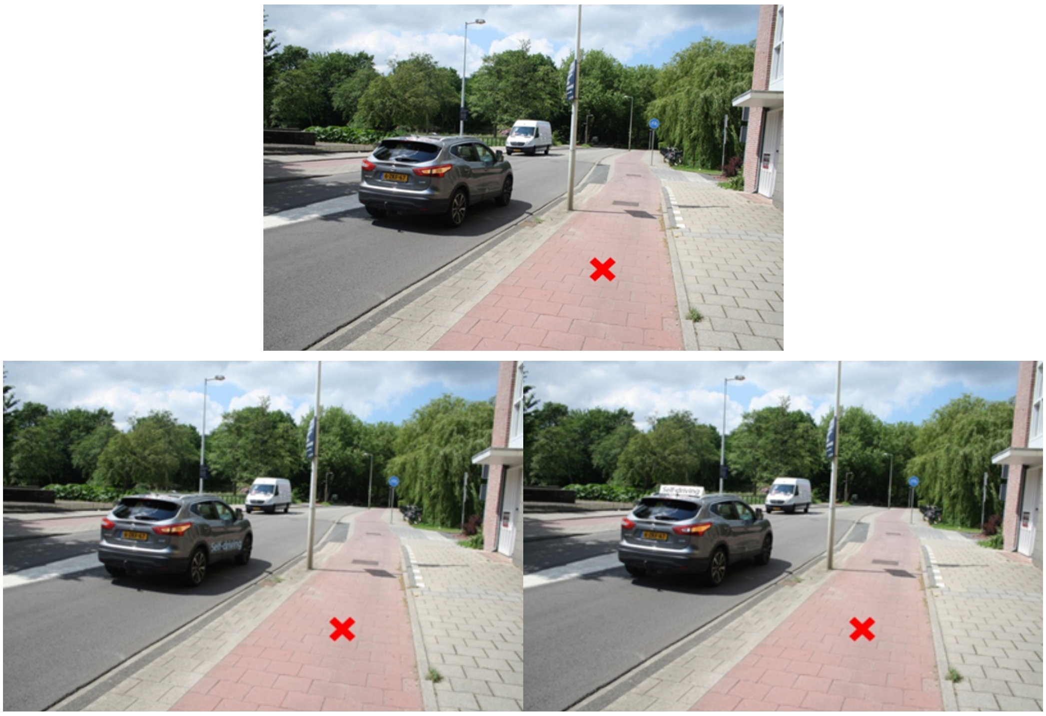

Figure 1: Example of a traffic situation where a cyclist will encounter a right turning vehicle with a traditional car (top) and a self-driving car (bottom) identifiable by a sticker (left) or roof name plate (right) saying “self-driving”.

The overall results indicate that cyclists were not surer to be noticed by an automated car as compared to a manually driven car, confirming the fairly cautious attitude of vulnerable road users towards automated vehicles. However, participants who had received instructions that stressed the positive safety features of the automated cars were surer they had been noticed by automated cars than participants who had received neutral information about the cars’ features. In this study overall no differences were found in the expectations of cyclists whether or not the car would stop for them. However, when they saw the photos for the second time (i.e. when they had been instructed how to differentiate between automated and manually driven cars), they were surer that the automated cars would stop. The cyclists themselves did not intend to behave differently in interactions with the different types of cars.

During this study some of the participants were equipped with an eye tracker. A preliminary analysis of the eye tracking data revealed that participants fixated longer on the vehicles during the first round of photos than during the second round. During this first photo set participants fixated longer on automated vehicles, in particular those with the sticker, than on manual vehicles.

The current paper presents the results of some further analyses of the eye tracking data that was collected by Hagenzieker et al. [2]. Eye tracking is a non-invasive method that allows us to visualize and quantify the search for visual information. Though not often used in a static environment such as photographs, the eye tracking data can give an indication of what the cyclists look at, at which moment and to what extent, and what they ignore. This in turn can shed some light on their visual search strategies when interacting with automated and/or manually driven vehicles in different traffic situations.

