Eco-driving Feedback Gauge as visual Distractor: A Simulator Study

Bachelor Thesis by

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Abstract

The ongoing development of electric vehicles brings with it new questions for human-machine-interaction research. Feedback devices in electric- and hybrid vehicles help drivers to understand the impact of their behaviour on the vehicle's energy consumption, but are they a potential source of distraction? This study investigates that question by taking eye-tracking measurements of 20 university students with driver's licenses in a virtual reality driving simulator. All participants drove a simulated electric vehicle in two conditions for 15 minutes each, once without and once with the feedback gauge on the dashboard. After the exclusion of ten participants due to motion sickness and errors in eye-tracking recording, the data was processed so that gazes and fixations to the dashboard were isolated. The dependent variables were the following: Time spent gazing at dashboard (in milliseconds and percentage of total gazes), number of gazes to dashboard, time spent fixating on dashboard (in ms and %), number of fixations on dashboard, and average fixation duration. A Wilcoxon paired samples test showed that the presence of a feedback gauge on the dashboard did not lead to significant differences for any of the variables. Therefore, the feedback gauge does not appear to be a distraction. Future research can build on both the findings and the methodology of this study to further investigate the visual aspects of electric vehicle driving.

Keywords: Electric Car, Eye Tracking, Driving Simulator, Distracted Driving

Eco-Driving Feedback Gauge as visual Distractor: A Simulator Study

Because of environmental concerns, the interest in electric vehicles (EVs) has had a resurgence. Compared to internal combustion engine cars (ICEC), EVs come with their own set of technological and human-machine-interaction challenges. Prominently, users experience range anxiety, which means that they are afraid that the EV's range will not satisfy their range needs. To enhance driver's efficacy, eco-driving feedback systems were added to the vehicle's dashboards. These devices keep track of how energy efficient the user is driving, incentivizing behaviour like smooth acceleration and driving at a constant speed. However, each additional feedback system is a potential source of distraction. Driver distraction has, because of its role in road safety, long been the subject of research. Especially visual distractions have been made out to be of import. This study is the first step of a project with the aim to examine the visual distraction caused by an EV's eco-driving feedback system. It is a simulator study, using eye-tracking to investigate drivers' gaze and fixation behaviour depending on the presence of said feedback system.

Background

Electric Cars

Even though electric vehicles (EVs) have been a part of the automobile industry since its first steps, the success of the combustion engine made them somewhat of a niche product from 1910-1990. More recently however, the pressure to reduce emissions and energy consumption put on humanity by global warming re-kindled the interest in and political support for electric cars. Exact numbers vary between studies, but electric cars produce 44 to 56 % (Well-to-Wheel) or 31 to 46 % (entire life cycle) less CO_2 than combustion engine vehicles, due to the higher energy efficiency of electric motors and the option to use renewable energy to charge the batteries (Moro & Helmers, 2017). But new technology always seems to come with new problems.

Range Anxiety

The perception of limited EV mobility resources is a barrier to purchasing intentions (e.g. Nilsson, 2011). Moreover, even active EV users face range-related trouble, more than in internal combustion engine vehicles (ICEVs): Technically, modern EV's battery capacities provide sufficient range for typical consumer needs, but drivers tend to underutilize available range

(Botsford & Szczepanek, 2009). This is because of *range anxiety*, which is defined as the "continual concern and fear of becoming stranded with a discharged battery in a limited range vehicle." (Tate et al., 2008, p. 3).

In order to find solutions for this, i.e. to enable users to utilize the full extent of an EV's range, a more detailed understanding of range experience and range anxiety is needed. Franke et al. (2012) suggested a four-level model of how the actual range an EV has relates to how far users end up feeling comfortable to go. The first level is cycle range, which is the baseline, so the actual capacity of the EV. Second is competent range, which is the range a user could achieve given their skills. In EVs, energy consumption is influenced by use characteristics with differing and possibly more complex dynamics than those in ICEVs, i.e. the driver has a bigger impact (Romm & Frank, 2006). But drivers seldomly only care for maximum energy efficiency, but rather have other motivations as well (for example getting from A to B quicker rather than slower), so there is a third level which is performant range. It is the range users can achieve by their eco-driving-related motivational strengths and habits. Lastly, comfortable range is the range drivers actually end up utilizing. It is defined as the highest trip distance between two charging points (or lowest remaining range status) that users are comfortable with. Franke et al. (2012) investigated factors that influence comfortable range, looking for ways to bring it closer to cycle range. They found factors at play similar to how individuals react to stress. There are mitigating personality traits, coping strategies and other individual differences that increase comfortable range. However, from a human factors' perspective (change the machine because one cannot change the user), one must look for things that point to human-machine-interface (HMI) design suggestions. Franke et al. (2012) give the following suggestions: "Supportive design of human–machine interfaces can reduce ambiguity and increase internal situational control beliefs [...] Adaptive assistance and information systems (in terms of remaining range situation and personal variables) could increase the impact of such designs even further." (Franke et al., 2012, p. 386) This means that to enable users to utilize the range of their EV more efficiently, the HMI needs to be designed in a way that supports the driver. The effect of the driver's behaviour on energy consumption, and thus the vehicle's range, should be made clear to the driver.

