Research article

Distracting or informative? Examining signage for cyclists using eye-tracking

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Abstract: There is great political motivation to improve conditions for cyclists to help solving the transport needs of the future. We used eye-tracking to collect data and analysed it using a novel machine learning approach. 40 cyclists in total were tasked with navigating a set route through the Oslo city centre. One group before the new infrastructure was in place and one group after. The analysis focused on developing a method that could be used to investigate how a new signage strategy impacted cyclists in Oslo. Improving signage could create safer traffic conditions for cyclists, while avoiding adding distracting elements. The algorithms developed were able to detect and categorize a variety of important objects. The signage system itself seemed to result in some route change among cyclists, but not all followed the suggested route. Qualitative analyses suggests that those who deviated cycled faster and looked less at signs, than those who chose the suggested route. The paper discusses strengths and weaknesses involved in this approach. While useful, one should be careful to conclude that gaze behaviour reflects the true inner consciousness of cyclists.

Keywords: cyclist, eye-tracking, machine learning, signs

1 Introduction

Norwegian authorities seek to enhance cycling conditions to encourage more people to cycle. One of the challenges to increase cycling shares in cities, is making it easy and accessible to find the safest, quickest, and most comfortable routes. One way to help cyclists find such routes are through signage.

Political goals have been set to increase cycling shares in Norway (Espeland & Amundsen 2012). It has been estimated that cyclists are more prone to serious accidents than many other road users, such as cars (Bjørnskau 2020). This highlights the importance of improving cycling environments, particularly in cities where most of the cycling occurs. While setting ambitious goals is important to create progress, research suggests that Norway is not meeting their ambitions in terms of cycling shares (Lunke & Grue 2018). Different conditions also affect cyclists differently, with females suffering more from adverse conditions than men do (Aasvik & Bjørnskau 2021). This could also extend to navigating complex traffic environments, where some groups suffer more from poor signage than others. Nonetheless, it accentuates the need for more systematic knowledge about conditions for cyclists.

The current system for bicycle signage is largely based on signage principles for motorists. Although cyclists share many similarities with car drivers, it is conceivable that they have other needs. Knowledge concerning cyclists' information needs and wayfinding strategies is very limited, and little is known about how well current bicycle signage actually works. Therefore, there is a need for increased knowledge on how bicycle signage best can be adapted to support wayfinding for cyclists and contribute to increased cycling.

In the Netherlands, Denmark and England, road markings have been tested as a supplement to sign posts. Evaluations show that the combination of road markings on the ground and signage is perceived as useful by cyclists, especially as it reduces the need to pick up the phone to reorient along the way (Hoeke *et al.* 2019; Jennings *et al.* 2016; Københavns kommune 2015). These studies, however, say little about how much and what kind of information should be presented. A simulator study by Brown *et al.* (2017) indicates that road markings on the ground are noticed and contribute to fewer wrong turns.

Moreover, they found that simple symbols in combination with bright colours such as orange or green appear to be most effective and conspicuous, while rich textual information reduces readability. So far, the research says little about the traffic safety implications of presenting information both on the ground and on signs at eye level. In general, it is important to limit the number of visual elements that road users must attend to, especially in complex traffic environments. Mixed traffic intersections have been found to draw the visual attention of cyclists, particularly experienced cyclists (Rupi & Krizek 2019). This may be because they are better suited to recognize important infrastructure and focus their attention on it. Cyclists visual focus has also been shown to be situationally dependent, and drawn towards objects with future collision potential (Kovacsova *et al.* 2018). The suitability of road marking may thus vary according to the complexity of the traffic environment, cyclists' experience, and the number of competing visual elements. Research is needed to better understand these differences and whether they help or distract the cyclist.
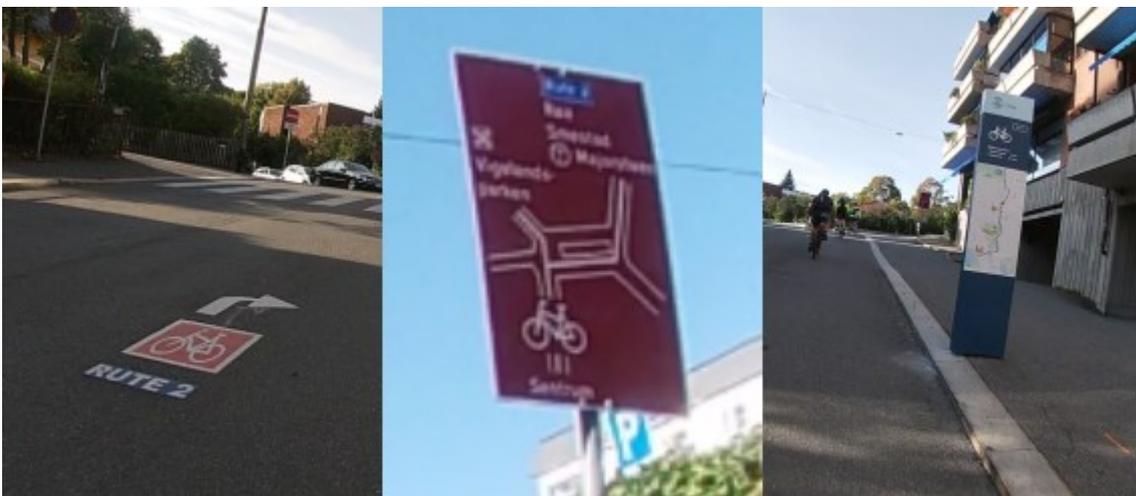

Figure 1 Examples of elements used for the new signage systems: road marking, with arrow and route identity; intersection sign; street pylon

Oslo city council recently implemented six different ways to improve route guidance for cyclists. These six measures are (some examples are shown in Figure 1):

- Road markings with a bike symbol and arrow
- Route identity
- Signage with trip times (rather than distance)
- Intersection route map signs, showing how the route continues through intersections

- Signage leading to the routes
- Street pylons, i.e., detailed information signs showing the full route.

These were previously investigated using road-side interviews and video recordings (Milch *et al.* 2019). Results suggested that while most participants use their smartphones to plan a route, few of them stop during their ride to check up on it. This means that cyclists in Oslo usually plan a route and rely on environmental cues to stay on their planned route. This has important implications for our understanding of how best to help cyclists navigate a dense city landscape.