In addition to the total fixation times that were analysed and reported by Hagenzieker et al. [2], we expanded the analysis of the eye tracking data by studying the effects of three additional measures: *time-to-first-fixation, dwell time from the start of the first fixation*, and *total number of revisits*.

Time-to-first-fixation shows how fast someone fixates a specific object and gives an indication of how much attention it attracts. As such it is a measure to describe bottom-up driven visual searches in which the attention is more or less automatically drawn to the object, e.g. because of its salience [3][4]. Time-to-first-fixation is also related to expectations [5]. If someone is looking for specific information and this information is located at the expected position, the time-to-first-fixation is faster than when located at an unexpected position. Time-to-first-fixation is often used in marketing and brand awareness research to see what advertisements attract most attention [6]. However, it has also been used in traffic research. For example, Siswandari & Xiong [7] used this measure as a means to investigate the comprehensibility of traffic signs. It turned out that the harder the traffic signs were to comprehend, the longer the time to the first fixation. To investigate whether this measure would also convey the ease or difficulty to recognize an automated vehicle in a traffic scene, we used time-to-first fixation in the present study.

Dwell time is the total time that someone has fixated a specific object or area of interest [8]. Dwell time is generally expressed as the percentage of the total time that a stimuli was available for inspection, and could be considered as a top-down search, i.e. searching actively for relevant information [3]. One of the determinants of dwell time is the level of interest of the observer for the object of interest: the longer the dwell time, the higher the level of interest [9]. Another determinant of dwell time is the similarity of objects when searching for a target object: the higher the similarity the longer the dwell time [8]. Finally, dwell times seem to be related to experience or familiarity: the less experience / familiarity, the longer the dwell time [10]. In our study we analysed the dwell times to get an indication of the active search of participants to identify the type of car: manual or automated. Given that photos were shown for a fixed amount of time before the questions were presented, the maximum possible dwell time for a particular object depends on when this object was fixated first [10]. Hence, for our study we calculated the relative dwell time from the start of the first fixation, i.e. the amount of time that an object was fixated as a percentage of the total time available from the start of the first fixation.

Finally, we look at the number of revisits on the area of interest. By this is meant the number of times participants look at the (automated or traditional) cars after their first fixation on it (i.e. revisits). By using this measure we aim to investigate whether a differential amount of revisits to the car, provides information on the comprehensibility. Revisiting an AOI may be linked to intentional processes to attempt to resolve comprehension problems or in order to integrate the information that is available in the target areas [11] The dwell time describes the total time an object was looked at and can consist of one long fixation or of two or more shorter fixations, while some other object has been fixated on in between. A series of shorter fixations, as compared to one long fixation points at more routine situations where a first shorter fixation does not give unexpected information; when people continue to look at an object, this is an indication that what they see is new or not expected. For example, inexperienced drivers are less likely to look at potential hazards than more experienced drivers [12], but once they do, they will continue to look ('stare') for a longer time [10]. This could be explained by the fact that inexperienced drivers are less familiar with hazards in traffic than experienced drivers.

In summary, the three main research questions of our small-scaled photo experiment are:

1. Time-to-first-fixation: Is there a difference in the time cyclists take to start looking at automated cars and at manually driven cars, and is this affected by experience / familiarity?
2. Total dwell time from the start of the first fixation: Is there a difference in the total time cyclists look at automated cars and at manually driven cars, and is this affected by experience / familiarity?
3. Total number of revisits: Is there a difference in number of times cyclists look again at automated cars and manually driven cars after their first fixation and is this affected by experience / familiarity?

In addition, and in a very exploratory manner, we looked at differences in these variables related to approach angle and priority regulation in the interaction.