Feedback Systems

A system that provides drivers with this feedback on their own influence on the vehicle's energy consumption is installed in many modern EVs. They will be from here on referred to as eco-driving feedback systems. Eco-driving feedback systems take the form of feedback gauges located on the dashboard that indicate how energy efficient the driver is driving at any given moment. The system takes the vehicle's telemetry and calculates energy use efficiency. Between manufacturers and car models, there are different designs and options available (see Figure 1 for a schematic example). They have in common that they incentivise eco-driving, for example by wording ("low efficiency" to "high efficiency") or colour coding (green to red).

Figure 1

Exemplary Dashboard with (left to right) Speedometer, Battery Charge Indicator and Efficiency Gauge

In conclusion, underutilization of EV range is due to more than only range anxiety. Interface design can support drivers to increase range utilization. However, adding more systems to a vehicle's dashboard means more things the driver needs to keep track of. This could potentially be detrimental to driving performance. There is a risk that an eco-driving feedback system is distracting to drivers.

Distracted driving

Researching distracted driving has been of interest to the scientific community for a while, since it is directly related to road safety: approximately 10.4% of crashes between 2000 and 2003 in the CDS (US-based Crashworthiness Data System) are caused by a distracted driver (Ranney, 2008). However, these investigations do not include eco-driving feedback systems as possible distraction sources. To see how such a feedback system could distract drivers, understanding driver distraction in general is necessary. Due to the complexity of the subject, different authors and institutions have offered different definitions and there is no single unified understanding or model of what precisely constitutes driver distraction (Kircher & Ahlstrom, 2017; Ranney, 2008). Different works of research have different focuses and come to different conclusions as to when a driver can be considered distracted (some studies for example differentiate between distracted and inattentive drivers (Kircher & Ahlstrom, 2017)) and what constitutes a source of distraction (e.g. only things inside the vehicle vs. also external stimuli (Ranney, 2008)). Even without a definitive model, a lot of research has been conducted on causes and effects of distracted driving. But, since eco-driving feedback systems are a relatively new development, there is little existing research on these systems specifically. Therefore, findings on other in-vehicle distractions have to serve as basis for expectations on how an eco-driving feedback system could interact with the driving task. Young et al. (2007), and Ranney (2008) reviewed existing driver distraction literature. There is a focus on mobile phones as distractors in the literature, which is reflected in the reviews, but there are some general findings to report as well. Although there is no clear definition of driver distraction, the phenomenon and aspects thereof are described in the literature. First, different tasks and objects can be the cause of distraction, such as eating, talking to passengers, or changing radio stations. According to Young et al. (2007), any activity competing for the driver's attention is potentially degrading to the driving performance, with accordingly severe consequences for road safety. But, because driving becomes partially automated with growing driver experience, drivers are able to split their attention between the driving task and a secondary task without any detriment to driving performance. If, however, a driver's engagement in a secondary task leads to them not being able to allocate sufficient attentional resources to the driving task, they are considered distracted and driving performance suffers. It follows that there must be factors that determine how much of a distraction a given secondary task causes. Some depend on driver- and situational characteristics, but there is one task-inherent factor that has been repeatedly found to influence the degree and amount of caused distraction: task complexity. Included in the review by Young et al. (2007) were several studies that investigated distraction by phone calls and found that distraction increased with conversation complexity (e.g. chatting about the weather would be less distracting than solving math problems over the phone). The external validity of these studies is debated, because what was used as experimental stand-in for phone conversations is argued to be too different from a naturalistic conversation. The underlying principle that increasing task complexity leads to more distraction is however supported by other studies. Young et al. (2007) reported on several studies which found that more complex navigation systems, where the driver has to look at and interpret a (digital) map, cause more distraction compared to systems that provide simple turn-by-turn instructions. It follows that the complexity of the task that it gives to the driver influences the distraction that might be caused by an eco-feedback gauge. The review by Ranney (2008), which supports the same conclusion regarding task complexity, gives a simple classification system of task complexity in three levels, taken from the 100-Car Naturalistic Driving Study (Klauer et al., 2006). They classified secondary tasks in three levels of complexity, based on the number of button presses and/or glances away from the road needed to complete the task: Complex (more than two presses/glances), moderate (at most two presses/glances) and simple (at most one press/glance). They found that drivers engaged in complex secondary tasks had a 3.1 times higher risk of involvement in crashes and near-crashes compared to drivers engaged in no secondary task. The associated risk increase for moderate tasks was 2.1, and for simple secondary tasks, no appreciable increase in risk was found. Hence, if assessing the state of an eco-feedback gauge can be done in one glance, the real-world risk of crashing can be assumed not to be significantly increased by that task. But, while a significant part, crashes and near-crashes are not all there is to distraction, so the effect of an eco-feedback gauge must be examined closer. As Ranney (2008) stated, experiments into driver distraction by secondary tasks are not accurate predictors of real-world effects, but an experiment can determine the *potential* distraction caused by a given task or system. To conclude, a driver's attention can safely be partially re-directed towards a secondary task, but if too much attention is needed for that secondary task due to the task's complexity, the driver becomes distracted.