One aspect of cyclist navigation that has received less attention, is the actual gaze behaviour of cyclists. While most people have a sense of what they need to look at to navigate safely and successfully, little is known about what cyclists choose to look at and for how long. Some research using eye-trackers suggests that optimal gaze behaviour requires an equilibrium of attention location between the central trajectory of the cyclist and lateral part of the environment (Mantuano *et al.* 2017). Another important fixation of cyclists is towards discontinuities of the infrastructure such as crosswalks or intersections. The researchers argue that more demanding infrastructure (i.e. a lack of separation between road users) lead to less fixation on hazardous elements (Mantuano *et al.* 2017). These interactions between infrastructure, situational demands, and cyclists needs to be better understood to promote cycling in the future.

There is also a risk that, in a dense city environment, overly information-heavy signage may become more of a distraction than informational. Situational dependencies of cyclists visual attention have been previously documented (Kovacsova *et al.* 2018). Perhaps even reducing signage to a minimum would be an improvement for cyclist safety, allowing them to spend all their attention resources on navigating traffic safely. Some research suggests that experienced cyclists to a larger extent fixate on complex traffic environments (Rupi & Krizek 2019), while others find that cyclists are no better at recognizing infrastructure hazards than non-cyclists (Brazil *et al.* 2017). The current research aims to add to this knowledge gap by finding novel ways of investigating what cyclists look at in everyday traffic environments. We also examine the level of information they need to navigate successfully, as this may lead to improving conditions for future cyclists.

Measuring gaze behaviour gives a novel insight into how cyclists use their visual attention for navigation. Visual attention can be viewed as a beam of light that shines on some aspects of our senses while ignoring others (Reisberg 2013). How we choose what to focus on can be determined by conscious deliberation (typically top-down) or by salient stimuli in our environment (typically bottom-up). Signage could in some ways fall a bit in-between these categories. They are typically coloured red in Oslo, along with the cycle lanes, and this coloration have been found to impact perceived safety, ease of visualization and visibility (Fyhri *et al.* 2021b). Ease of visualization is particularly linked to how familiar participants are with this infrastructure. In a busy environment, it would be easier to find these signs if the cyclists know what to look for. Such a visual priming would also be advantageous because it eases visual processing of stimuli (Reisberg 2013; Kristjánsson & Campana 2010).

There is a complex and dynamic interaction between bottom-up and top-down visual attention (Connor *et al.* 2004). This could also be linked with the inherent difficulty in measuring cognitive inattention among car drivers (Regan & Strayer 2014). These findings all suggest that simply asking cyclists what they find distracting and sources of visual information they prefer, may not be a straight-forward process. Using more objective data, such as analysing gaze behaviour, may be another way to learn more about how to best design signage for cyclists.

However, gaze behaviour represents a complex entity. There is not necessarily a clear link between gaze fixation and conscious awareness, as cyclists' could notice elements in their peripheral vision or movement without directly looking at it (Reisberg 2013). Wayfinding is an

activity that requires some conscious deliberation, but this deliberation could be affected by sensory information that does not itself reach conscious awareness. One critical approach would be to investigate gaze behaviour and how it changes in demanding or non-demanding environments or while using different signage strategies. Other distractions from critical traffic-oriented gaze behaviour could also be explored.

Eye-tracking (ET) is a way to gather data about how people use their visual attention. This has proven useful in many settings and may yield useful information about signage. This has for instance recently been tested using mixed reality paradigms with success (Cai *et al.* 2018). Research has also used ET to investigate how to design and place signs to capture the right amount of attention (Tang 2020). Their results are positive and shows that ET is a useful way to investigate these research questions. However, there is still uncertainty about how best to analyse and interpret the data. People can react to stimuli of which they are largely unaware, or may fail to perceive stimuli that are in plain sight (Sagberg *et al.* 2016; Zhang *et al.* 2015; Reisberg 2013). A clinical demonstration of this is the condition known as *blindsight* where clinically blind patients are able to act upon visual stimuli (Cowey 2010). This complicates the interpretation of ET data, because we cannot draw conclusions from gaze behaviour to awareness.

2 Research questions

This study's aim was twofold. The first is to investigate new methods to analyse how measures for route guidance affect cyclists in real traffic environments. Second, we examine the effect of the new wayfinding system itself, in terms of ease of use and traffic safety. In the current article we present our approach to gathering and analysing data collected using eye-tracking for cyclists, and a discussion of how these data could be used and interpreted. This approach could yield objective data about cyclists' gaze behaviour and navigational needs. Our research questions were: (*1*) to what extent was the new signage strategy employed by Oslo city council helpful information, i.e. that it affected route choice, or was experienced as positive; and (*2*) to what extent is the strategy a distracting element? More precisely, we wanted to explore whether the increased amount of route information that was provided to the cyclists, was detrimental to their attention to other road users.

3 Methods

3.1 Participants and procedure

Participants were primarily recruited among parents of kids in school band from the other side of Oslo, for both pre- and post-intervention data collections. In addition, to reach our goals of 20 participants in both pre- and post-samples, invitations were sent to 'Young Friends of the Earth Norway'—a national climate organization aimed at youth. They were all incentivized to participate by offering a 500 NOK gift certificate per participant that was given to the school band's fund for instrument purchase. The reasoning behind the sampling strategy was that we wanted to investigate the effect of the new system in a population which had the potential to become 'new cyclists'. Therefore, we aimed to recruit participants with some, but not much cycling experience, and participants with little knowledge about the local route. The invitations to participate included generic information about the experiment and two screening questions (that did not reveal the task or route) were asked to ascertain this. They were told that they would be finding their way to a destination using a bike, but without using their phones or a map while riding, but they could check before starting the route.

The route was estimated to take about 20 minutes to complete. Pre-intervention data was collected in June 2020, and post-intervention data was collected in September 2020. Our recruited

cyclists chose somewhat different routes, but all ended up at the right location. 20 participants completed the test run pre-intervention and 28 completed the test run post-intervention.