2. Method

2.1 Participants

A total of 35 participants participated in the study: 17 women with an average age of 29.7 years (SD: 13.1; range: 19-58) and 18 men with an average age of 28.8 years (SD: 13.2; range: 18-61). They were recruited at the Delft University of Technology in the Netherlands through social media and flyers. Participants were required to be older than 18, master the Dutch language, and be regular cyclists: out of 35 participants, 32 cycled at least 1-3 days a week but 21 participants cycled every day. The eye movements were recorded for nine of these 35 participants: three women with an average age of 25.7 years (SD: 2.73; range: 25-32) and nine men with an average age of 25.7 years (SD: 2.73; range: 25-32). These participants did not wear glasses, as this interferes with the eye tracker.

2.2 Material

Participants had to judge 30 photos of traffic situations from the perspective of the cyclist. The photos depicted ten different situations and each situation was shown three times: once with a manually driven car, once with an automated car recognisable by a roof name plate saying 'self-driving', and once with an automated car recognisable by a sticker on the front door, also saying 'self-driving' (see Figure 1). In each situation there was an imminent interaction with a passenger car. The cars approached from the right (four situations), left (one situation), from the front (two situations) or from behind (three situations). In five situations the cyclist had priority and in the other five the car had priority.

2.3 Independent variables

The participants were randomly assigned to one of two between-subjects conditions. Before the experiment, the participants received one of two instructions. In one condition the instruction emphasised the positive aspects of automated driving including the safety aspects of automated vehicles. In the other condition the information about the features of automated driving were formulated more neutrally. Of the nine eye tracker participants, five participants received the positive instruction and four the neutral instruction.

Furthermore, there were four within-subjects conditions:

1. Car type, consisting of three levels: automated with roof name plate, automated with sticker, and traditional.
2. Familiarity, consisting of two levels: first round of presentation before explicit explanation how to identify an automated car and the second round of presentation after the explanation.
3. Priority, consisting of two levels: cyclist priority or car priority
4. Approach angle, aggregated into two levels: approaching from a side road (left or right) or approaching on the same road (from behind or from ahead)

2.4 Dependent variables

For each photo, the participant had to answer three questions: (1) How sure are you that the car noticed you?, (2) How sure are you that the car will stop if you continue cycling?, and (3) What would you do as a cyclist in this situations? We refer to Hagenzieker et al. [2] for more details and results of this part of the study. For this paper we focus on the visual search strategy. Three measures were used to describe this visual search strategy: 1) time-to-first-fixation, 2) dwell time from start of first fixation, 3) total number of revisits.

2.5 Apparatus

The photos were shown on a laptop with a screen size of 23 inch. Eye movements were recorded with a Pupil Lab's head mounted binocular eye tracker [13]. This eye tracker uses dark pupil position and corneal reflection to determine the gaze direction. It is equipped with a world camera that films the world from the participant's perspective and two infrared eye cameras. The output shows the video of the world camera on which the gaze positions are superimposed. After calibration, the eye tracker is able to accurately track the eye movement and gaze direction at a refresh rate of up to 60 Hz. In this study, a refresh rate of 30 Hz (30 frames per second) was used.

2.6 Procedure

Participants were individually tested at Delft University of Technology. Each participant first read the instruction and then signed the informed consent. Then, the eye tracker was mounted and calibrated. Subsequently, participants completed a few background questions about age, gender, bicycle use and bicycle speed. The actual experiment started with a practice photo after which the experimental photos were presented in random order. Each photo was shown for 8 seconds. After the first round of 30 photos, the participants were asked whether they had noticed that some photos contained self-driving vehicles. They were also asked which manipulation (roof name plate or sticker) they preferred as indicator of an automated vehicle. Then the 30 photos were presented again, in a different randomized order. Finally, the participants had to complete two short questionnaires, one about trust in self-driving technologies and one about sensation seeking, but the current paper does not consider these (see Hagenzieker et al., [2] for more information). After the experiment, the experimenter gave an explanation about the study and the participant could ask questions. Participants received a 10 euro gift coupon as reward. The entire experiment lasted approximately 30 minutes.