Measuring (visual) Distraction in Drivers

Driving has long been characterized as a mainly visual task (Kramer & Rohr, 1982) because most of the information in driving is taken in visually (Sivak, 1996). However, Hughes and Cole (1986) suggest that up to 50% of visual attention might be spare, i.e. not needed for driving related tasks. Green and Shah (2004) pointed out that for safety reasons, non-driving related tasks should have lower attention priority. This means that in a routine driving scenario, approximately 40% of visual attention could be allocated to non-driving tasks. In their work, these tasks encompassed dialling phone numbers, typing addresses into the satnav, changing radio stations etc.

For measuring visual distraction, eye-tracking is the standard in the field (Papantoniou et al., 2017). Three types of eye movements are described that can be recorded to measure distraction. These are fixations, saccades, and smooth pursuits. Fixations, as the name implies, occur when a person is resting their gaze on the same object and the eyes are almost motionless. The positions of these fixations indicate the allocation of attention to a stimulus, while the duration correlates with the amount of perceived information from the fixated source (Hayhoe, 2004). Saccades are the movements used for quickly switching between points of fixation. Smooth pursuits are of special interest to the driving context, according to the authors: They serve to stabilize an object on the retina so that visual information can be perceived while the object is moving relative to the observer. In the context of driving, smooth pursuits have a particularly important function; they capture information from the dynamic driving scene when the observer tracks a moving object, such as a passing vehicle (Papantoniou et al., 2017). The combination of measured fixations and smooth pursuit movements indicate how a distraction interferes with how drivers acquire visual information (Liang et al., 2007). Several studies have demonstrated the usefulness of eye-tracking data for measuring distraction. For example, Zhang et al. (2006) showed the link between several glance measures and driving performance. They predicted that for every 25% increase in total glance duration, reaction time increases by .39s and deviation of lane position increases by .06m (Zhang et al., 2006). Liang and Lee (2008) have successfully used the combination of eye tracking and driving performance data to train different neural networks to detect driver distraction, further showing that these measures are important predictors of distraction.

Birrell and Fowkes (2014) used eye-tracking to investigate the allocation of gazes in a real-world driving scenario. In their experimental condition, drivers received eco- and safety related car telemetry feedback through a smartphone application. They performed this study in a camera-rigged, manual gearbox combustion engine car, driving a predetermined route through the UK countryside, motorway, and urban areas. For eye-tracking, they recorded raw video footage of their participants and hand-coded glances to predefined areas. Said areas were the following:

- IVIS – the eco- and safety driving feedback system.
- Mirrors – left- and right-wing mirrors, rear-view mirror.
- Driving equipment – or vehicle controls (instrument panel, gear stick, handbrake etc.)
- Road: centre – centre of the roadway, which may not always be straight ahead when cornering or when ‘tracking’ an object from centre to off-centre.
- Road: off-centre – looking out of the windscreen (but not centrally) or side windows (but not mirrors).
- Other – glances to the experimenter, non-driving related in-vehicle equipment (e.g. HVAC controls) or any other unspecified glances (daydreaming or where a glance cannot be determined).