Participants met up at a set location in downtown Oslo and were sent in a starting direction that corresponded to an entry-point on a designated bike-route. This ensured that they would rely on signage and that they would immediately encounter the relevant test-route. Those who did not have a bike got a rental bike. Participants were outfitted with the eye-tracking glasses and a GoPro camera (with GPS-tracking) that filmed straight ahead. Before they started their trip, they read and signed an informed consent. Upon reaching the goal location, they were debriefed and answered a short semi-structure interview about what type of information they had noticed, and the extent to which that had found this information useful. For more details on these data, see (Fyhri *et al.* 2021a).

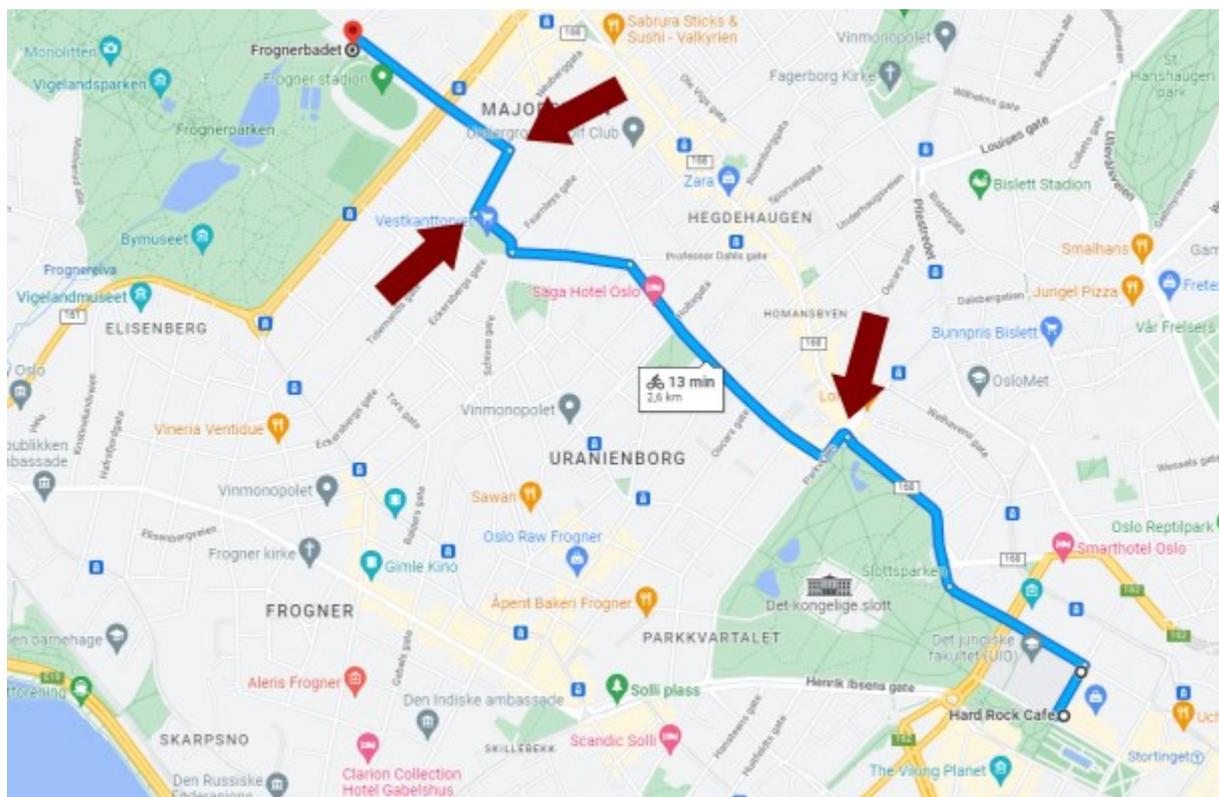Figure 2 shows a map of the suggested route cyclists were asked to ride.

Figure 2 The cycling route through the Oslo city centre: three typical intersections where people would deviate from the route indicated with red arrows (adopted from *GoogleMaps*)

3.2 Analysis

Route choice was analysed by counting number of participants who chose (the whole and segments of) the desired route pre- and post-intervention, based on GPS data from a GoPro camera.

The eye-tracker glasses participants used were Pupil Labs Invisible. These are non-invasive and just require participants to wear glasses that are connected to a smartphone. Two cameras track the eye movements while a third captures what participants are looking at. The software also yields a basic processing of data, showing a red circle in the video highlighting what participants were looking at during their trips. This rudimentary analysis of data was used qualitatively to link the route choice data with a simple analysis of element detection, to link with interview data, but was lacking in detail to do machine learning analyses.

3.2.1   Machine learning algorithm

We further processed the raw data using algorithms developed by Epigram AS. This object detection analysis had the intention to automatically categorize what participants were looking at. If this could be done reliably, we could compare the categorizations for the pre- and post-intervention data collections to look for changes in gaze behaviour.
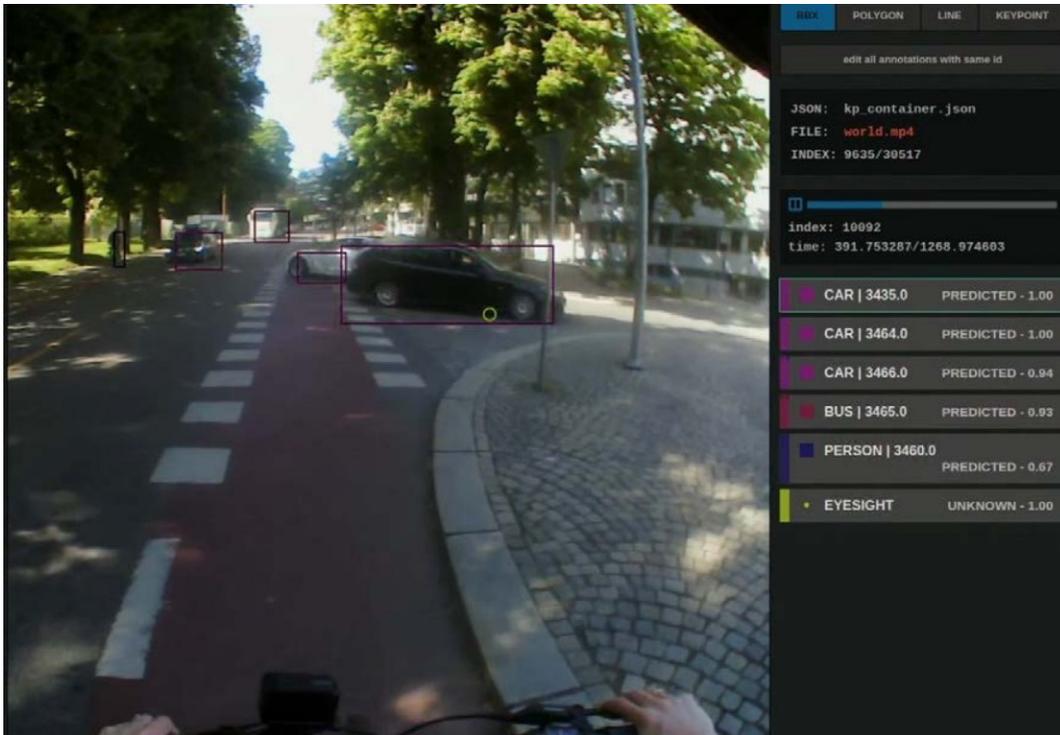