2.7 Analyses

For the analyses the number and length of fixations within the Area of Interest (AOI) were determined. The AOI was defined as the car. Only fixations equal or longer than 200ms were included [14]. *Time-to-first-fixation* was calculated by counting the number of frames between presentation of the photo and the start of the first fixation and dividing it by 30 (30 frames per second). The relative *dwell time* was calculated by summing the length of all fixations ($\geq$ 200ms, including the first fixation) in the AOI, and expressing it as a percentage of the total remaining time after the start of the first fixation. Finally, we looked at the total number of times the participants revisited the various AOI's, namely the cars in the photos representing the self-driving and traditional cars, during the first 8 seconds the photos were presented. This was calculated by taking the number fixations on the cars in the photos that were preceded by a fixation that was not on the cars in the photos. On one photo, one participant did not fixate on the AoI at all. This was coded as missing.

Repeated measures analyses of variance (ANOVAs) were conducted and a significant level of $p<0.05$ was applied. Note that the ANOVA results are in fact based on two experimental designs. In both designs, the within-subjects factors Car type and Familiarity and the between-subjects factor Instruction was used. Additionally, in one design the within-subjects factor Priority was used and in the other design the within-subjects factors

Approach angle was added. We do not report on the first order interactions between Instruction and Priority, Instruction and Approach angle or the second order interactions of Instruction by Car type by Priority and Instruction by Car type by Approach angle. These interactions were not of any interest to us nor were they significant.

3. Results

In this section we will report the results on the three main questions: (1) Time-to-first-fixation: Is there a difference in the time cyclists take to start looking at automated cars and at traditional cars, and is this affected by experience / familiarity?, (2) Total dwell time from the start of the first fixation: Is there a difference in the total time cyclists look at automated cars and at traditionalcars, and is this affected by experience / familiarity? And (3) Number of revisits: Is there a difference in number of times cyclists look at automated cars and at traditional cars and this affected by experience / familiarity? Additionally, we will report on the differences in these variables related to Approach angle and Priority. We first looked at the between-subject factor Instruction. The Analysis of variance showed no main effect of Instruction (A or B) in both designs, nor were there any significant interactions with other factors. This was the case for both time-to-first-fixation and dwell time. Therefore, all results reported are based on the data acquired from both groups together.

3.1 Time-to-first-fixation

See Table 1 for means and standard deviations and Table 2 for the repeated ANOVA results for this section. The results for Time-to-first-fixation showed no main effects of Car type or Familiarity. Furthermore, we found no significant interaction effect for Time-to-first-fixation between Car type and Familiarity. Thus, the time participants took for their first look at the automated cars or traditional cars did not differ. Also, there was no difference of time-to-first-fixation between the two photo rounds.

Table 1: Means of Time-to-first-fixation (seconds) for Car type and Familiarity (round 1 and 2)

Car type	Traditional	Roof name plate	Sticker	Sig.
	Mean(SD)	Mean(SD)	Mean(SD)	
Overall	1.13(0.37)	0.92(0.32)	1.09(0.44)	NS
Round 1	1.29(0.69)	1.03(0.46)	1.17(0.58)	NS
Round 2	0.98(0.33)	0.83(0.27)	1.00(0.35)	

Table 2: ANOVA results for Time-to-first-fixation

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Car type	0.808	2	0.404	1.429	0.272
Familiarity	1.464	1	1.464	2.430	0.163
Car type*Familiarity	0.07	2	0.035	0.175	0.841

3.2 Dwell time after the first fixation

Table 3 reports on the means and standard deviations and Table 4 reports the ANOVA results. With dwell time from the start of the first fixation, a repeated measures ANOVA revealed a statistically significant main effect for Familiarity ($F(1,7)=9.631$, $p=.017$; See Table 4). The participants had longer dwell times on the cars, regardless of which type of car, during the first photo round ($M=26.40$, $SD=7.96$) compared to the second photo round ($M=17.94$, $SD=10.38$). We also found a statistically significant interaction effect for dwell time between Car Type and Familiarity ($F(2,14)=4.134$, $p=.039$; See figure 2). Post hoc tests using the Bonferroni correction revealed a significant difference in Dwell time for the sticker condition (<.01) between the first photo round and second photo round (See Table 4), while this was not the case for the traditional nor for the roof name plate conditions.