They found that drivers spent an average of 4.3% of their time looking at the feedback system, at an average of 0.43 s per glance, with no glances of greater than 2 s, accounting for 11.3% of the total glances made. Moreover, they found that, compared to the control group, those glances were redirected from spare, off-centre glances. This means that drivers did not spend less time looking at things critical to the driving task, i.e. the centre of the road, mirrors, speedometer etc. In summary, eye-tracking can be used to measure visual distraction as well as the allocation of visual attention in drivers.

Driving Simulators

For the present study, rigging a real car with cameras and a feedback system is beyond the scope. Therefore, a driving simulator has to be used. Generalization of results from driving simulators must be well adjusted based on the simulators fidelity and realism (Papantoniou et al., 2017). So, one must only generalize, where a given behaviour yields the same result, both in the simulator and the real world. Which aspects of driving those are, depends on the simulator. For example, lateral control measures are affected by the handling characteristics of the driving simulator, which can be vastly different from real cars that participants are used to. A slight delay between user input and system reaction can lead to slight swerving behaviour, as the driver tries to keep the car straight. The perception of speed varies from the real-world counterpart. Without proprioceptive, acoustic, and haptic feedback, participants are not being able to gauge how fast they are going without looking at the speedometer. On a more conceptual level, previous studies have shown that findings from lab experiments about driver distraction by in-car systems can only serve to assess the potential distraction, not predict the real-world impact of these systems (Ranney, 2008).

This Study

The present study is the first step, the pilot, of a larger project which seeks to answer this question: Is an in-vehicle feedback system for eco driving a road safety compromising visual distraction? The overall plan to answer this question consists of a few steps. First, to adapt the approach of Birrell and Fowkes (2014) by determining where drivers are looking at, for how long and how often. Based on previous findings, we expect that drivers reallocate spare gazes to look at the feedback system and do not look significantly less to areas critical for driving (Birrell & Fowkes, 2014). The next step would be to see if the eye tracking data correlates with other distraction measures, for example car control measures. Linking the visual distraction measures with car control measures will also be an indication of the actual effect of visual distraction. Because "if there is no effect of distraction on control, there is no distraction" (Sheridan, 2004, p. 1). Thereby we can answer the final part of the question concerning road safety: does the presence of an eco-driving feedback device lead drivers to exhibit an impeded control of the vehicle. The very first step, however, is to check if drivers even look to the dashboard more if there is an additional feedback gauge present. That is the role of this study. Because if there is no evidence of additional visual attention being directed towards the dashboard, one could hardly speak of a source of distraction there. The present study also serves to pilot the methodology of using a virtual reality (VR) driving simulator with eye-tracking capabilities. For the present study, a within-subject experiment is conducted. Based on what the utilized software supports, fixation- and gaze measurements are taken. These are two kinds of eye-tracking measures, where a gaze means an individually recorded glance and a fixation is a cluster of gazes close to one another in time and space. The experiment includes two conditions, one with and one without an eco-driving feedback gauge on the dashboard. Based on the findings of Birrell et al. (2014), we expect an increase in the number glances to the dashboard because of the gauge. They also found that average fixation duration did not change significantly, so we expect to find the same.

Method

Participants

This study comprised a convenience sample of 20 Dutch and German students from the University of Twente, recruited through the internal online recruitment system SONA. The study was listed on the system's webpage. Requirements were to be 18 years of age or older and to be in possession of a driver's license. The study was approved by the university's ethics committee and participation was voluntary. All participants gave informed consent prior to taking part. The data of four participants had to be excluded, because they had to stop the experiment early due to motion sickness. The data of two participants was excluded, because there was no eye-tracking recorded. Four more participants' data was excluded during the process of data analysis due to compromised eye-tracking data, where for example the eye-tracking stopped recording a few minutes into the experiment, or only one of the two conditions was properly recorded. Participants before exclusion were aged between 19 and 25 years (M = 21.5 years, SD = 3,2 years), 10 were female, 10 male. Ownership of a driver's license ranged from half a year to eight years (M = 4 years, SD = 2,3 years). Five reported owning a car. Two reported driving (almost) every day, five reported driving multiple times a week, three reported driving once a week and 10 reported driving less than once a week. Most (n = 17) had never driven an electric vehicle but some reported having been passengers (n = 10). Seven had no prior experience with VR, the rest had only little.