Figure 3 Example of analysis from eye-tracker video: eyesight, categorizations, and actual footage

Figure 3 shows what categorization of road users typically looked like. The neural networks for traffic object identification were pre-trained networks based on FasterRCNN NAS (Zoph *et al.* 2018). The goal was to build models that could detect pedestrians, cyclists, motorists, but also signs in the videos retrieved using Pupil Labs' glasses. The pretrained model was further trained on two sets of categories, one using a BelgiumTS (Timofte *et al.* 2014) for signs and another trained on a COCO object dataset for road users[1] (Lin *et al.* 2014). The model was used to detected objects in single frames. Each sequence of video was post-processed with a tracking-algorithm based on a Kalman filter to be able to follow single objects over a span of time. This was done to let us follow the same unique object even if participants turned their head so that the object disappeared temporarily out of frame.

At the end, the information about gaze behaviour and where participants were looking within the captured video were coordinated with detections and categorizations from the algorithms. Gaze was coordinated with tracked objects. If an object moved within a 30-pixel margin, the object was counted as observed by the participant.

Figure 4 shows one of the graphs produced by this procedure. The x-axis represents time. The first row, 'eye-sight', shows when participants gaze behaviour was tracked accurately. Each object type (persons, bicycle, etc.) is represented by two lines. The first (upper) line indicates the object being present in the video, whereas the second (right underneath) shows whether the object was looked at by the participant. For example, persons (i.e. pedestrians) seem to be

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[1] The subset of COCO with labels amongst: person, bicycle, car, motorcycle, bus, truck, traffic light, stop sign and filtered out images containing a 'representation' of the object, but not a real instance.

important road users for the cyclist to look at, while the cars are rather kept in the peripheral vision. Such figures can be used to analyse changes in gaze behaviour before and after new signage measures for cyclists are employed.
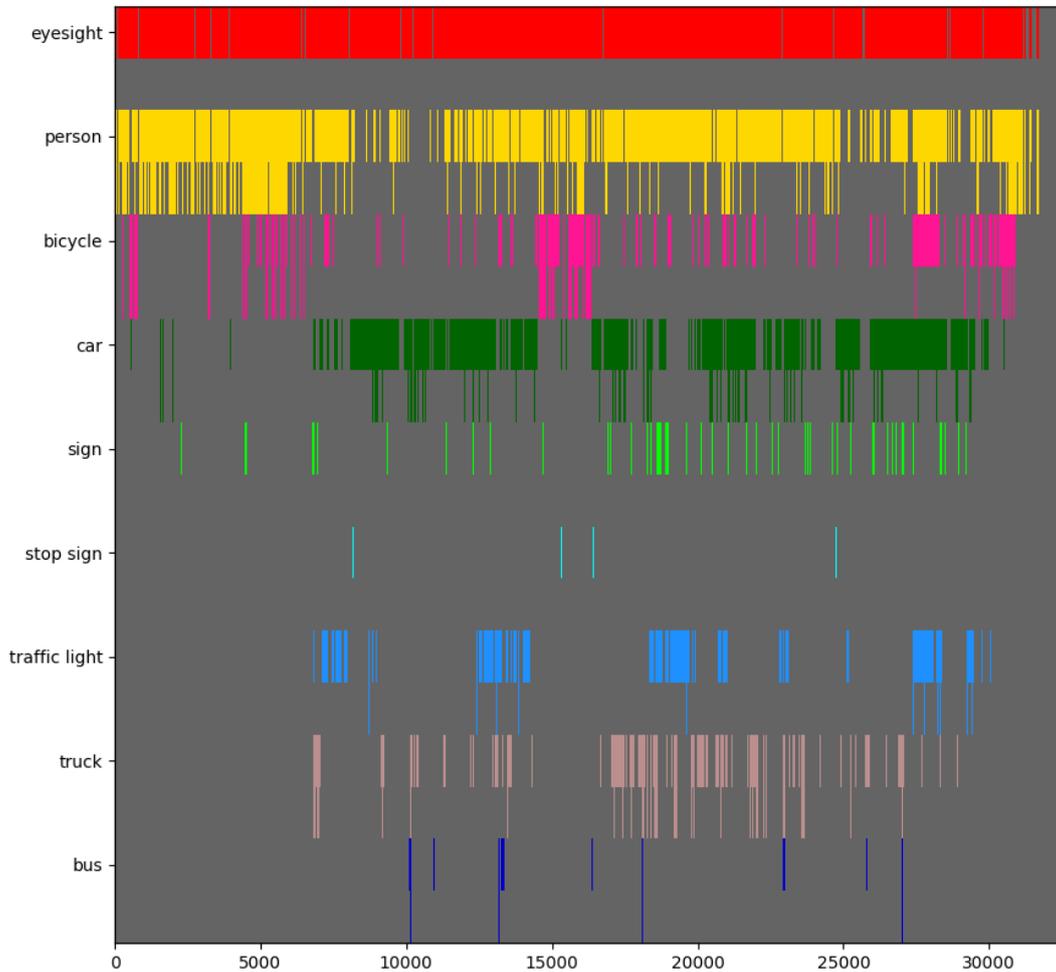

Figure 4 Objects looked at by a participant during a route travel

The algorithm performed poorly when tasked with analysing road markings. In one of the iterations, it categorized a cycle lane marking depicting a bicycle as an actual bicyclist. This problem was given some time and attention but remained difficult to solve in the current framework. This is inherent to the models' pre-training where the pre-training dataset did not differentiate 'representations' of an object with the true object itself. Therefore, we simply did not try to further classify road markings in our analysis and rather focused on the other aspects.