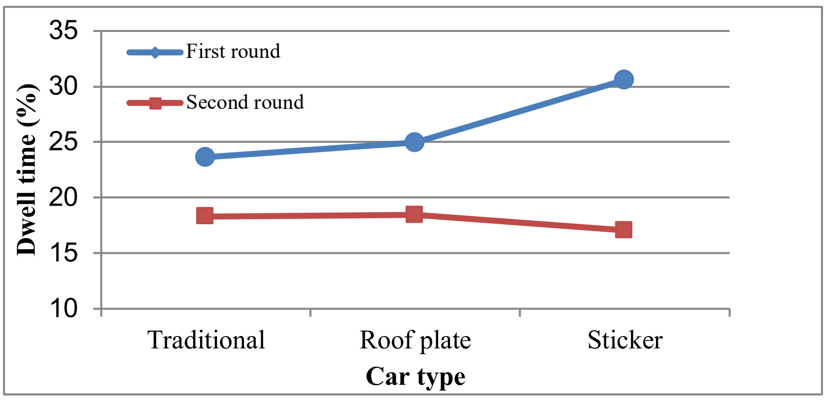

Figure 2: Dwell times (%) for each car type manipulation (Traditional, Sticker and Roof name plate) for Familiarity (first and second round)

We found no significant main effects for Car type, however, the means show the same tendency as the above reported interaction effect. The mean for the sticker condition is somewhat higher compared to the traditional and roof name plate condition (See Overall means in Table 3), indicating that participants looked longer at the car with a sticker on the side than at the other two cars.

Table 3: Means (%) and Standard deviations of dwell time after the start of the first fixation; *=*p*<0.05

	Traditional	**Roof name plate**	**Sticker**	**Sig.**
	Mean(SD)	Mean(SD)	Mean(SD)	
Overall	20.98(8.16)	21.70(8.99)	23.83(9.28)	NS
Round 1	23.64(9.13)	24.95(9.01)	30.59(9.69)*	*
Round 2	18.31(9.18)	18.45(11.29)	17.06(11.43)*	

Table 4: ANOVA results of dwell time

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Car type	177.661	2	88.830	1.930	0.182
Familiarity	1759.748	1	1759.748	9.631	0.017
Car type*Familiarity	363.153	2	181.577	4.134	0.039

3.3 Number of revisits

Table 5 reports on the means and standard deviations and Table 6 reports the repeated ANOVA results. The results for the number of revisits showed no main effects of Car type or Familiarity. Furthermore, we found no significant interaction effects for the total number of revisits between Car type and Familiarity. This shows that participants did not revisit the photos showing automated cars more or less often than the photos showing traditional cars, nor did we find a difference in how often participants revisited the AOI's between the two photo rounds.

Table 5: Means (%) and Standard deviations of total number of revisits; *=*p*<0.05

	Traditional	**Roof name plate**	**Sticker**	**Sig.**
	Mean(SD)	Mean(SD)	Mean(SD)	
Overall	2.08(0.54)	2.11(0.56)	2.11(0.54)	NS
Round 1	2.19(0.59)	2.44(0.67)	2.36(0.50)	NS
Round 2	1.98(0.66)	1.78(0.65)	1.86(0.67)	

Table 6: ANOVA results of total number of revisits

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Car type	0.035	2	0.017	0.160	0.854
Familiarity	1.601	1	1.601	4.387	0.081
Car type*Familiarity	0.428	2	0.214	2.888	0.095

3.4 Additional findings: Priority and Approach angle

This section reports on the results of the variables Priority or Approach Angle (See section 2.3).

3.4.1 Time-to-first-fixation

Regarding time-to-first-fixation, we found a significant main effect for Approach Angle: (F(1,7)=18.580, *p*=.004). Participants fixated faster on the cars, regardless of Car type, when the car approached them from behind or from the front (M=0.91, SD=.33) than when the car approached from the left or right (SD=1.18, SD=.34). There was no significant main effect for Priority, nor any significant interaction between Car type and Priority or Approach angle. We found also no interaction between Familiarity and Priority or Approach Angle (See Tables 7 and 8 below).