Materials

Software

The driving simulator program was programmed in Unity (version 2019.2.21f1). It is an ongoing project being run by students. It utilizes pre-existing plugins like Fantastic City Generator, iTS (intelligent traffic system), Logitech SDK for handling user input and Vehicle Physics by NWH. The version of the software that the present study ran on could only simulate combustion engine cars, so the engine sound was turned off to mimic an electric car.
The driving environment was a closed city road system with clear weather and medium traffic. Traffic in this case entailed other cars (passenger cars, busses, trucks), but no pedestrians, bikes etc. Operational traffic lights govern the behaviour of the traffic.

Hardware

Participants interfaced with the simulation through a Varjo VR headset and a Logitech G920 force feedback steering wheel with pedals (see Figure 2). An automatic gearbox was used to further simulate an electric vehicle's behaviour, accordingly only the brake- and accelerator pedal were used.

Figure 2

Driving Simulator Setup with Participant wearing the VR Headset

Car interior

The use of VR allowed for the participant to sit in a fully rendered 3D model of a generic (i.e. brand-less) sedan car. All functional elements (Radio etc) were represented by images. Only the dashboard was fully animated. It consisted of, from left to right, an eco-driving feedback gauge (only displayed in experimental condition, this spot was left empty in the control condition), a battery charge indicator, and a speedometer (0-260 km/h) (see Figure 3). The circular feedback gauge ranges from green, for high energetic efficiency to red, for low efficiency with an analogue needle indicating the current state. It works in a simplified way compared to its real counterpart: An algorithm tracks the engine's revolutions per minute. If the deviation between the current and the previous value exceeds a critical number, the gauge moves towards "low efficiency". Thereby, the system gives constant feedback, incentivising smooth acceleration and braking, as well as driving at more constant speeds, all of which contribute to more energy efficient driving.

Figure 3

Participant's View of the simulated Dashboard and Windscreen

Route

There were two routes predetermined, one for each condition. They were the same for each participant. To make participants follow the route, instructions were given to the participant verbally, since voice instructions are considered to be less distracting than a visual display (Young et al., 2007). The instructions were not standardized, but kept short and concise (e.g. “turn right at the next intersection, please”, “please go left at the traffic light”). Participants were instructed to drive straight unless told otherwise. If the route was left due to an error on either the experimenter’s or the participant’s part, the shortest way to get back on track was determined by the experimenter and the corresponding instructions were relayed.

Data Collection

Eye-tracking was recorded with the software iMotions 8. Cameras in the Varjo VR headset tracked the eye’s position and the software calculated where the participant was looking and stored the X and Y coordinates at 60 Hertz. iMotions afterwards superimposed the calculated gaze points onto a recording of what the headset displayed. If a cluster of gaze points was very close in time and space, iMotions recognized it as a fixation.

Design

We employed a 2x1 within-subject design. In the experimental condition, participants drove with the efficiency feedback gauge; in the control condition, they drove without it. Participants all first went through the control, then the experimental condition. To mitigate learning effects, there was a separate route to be driven for each condition. The independent variable was the presence of the feedback gauge. The dependent variables were the time spent gazing at dashboard (in milliseconds and percentage of total gazes), number of gazes to dashboard, time spent fixating on dashboard (in ms and %), number of fixations on dashboard, and average fixation duration.