4 Results

4.1 Effects of the new system on route choice and experiences

Figure 5 shows route choice of all participants, pre- and post-intervention. The figure is based on GPS points and illustrates with colour coding (dark red being highest density) which specific elements of the route most cyclists chose to use.

As cyclists could make route choice decisions at several points, and indeed did so, the analysis is not a simple matter of just counting number of correct/incorrect route choices. Rather, we count the number of cyclists making 'right' or 'wrong' (according to the guided route) route decisions at certain critical intersections.
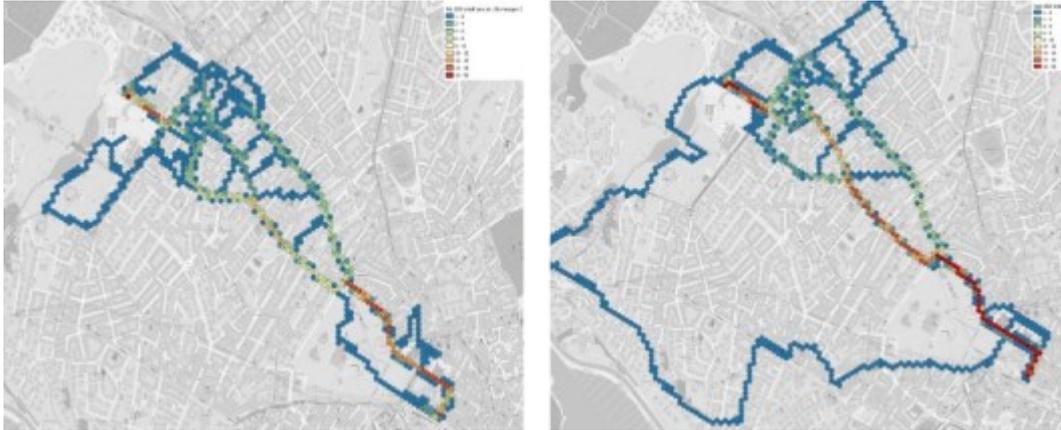
Figure 5 Route choice, pre-intervention (N = 20) and post-intervention (N=28)

We identified three such intersections on the route (also marked on the map in Figure 1). Table 1 shows route choices, pre- and post-intervention, at these three intersections.

Table 1 Share of participants following the intended route, pre- and post-intervention

	Pre-intervention		Post-intervention	
	%	N	%	N
1; Parkveien; Left	61%	18	73%	26
2; Professor Dahls gate; Right	25%	8	47%	17
3; Maries gate; Left	17%	6	40%	10

The number of participants that chose the correct route in its entirety was one in the pre-intervention situation and four in the post-intervention situation. So, even if there was a slight increase, most cyclists did not strictly follow the signed route, even after the intervention. The share who followed the intended route increased with 12% from pre- to post- intervention at the first intersection, 22% at the second intersection and 13% at the last intersection. The largest 'loss' of participants was made at the last intersection, where 60% chose to not follow the signed route, even post-intervention. This intersection was at the bottom of a hill, where the cyclists would have gained quite some speed, and the intersection would in most instances be quite busy, with traffic arriving from all four legs at the same time.

4.2 What did the cyclists notice, and how was that related to route choice?

To explore further how the signage system influenced route choice we investigated the post-intervention data collected from the first section of the route, ending at intersection 1 (Parkveien). Of the 28 cyclists who followed this part of the route, the eye tracker data was usable for 19 participants.

We analysed the data manually by recording which information items they looked at. We defined 'looked at' as:

1. that the gaze rests on the object, and/or
2. that the gaze clearly moved in the direction of the object, e.g. from the roadway to a sign, and then back to the roadway.

Based on the assumption that the choice the cyclists made at the intersection says something about the type of cyclist they are, or how they have absorbed information, it is interesting to compare these two groups of cyclists. Table 2 summarizes the findings from both the qualitative analysis of video/eye tracking data and from the interviews and shows what characterizes left-turning and right-turning cyclists.

Table 2 Characteristics of left and right turning cyclists

	Turned left (correct)	Turned right (wrong)
Time use	03:27	03:07
Noticed road markings (max 5), avg	4,4	4,6
Noticed route signs (max 3), avg	3	1,8
Noticed last road marking	8	2
Overlooked last road marking	2	0
N participants	14	5

Those who turned right cycled faster and looked less at the signs than those who turned left. But there was no difference in how many of the markings on the ground they had seen.

The question then is whether they have seen the marking and not understood it (e.g. not noticing the left arrow on the last one), or whether they have seen it and not thought of it as relevant to them (e.g. not were aware that they must follow route number 2). Of the right turning cyclists, 2 out of 5 noticed the last road marking (with a left turning arrow). It was quite clear from looking at the video data that most of the right turning cyclists had a clear idea of which route they were going to follow, and that they did not let the route information influence this decision. Interestingly, in the debriefing interview, two of them admitted that they had lost a bit track of the route after the first intersection. They had simply followed a known route in the general direction they were heading to, but then at some point they felt they should have made a better choice to avoid a very challenging and busy intersection.

It is also interesting to note that a significant number (6 out of 14) of the left turning cyclists did not appear to notice the last road marking. It is hard to know if these cyclists actually missed this information (but had got it from a road sign earlier on the route) or if they did in fact see it in the peripherical vision. If the peripherical vision is at work here, it means that the cyclists from the exposure to the first four symbols on the route had recorded a visual imprint of the symbol (including the arrow), so that no focal vision was needed to gain the visual information required to make a route decision.

4.3   Distraction analysis

An important aspect to investigate in this project was whether the new signage strategy worked as intended to help cyclists, or whether the information became overwhelming. The analysis presented in this paper could help illuminate this problem by comparing categorizations of gaze behaviour from cyclists before and after the new strategy was implemented. Figure 5 shows that much variation in what paths the participants actually travelled on, therefore we chose a segment of the route and submitted it to analysis. Figure 6 shows the aggregate percentage of time spent observing different road users or signs on this segment, divided by pre- and post-intervention period.