Table 7: Means and Standard deviations for Time-to-first-fixation of factors Priority and Approach angle

Car type	**Traditional**	**Roof name plate**	**Sticker**	**Sig.**
	Mean(SD)	Mean(SD)	Mean(SD)	

Priority cyclist	0.89(0.61)	0.90(0.59)	0.91(0.64)	NS
No priority cyclist	1.38(0.40)	0.94(0.35)	1.25(0.36)	
Approach from left-right	1.30(0.44)	1.08(0.39)	1.15(0.43)	NS
Approach from behind-from the front	0.97(0.43)	0.77(0.27)	1.00(0.52)	

Table 8: ANOVA results of Time-to-first-fixation for the factors Priority and Approach Angle

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Priority	2.416	1	2.416	2.575	0.153
Car type*Priority	1.057	2	0.529	1.834	0.196
Familiarity*Priority	0.021	1	0.021	0.03	0.868
Approach angle	2.079	1	2.079	18.580	0.004
Car type*Approach angle	0.194	2	0.097	0.842	0.452
Familiarity*Approach angle	0.251	1	0.251	0.583	0.470

3.4.2 Dwell time

With Dwell time from the start of the first fixation, we found no significant main effects for Priority or Approach angle. Participants did not look longer or shorter at the cars when these had priority or when they themselves had priority. Also, they did not look longer or shorter when the car approached from the left or right, or from behind or from the front. There were also no significant interaction effects for Dwell time after first fixation between Car type and either Priority or Approach Angle. Furthermore, we found no interaction between Familiarity and Priority or Approach Angle (See Tables 9 and 10 below).

Table 9: Means and Standard deviation for Dwell time of the factors Priority and Approach angle

Car type	Traditional	Roof name plate	Sticker	Sig.
	Mean(SD)	Mean(SD)	Mean(SD)	
Priority cyclist	21.28(7.49)	24.84(10.84)	27.05(11.37)	NS
No priority cyclist	20.66(9.74)	18.57(10.38)	20.60(10.88)	
Approach from left - right	22.30(9.91)	21.90(11.28)	25.63(10.43)	NS
Approach from behind – from the front	19.65(7.27)	21.51(8.30)	22.02(8.90)	

Table 10: ANOVA results of Dwell time for the factors Priority and Approach

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Priority	613.631	1	613.631	3.002	0.127
Car type*Priority	221.198	2	110.599	2.091	0.160
Familiarity*Priority	38.731	1	38.731	1.020	0.346
Approach angle	90.530	1	90.530	1.848	0.216
Car type*Approach angle	53.539	2	26.770	0.899	0.429
Familiarity*Approach angle	8.430	1	8.430	0.241	0.639

3.4.3 Number of revisits

Finally, when looking at the number of revisits, we found a significant main effect for Priority. Participants revisited the car more often when the cyclists themselves had priority (M=2.23, SD=0.50) compared to when they did not have priority (M=1.97, SD=0.58), regardless of Car type: $F(1,7)=6.018$, p=.044). We found no significant interaction effects for the total number of revisits for Priority and Car type.

We found no significant main effects for Approach Angle. There were also no significant interaction effects for the number of revisits between Car type and either Priority or Approach Angle. Furthermore, we found no interaction between Familiarity and Priority or Approach Angle (See Tables 11 and 12 below).