Procedure

The experiment took place in the BMS lab of the University of Twente and took between 60 and 90 minutes per participant. Participants signed up through the SONA system. Upon arrival on site, they were greeted by the researcher and got the procedure explained to them. They were also informed that some people experience motion sickness in VR and that they, should it happen to them, could interrupt or end the experiment at any given time without repercussions. After that and having been given the opportunity to ask questions, participants signed the informed consent form. They were then instructed on how to adjust their sitting position, as well as how to put on and adjust the VR headset. Then the simulation was started and the virtual camera position in the car was adjusted to match the participant's real sitting position. Once set up, participants were given five minutes (time stopped by researcher) to drive around without any measures being taken nor a dictated route. This was so they could familiarize themselves with the behaviour of the car and adjusting to VR. They were instructed to drive like they would in the real world, i.e. to follow traffic laws. During and after the training drive, eventual questions were answered. Next up, the eye-tracker needed to be calibrated. This short process entailed following a dot that moves around the VR screen with one's gaze. Then, participants drove for 15 minutes in the control condition. The route was a predetermined path (specific to the condition) through the digital city. The instructions for where to drive were given verbally by the experimenter. Participants were reminded to adhere to the traffic rules. After the control condition, there was a five-minute break in which participants could take off the VR headset. The break duration was adapted to allow for eventual signs of motion sickness to fade. After the break, the eye-tracker was re-calibrated for the second round. That second round was the experimental condition, another 15-minute drive of the second predetermined route. This time, the eco-feedback gauge was present. In addition to again being reminded to adhere to traffic laws, the gauge was pointed out to them and briefly explained in function. After the driving tasks were completed, participants were thanked for their participation and given room to make any final remarks and/or ask questions. They were also offered the option to share their email address in case they wanted to be informed about the results of the study.

Measures

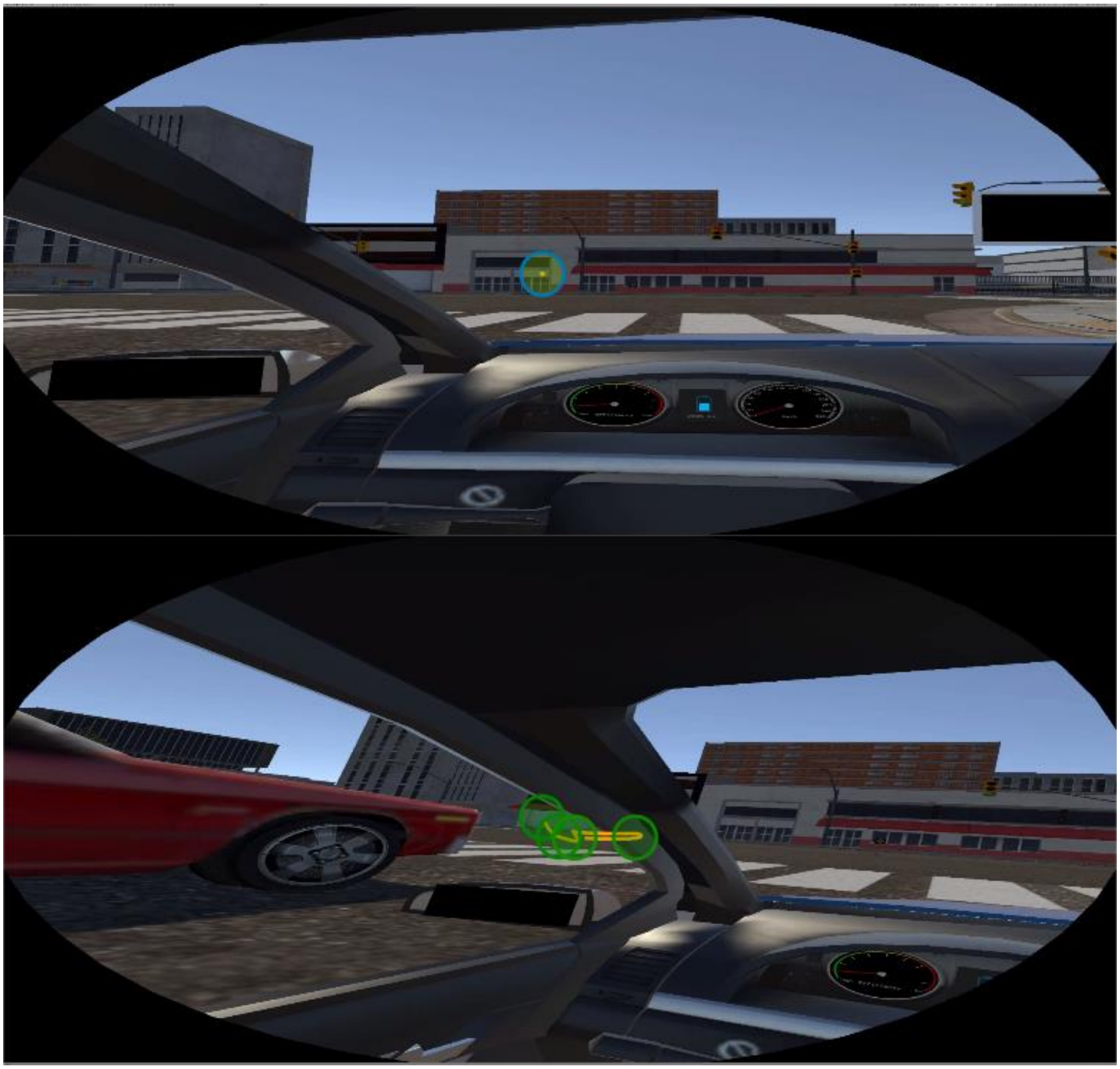
As mentioned before, what participants saw in the VR headset was recorded with their calculated gaze point superimposed onto the footage. The car and its environment were then subdivided into different areas of interest (AOIs), for which the amount and duration of gazes and fixations directed to them was calculated. This methodology is adapted from Birrell and Fowkes (2014). Due to time restrictions given by the scope of this study, not the entire footage of two times 15 minutes per participant could be analysed, only one minute of each 15-minute block. Minute 12 was chosen, so that the battery would have already significantly discharged, and participants would therefore have an incentive to look at the dashboard to monitor their energy use, but enough time had already elapsed to make sure drivers were accustomed to the situation. The number of AOIs was also reduced to only one, the dashboard. Because the exact gaze position projected by the software was observed to have varying accuracy (e.g. by always being slightly to the left of what the participant actually looked at), the entire dashboard was tracked instead of focussing on the individual instruments. iMotions collects gaze and fixation measurements, of which the following were used for analysis: Gaze time spent on AOI (in milliseconds and in percent of total time) number of gazes on AOI, number of fixations on AOI, time spent fixating on AOI (in ms and %), and average duration of fixation on AOI.