None of the differences between pre- and post-periods were found to be significant at a $\alpha < 0.05$-level. The most important finding is the variability within each category. 'Persons' seem to be the most looked at, with cars and cyclists also being looked at a lot. We found no meaningful difference in time spent looking at signs. Time spent looking at route symbols in the road was not recorded.
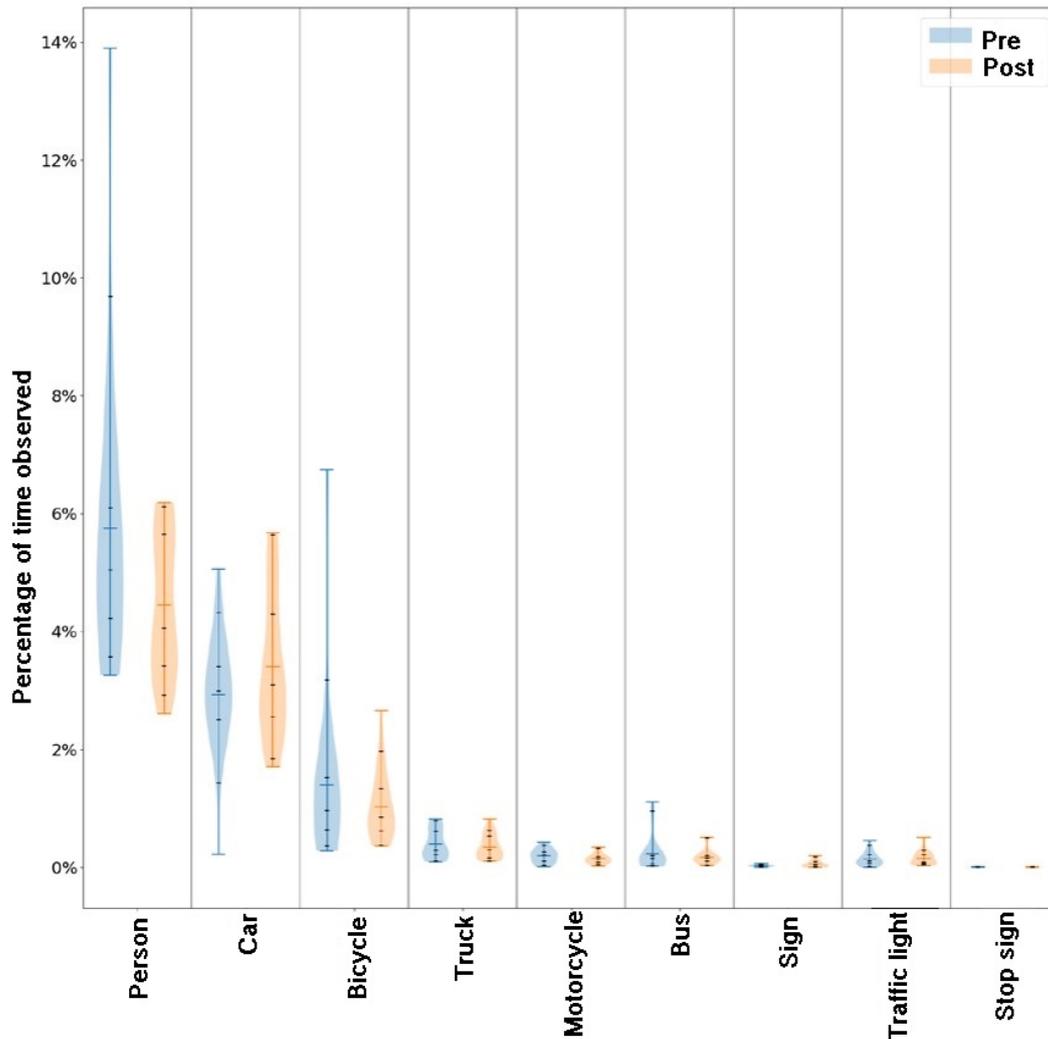
Figure 6 Time spent looking at different road users or signs, aggregated across participants (the median is represented by a longer line within the columns)

5   Discussion

Adding new information elements in already complicated traffic environment involves a potential risk. Our results indicate that the new elements introduced as part of Oslo city's new signage strategy did not lead to less attention to other road users. Improving signage for cyclists could help bring about a future less reliant on private cars for city transport. Having more easy-to-understand signage could also improve traffic safety by moving cyclists' perception away from interpreting which route to choose and towards navigating traffic safely. Our results suggest that novel methods of gathering and analysing data could be useful for improving conditions for cyclists. The machine-learning approach opens a door to analyse large quantities of data in a way that is not feasible with other more qualitative analyses.

The discussion remains as to the validity of ET data. There is reason to believe that what people fix their gaze on is more likely to be consciously perceived, but it is not always the case. Additionally, people may be consciously or unconsciously aware of stimuli outside of their visual fixation. This is an inherent problem with analysis of ET data that is hard to avoid. One could argue that larger amounts of data cold amend this issue, as people vary in their perception. At the very least, this would leave a model explaining what cyclists fix their eyes on while cycling.

Whether or not they actively perceive these stimuli would need other kinds of data collections to assess.

Although one of the main benefits of doing automated data analysis is the ability to process larger amounts of data, the data collection process is still arduous. Recruiting a varied sample of the general public to do a 20-minute bike trip requires good incentivization and researchers waiting at the start and finish. The limited storage and battery capacity of the ET glasses, in addition to changing schedules of participants, means that data collection will take weeks to complete. There was also a concern that we would mainly recruit people who were already quite comfortable cycling in the city centre of Oslo. Future research should seek to improve on these points. Still, a core strength of our automated analysis is that the entire video was analysed quickly, as opposed to analysing still images or manually analysing entire 20-minute videos.

Analysing data using machine learning in this fashion also carries other benefits. A significant benefit is that researchers can get less bias in their analyses. If one algorithm is set to categorize larger sets of data, it will produce results based on the same methods without any subjective leanings, minimizing the need for countermeasures such as inter-rater reliability. Reliable analyses could mean easier interpretation of results, as least within studies using the same algorithm.