Table 11: Means and Standard deviation for number of revisits of the factors Priority and Approach angle

Car type	Traditional	Roof name plate	Sticker	Sig.
	Mean(SD)	Mean(SD)	Mean(SD)	
Priority cyclist	2.11(0.50)	2.34(0.59)	2.24(0.54)	NS
No priority cyclist	2.06(0.67)	1.88(0.61)	1.97(0.64)	

Approach from left - right	2.01(0.58)	1.96(0.61)	2.02(0.59)	NS
Approach from behind – from the front	2.16(0.75)	2.27(0.69)	2.19(0.51)	

Table 12: ANOVA results of the number of revisits for the factors Priority and Approach

Analysis	Sum of sq.	df	Mean sq	F	Sig.
Priority	2.116	1	2.116	6.018	0.044
Car type*Priority	0.784	2	0.392	2.533	0.115
Familiarity*Priority	0.200	1	0.200	2.054	0.195
Approach angle	1.431	1	1.431	2.717	0.143
Car type*Approach angle	0.179	2	0.089	0.373	0.695
Familiarity*Approach angle	0.451	1	0.451	0.833	0.392

4. Discussion and conclusion

This paper is a follow up-study on previous research by Hagenzieker and colleagues [2]. Results of that study indicated that cyclists were not surer that they were noticed by an automated car compared to a manually-driven car. This confirmed the fairly cautious attitude of vulnerable road users towards automated vehicles. However, when participants received an instruction that stressed the positive safety features of automated cars they became surer that they were noticed by automated cars compared to participants who received a neutral instruction. Additionally, participants who viewed the photos for the second time reported feeling surer that the automated car would stop for them than in the first round of photos. Preliminary eye tracking results showed that participants spent more time looking at the cars during the first photo round compared to the second photo round. The current paper aimed to further look into the eye tracking data that was collected to shed more light on the results found in Hagenzieker et al [2]. Three additional questions were explored by using three different eye tracking measures: (1) time-to-first-fixation, (2) dwell time from the start of the first fixation and (3) the number of revisits. Note however, that due to the small number of participants, the results are only an indication.

We found no differences in the time that participants took to have a first look at the automated and traditional, manually driven cars, nor did this differ between the first and second round. The automated cars were thus not looked at earlier than the manual cars. This could mean that the roof name plate and sticker condition did not evoke a bottom-up driven visual search and thus attract attention [3][4]. This may be due to a lack of saliency: more visually salient items capture more attention than less salient items [15]. Especially in consumer choice situations, visually more salient advertisements have been shown to be looked at faster than less salient ones [16]. In the case of the roof name plate, a possible explanation could also be that it resembles the looks of a driving instructor car; the experience that cyclists may have with such cars could have diminished the attention grabbing properties because these are simply not new to them. Cyclists could therefore have used experience based schemata to recognize the situation [15].

Another finding is that the cyclists spent more time looking at the cars, regardless of car type, during the first photo round as compared to the second round. Huestegge et al, [17] found similar results. In a picture study they examined whether experienced and inexperienced drivers judged hazardous situations differently. Participants had to judge traffic scenes which demanded a braking response or a speed reduction (low, medium of high braking affordance) by pressing a button. A similar eye tracking measure was used: The time between the start of the first fixation and the response of pressing the button. Interestingly, they found that inexperienced drivers spent more time looking at the hazardous situations compared to the inexperienced drivers. Yet another study also found that experience helped drivers to process hazards more quickly [10]. Although these studies used different paradigms than ours, it is interesting to see that also here experience appears to decrease the time that cyclists needed to extract and process the information, in this case from the appearances of automated cars.

We also found that cyclists looked longer at the car with a sticker during the first photo round compared to the second photo round. This is in line with earlier results [2], where cyclists also spent more time looking at the sticker condition during the first photo round compared to the second photo round. This is not surprising, because we also found no differences in the time it took cyclists to start looking at the cars (so there is no difference between this measure and the total time cyclists spent looking at the cars). Interesting, however, remains the fact that the sticker condition was looked at longer during the first photo round in both cases. This could indicate that cyclists needed more time to extract and process the information needed compared to the roof name plate and traditional car manipulation [2][10]. Another possible explanation could be that the sticker condition was more difficult to see or read in some photos, which could also have extended the time cyclists had to look.