Data Processing

The goal was to be able to tell how often and for how long participants looked at a specific object in the simulation, namely the dashboard. The data was collected using iMotions 8 and in its initial state, that data consists of a screen recorded video footage of what the participant was seeing through the headset, overlaid with a gaze point projection (see Figure 4). The following processing of the footage was done to convert the data of where the participant was looking, into data of what the participant was looking at. The challenge therein is that, as visible in Figure 4, not only the gaze, but the footage itself moves around. Therefore, keeping track of the dashboard requires processing of the data. iMotions supports this process with its feature “automated AOI”. The software tries to track an outlined object across the footage and is then able to calculate gaze and fixation data related to that area (see Figure 6).

Figure 4

Recording of Participant's View of the Simulation with extrapolated Gaze Mapping



Note. This figure is made up of two screenshots of the recording. The second screenshot was taken from a moment shortly after the first one. In the meantime, the participant turned their head; gaze projection and the footage moved accordingly.

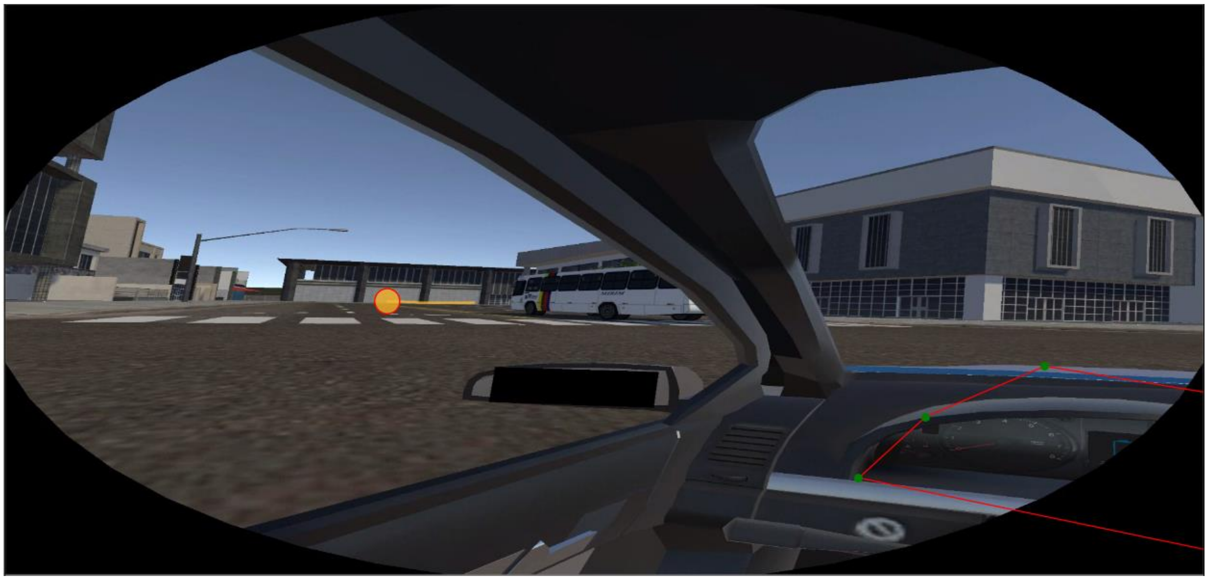
The automatic tracking of a thusly marked object is however not consistently precise or reliable, therefore, the entire tracked footage had to be watched back and the AOI has to be checked and adjusted. (see Figure 6) This was the bottleneck in the methodology of the present study. All previously mentioned limitations in methodology (limiting footage duration and number of AOI) were a result of this.