Because of the inherent difficulty in assessing the degree to which people get distracted by signage, ET research should be interpreted with caution. For cyclists, it is also difficult to precisely determine what would be an adequate visual fixation and what should be counted as distraction. Previous research has suggested that an equilibrium between central elements in the cyclists' trajectory is a key point of fixation (Mantuano *et al.* 2017), and that demanding infrastructure may retract from this fixation. It is of importance to notice and be aware of extraneous elements such as larger vehicles because these pose risk to your safety as a cyclist. However, they would also need to use some attention on primary navigation, and this attention split will vary based on the traffic environment and experience level of the cyclist (Rupi & Krizek 2019; Kovacsova *et al.* 2018). Future research could seek to develop methods and models for assessing 'correct' and 'incorrect' uses of visual attention for cyclists.

There is also an unresolved issue regarding variability among cyclists. Some are naturally less acquainted with certain traffic situations and may require more attention to safety rather than navigation. Similar issues are discussed for car drivers, where variability among drivers have been found greater than variability among measures tested (Grahn & Taipalus 2021). These concerns would also apply to analysing ET data from cyclists. Automated analyses using machine learning, such as the one conducted in this paper, would be preferable, because it does not imply a correct way of distributing one's attentional resources.

The current paper complemented ET-data with interviews shortly after the completed ride and thus could also offer insight into what cyclists were aware of. Still there were some limitations. The ride lasted for some 20 minutes, and it was not easy for the riders to remember precisely what they had noticed along the route. Research from driving simulators indicate that car riders can forget as much as 50% of clearly noticed other road users, even after just some few seconds (Robbins *et al.* 2019).

To get more precise data about cyclists' conscious deliberation, participants could cycle a short distance covering one particular element of infrastructure, before partaking in an interview. This would focus results on one specific element at a time and allow for more direct interpretation of their answers. This eliminates some conjecture about whether participants fully perceived the elements in question and narrows down the margin of error on the part of the cyclist. The issue still would remain as to what degree people are aware of the determinants of their behaviour, but this could be a step towards deeper insight. Another approach could be to compare different traffic conditions. Here, cyclists could encounter busy or quiet intersections with

differing presence of signage, road markings or other road users. Taking cycling experience and route familiarity into account could also help improve our understanding of variations between participants. Future research could employ complimentary data collections to improve on our methods.

The analysis from the machine learning algorithm suggested that cyclists were not distracted by the new road signs and symbols. The fact that not all participants adhered to the suggestions about what route to follow, supports this finding. This was also quite clear when observing the gaze movements from the cyclists. As the traffic environment became more complex, attention to route guidance information became subordinate, as was exemplified at the last intersection we analysed.

There was a difference in how easy it was to interpret the gaze of the participants, since some participants had more clear and calm gaze movements than others. The lighting conditions also create some challenges, since many of the recordings were made in clear weather. The contrasts then mean that it can be difficult to see objects that are in light or shadow, respectively. Furthermore, it is not possible from the video recording to identify objects that are far away (they do not appear in the image, or the point of view is not precise enough to distinguish which objects the participant is actually looking at, you cannot see whether it is the sign or just the 'horizon'). But in most cases, it was possible to make an interpretation of what was seen.

Our analyses should be considered preliminary. These are data points from quite few cyclists. The primary outcome of this study is the investigation of novel ways of gathering and analysing data to solve problems for the future of transport. ET and machine learning proved useful in categorizing gaze behaviour and fixation, but one should be careful in drawing conclusions about inattention or distraction from this.

6   Conclusions

This paper trialled a novel method of analysing ET-data from cyclists in a dynamic traffic environment. We found that the machine learning algorithms were able to detect and categorize important infrastructure and road users. Supplementary qualitative analyses were conducted for key points of the route cycled by participants. The examined intervention was found to affect cyclist behaviour to some extent, particularly for slower cyclists. The knowledge gained from this work could help guide future infrastructure decisions, especially for signage and guidance. This is also an important step forward for future research, that should continue to explore machine learning as a way of investigating the information needs of cyclists. Researchers could also improve the data models from this paper to include other factors, such as road markings.

CRediT contribution statement

Ole Aasvik: Data curation, Formal analysis, Investigation, Writing—original draft, Writing—review & editing. **Aslak Fyhri:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing—review & editing.

Declaration of competing interests

The authors declare no competing interests.

References

Aasvik, O., T. Bjørnskau (2021), 'Cyclists' Perception of Maintenance and Operation of Cycling Infrastructure—Results From a Norwegian Survey', *Frontiers in Psychology*, 12, 696317, https://doi.org/10.3389/fpsyg.2021.696317.

Bjørnskau, T. (2020), 'Risiko i veitrafikken 2017/18' [Road traffic risk in Norway 2017/18] (Oslo, Norway: Institute of Transport Economics), TØI rapport 1782/2020, https://www.toi.no/getfile.php?mmfileid=54458, accessed 4 September 2022.

Brazil, W., A. O'Dowd, B. Caulfield (2017), 'Using eye-tracking technology and Google street view to understand cyclists' perceptions', presented at *IEEE 20th International Conference on Intelligent Transportation Systems* (Yokohama, Japan: 16–19 October 2017), https://doi.org/10.1109/ITSC.2017.8317619.

Brown, H., C. Sun, Z. Qing (2017), 'Investigation of Alternative Bicycle Pavement Markings with the Use of a Bicycle Simulator', *Transportation Research Record: Journal of the Transportation Research Board*, 2662, 143–151, https://doi.org/10.3141/2662-16.

Cai, L., R. Yang, Z. Tao (2018), 'A new method of evaluating signage system using mixed reality and eye tracking', presented at *4th ACM SIGSPATIAL International Workshop on Safety and Resilience* (Seattle WA, USA: 6 November 2018), https://doi.org/10.1145/3284103.3284105.

Connor, C. E., H. E. Egeth, S. Yantis (2004), 'Visual attention: bottom-up versus top-down', *Current Biology*, 14 (19), R850–R852, https://doi.org/10.1016/j.cub.2004.09.041.

Cowey, A. (2010), 'The blindsight saga', *Experimental Brain Research*, 200, 3–24, https://doi.org/10.1007/s00221-009-1914-2.

Espeland, M., K. S. Amundsen (2012), 'Nasjonal sykkelstrategi 2014-2023' [National cycling strategy 2014-2032] (Oslo: Vegdirektoratet), No. 7, https://www.vegvesen.no/globalassets/fag/fokusomrader/miljovennlig-transport/sykkeltrafikk/sykkelstrategi.pdf, accessed 24 September 2022.