Additionally, we found that cyclists started to look earlier at the cars that approached from the front or from behind as compared to cars that approached from the left or right. We suspect that this is an artefact caused by the location of the vehicles in the photos. The cars approaching from the front or behind were usually located more centrally in the photos than those that approached from the left or right. Participants may have started looking at the centre of the photos, and it then obviously took more time to move to a more peripheral part. Also in real driving similar tendencies are typically observed in drivers, where the fixation location most favoured by experienced drivers is straight ahead [18]. An explanation as to why participants did not look at autonomous vehicles any quicker than manually driven vehicles could be that one of the objectives was to identify what kind of vehicle was being depicted. Therefore, all vehicles could have received more or less the same time-to-fixation because the participant did not know what kind of vehicle it was yet.

Finally, the results on the number of revisits revealed that participants revisited the cars more often when the cyclists themselves had priority compared to the situations where they did not. This could be because the cyclists tend to keep more of an eye on the cars to determine if they are indeed being given priority as compared to when the cyclists have to give priority. As mentioned earlier, revisiting a specific AOI could be meant to resolve comprehension problems or to integrate information that is available in the target areas [11]. Then, simply detecting the vehicle might be sufficient to plan their actions, while waiting for a car to stop and give priority could require more attention and revisiting.

Some discrepancies have also come to light when comparing results with earlier findings, where participants who received a positive instruction reported to be surer that they were noticed by automated cars as compared to when receiving a neutral instruction [2]. A positive or more neutral description of the capabilities of automated driving did not, however, elicit differences in eye movement behaviour. Furthermore, it is clear in both studies that there is an effect of familiarity, however, in different ways. In the current study in the sense that cyclists did not look longer at the automated cars anymore during the second round, whereas in [2] cyclists were more sure that the automated car would stop for them as compared to the manually-driven car. The eye tracking data showed that cyclists only looked longer at the cars with a sticker and not at the car with a roof name plate. These findings illustrate that the relationship between eye movement data and other measures is not straightforward.

The results of the present study should be treated with caution. First, due to the limited sample size of nine participants that was included in this study. Secondly, glance behaviour of cyclists could be different in the real world compared to a lab setting and using static images. Static images do not convey information about the speed of the car that the participants are interacting with. Cycling requires steering, pedalling and maintaining balance, all whilst monitoring the road and environment [19]. These additional demands could not be accounted for in this study. However, static images can be useful and have been used in traffic research. For example, Siswandari and Xiong [7] used static images of road signs to determine their comprehensibility. It turned out that the images that depicted harder-to understand road signs had longer time to first fixation compared to the signs that were easier to understand. Huestegge et al [17] also used static images to examine whether inexperienced drivers judged traffic situations differently compared to experienced drivers. Nonetheless, it might be useful to do a comparable study with the use of video depicting comparable traffic situations as in the static images to explore eye-movement patterns in a dynamic setting. Thirdly, regarding the minimal fixation during, this study used a cut-off point of 200ms. Fixations around the 100ms mark might not be uncommon in traffic behaviour and a smaller cut-off point should be considered in future studies. Finally, perhaps the visibility and readability of the various ‘automated’ car indicators were insufficient in some of the photos. Although none of the participants mentioned this, the size and angle of the car varied within the set of photos, and could have influenced the results. A planned follow up study will take this aspect into account.

However, it remains speculative in what way the present findings could be transferred to real traffic situations. In a follow up study we examine in real life how various outer characteristics that indicate automated cars (similar to those used in the photos of the present study) affect road user behaviour [20]. One of the potential problems regarding self-driving vehicles is also that humans become too complacent towards them too soon. Even though our studies could suggest that humans adopt a cautious attitude towards self-driving cars, it is unknown for how long this cautious attitude stays. It is feasible that after a certain amount of exposure, people begin to drop the cautious attitude prematurely, particularly if the experience with the autonomous vehicles is positive. This could have dangerous consequences if the capabilities of self-driving cars turn out to be less than expected. Therefore, we recommend that future studies aim to investigate this topic further, using dynamic stimuli rather than static images; a higher sample size; and with a certain amount of exposure to self-driving vehicles in action, so as to gain trust of the participant.

5. References

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