Fyhri, A., O. Johansson, I. S. Hesjevoll (2021a), 'Ny sykkelveivisning i Oslo: Før- og etterundersøkelse av forsøksstrekningen "Rute 2"' [A new approach to route guidance for cyclists - a field study with eye trackers and GPS tracking] (Oslo, Norway: Institute of Transport Economics), https://www.toi.no/getfile.php?mmfileid=55299, accessed 24 September 2022.

Fyhri, A., K. Karlsen, H. B. Sundfør (2021b), 'Paint it red-a multimethod study of the nudging effect of coloured cycle lanes', *Frontiers in Psychology*, 12, 662679, https://doi.org/10.3389/fpsyg.2021.662679.

Grahn, H., T. Taipalus (2021), 'Refining distraction potential testing guidelines by considering differences in glancing behavior', *Transportation Research Part F: Traffic Psychology and Behaviour*, 79, 23–34, https://doi.org/10.1016/j.trf.2021.03.009.

Hoeke, L., J. de Kruijf, J. Soemers (2019), 'Wayfinding op snelfietsroutes' [Wayfinding on fast bicycle routes] (Breda, the Netherlands: Breda University of Applied Sciences), https://pure.buas.nl/ws/portalfiles/portal/1000608/Hoeke_Kruijf_Soemers_Rapportage_onderzoek_wayfinding_snelfietsroutes.pdf, accessed 24 September 2022.

Jennings, K., H. Milton, A. Munyama (2016), 'Quietways Wayfinding User Testing: Debrief to London Grid Board' (London, UK: 2CV & Transport of London), https://content.tfl.gov.uk/quietways-research.pdf, accessed 24 September 2022.

Kovacsova, N., C. Cabrall, S. Antonisse, *et al.* (2018), 'Cyclists' eye movements and crossing judgments at uncontrolled intersections: An eye-tracking study using animated video clips', *Accident Analysis & Prevention*, 120, 270–280, https://doi.org/10.1016/j.aap.2018.08.024.

Kristjánsson, Á., G. Campana (2010), 'Where perception meets memory: A review of repetition priming in visual search tasks', *Attention, Perception, & Psychophysics*, 72 (1), 5–18, https://doi.org/10.3758/APP.72.1.5.

Københavns kommune (2015), 'Evaluering af Albertslundruten under projekt "Afmærkning og identitet på Supercykelstierne"' [Evaluation of the Albertslund route under the project "Marking and identity on the Supercycle trails"] (Copenhagen, Denmark: Teknik- og Miljøforvaltningen).

Lin, T.-Y., M. Maire, S. Belongie, *et al.* (2014), 'Microsoft COCO: Common Objects in Context', presented at *European Conference on Computer Vision* (Zurich, Switzerland: 5–12 September 2014), https://doi.org/10.1007/978-3-319-10602-1_48.

Lunke, E. B., B. Grue (2018), 'Sykling og sykkelmål' [Cycling and cycling goals] (Oslo, Norway: Institute of Transport Economics), TØI-rapport 1676/2018, https://www.toi.no/getfile.php/1349561-1547206572, accessed 24 September 2022.

Mantuano, A., S. Bernardi, F. Rupi (2017), 'Cyclist gaze behavior in urban space: An eye-tracking experiment on the bicycle network of Bologna', *Case Studies on Transport Policy*, 5 (2), 408–416, https://doi.org/10.1016/j.cstp.2016.06.001.

Milch, V., A. Fyhri, T. de Jong, F. Sagberg (2019), 'Hvordan vise veien? Grunnlag for nytt veivisningskonsept for syklende i Oslo og Akershus' [Showing the way: Baseline report for a new bicycle wayfinding concept in Oslo and Viken] (Oslo, Norway: Institute of Transport Economics), TØI rapport 1726/2019, https://www.toi.no/getfile.php?mmfileid=52352, accessed 24 September 2022.

Regan, M. A., D. L. Strayer (2014), 'Towards an Understanding of Driver Inattention: Taxonomy and Theory', *Annals of Advances in Automotive Medicine*, 58, 5–13, https://pubmed.ncbi.nlm.nih.gov/24776222/.

Reisberg, D. (2013), *Cognition: Exploring the Science of the Mind* (New York, USA: W. W. Norton & Company) 5th International Student Edition.

Robbins, C. J., H. A. Allen, K. A. Miller, P. Chapman (2019), 'The "Saw but Forgot" error: A role for short-term memory failures in understanding junction crashes?', *PloS One*, 14 (9), e0222905, https://doi.org/10.1371/journal.pone.0222905.

Rupi, F., K. J. Krizek (2019), 'Visual Eye Gaze While Cycling: Analyzing Eye Tracking at Signalized Intersections in Urban Conditions', *Sustainability*, 11 (21), 6089, https://doi.org/10.3390/su11216089.

Sagberg, F., A. Høye, H. B. Sundfør (2016), '"Jeg så ham ikke": Temaanalyse av uoppmerksomhet ved dødsulykker i trafikken' ["I didn't see him": Inattention as a factor in fatal road crashe] (Oslo, Norway: Institute of Transport Economics), TØI rapport 1535/2016, https://www.toi.no/getfile.php/1344924-1494240499.

Tang, M. (2020), 'Analysis of signage using eye-tracking technology', *Interdisciplinary Journal of Signage and Wayfinding*, 4 (1), 61–72, https://doi.org/10.15763/issn.2470-9670.2020.v4.i1.a56.

Timofte, R., K. Zimmermann, L. Van Gool (2014), 'Multi-view traffic sign detection, recognition, and 3D localisation', *Machine vision and applications*, 25 (3), 633–647, https://doi.org/10.1007/s00138-011-0391-3.

Zhang, Y., C. Fu, S. Cheng (2015), 'Exploring Driver Injury Severity at Intersection: An Ordered Probit Analysis', *Advances in Mechanical Engineering*, 7 (2), 567124, https://doi.org/10.1155/2014/567124.

Zoph, B., V. Vasudevan, J. Shlens, Q. V. Le (2018), 'Learning Transferable Architectures for Scalable Image Recognition', presented at *IEEE/CVF Conference on Computer Vision and Pattern Recognition* (Salt Lake City, UT, USA: 18–23 June 2018), https://doi.org/10.1109/CVPR.2018.00907.

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