Figure 5

Footage in iMotions AOI Editor, AOI drawn around the Dashboard (red Lines, green Corners)

Figure 6

The automated AOI has left the Dashboard that it was supposed to track and needs to be manually readjusted.



While in the process of creating AOI, participants with missing or incomplete eye-tracking data were noticed and excluded. The final dataset consisted of one minute of footage per condition per participant (n = 10), with the dashboard tracked as an AOI. This was then exported, wherein iMotions calculated the aforementioned gaze- and fixation data for the AOI (gaze time spent in ms and percent, gaze count, fixations count, fixation time spent in ms and percent, average fixations duration).

Data Analysis

The resulting dataset was tested for normality using the Shapiro-Wilk test, which showed normal distribution for the control condition variables, but not the experimental condition. Therefore, a Wilcoxon signed rank test was used to test for differences between control- and experimental condition for all variables. The variables are gaze time spent in ms and percent, gaze count, fixations count, fixation time spent in ms and percent, and average fixations duration.

Results

Gaze

In the control condition, participants spent an average of 2272 milliseconds (*SD* = 3126 ms) looking at the dashboard across one minute of analysed footage. That is an average 3.6% of total recorded gaze time (*SD* = 5.1%), in an average of 3.6 individual gaze events (*SD* = 4.67). Participants in the experimental condition spent an average of 2000 ms (*SD* = 1324 ms) looking at the dashboard, which was 3.4% (*SD* = 2.27%) of the time, in an average of 4.7 (*SD* = 2.54) individual gaze events. See Table 1 for detailed descriptive statistics.

The first hypothesis was that participants in the experimental condition would direct more gazes at the dashboard compared to the control condition. A Wilcoxon signed rank test for differences showed no significant differences for mean time spent in milliseconds (p = .39), percent (p =.37), or gaze count (p = .59) between conditions (see Table 1). This does not support the hypothesis.

Table 1

Descriptive Statistics and Wilcoxon Signed Rank Test for Gaze Measures

	Control Condition (N = 10)				Experimental Condition (N = 10)				Wilcoxon Signed Rank Test	
	M	*SD*	min	max	*M*	*SD*	min	max	*Z*	*p*
Time spent (ms)	2272	3126	0	10400	2000	1324	0	3824	36	.386
Time spent (%)	3.6	5.10	0	17	3.4	2.27	0	7	30	.371
Count	4.3	4.67	0	13	4.7	2.54	0	8	27	.593

Note. Time spent refers to total time spent gazing at the dashboard, measured once in milliseconds and once in percent of total time. Count means the number of gazes to the dashboard.

Fixations

In the control condition, participants spent an average of 1885 ms (*SD* = 2929 ms) fixating on the dashboard. That is an average of 3.1% of the time (*SD* = 4.89%), in an average of 12.7 individual fixation events (*SD* = 20.75). The average fixation duration was 122 ms (*SD* = 98). In the experimental condition, participants spent an average of 1567 ms (*SD* = 1314) fixating on the dashboard. That is an average of 2.7% of the time (*SD* = 2.21), in an average of 12.5 individual fixations (*SD* = 10.48). The average fixation duration was 115 ms (*SD* = 80). See Table 2 for detailed descriptive statistics.

The second hypothesis was that the average fixation duration would not be different between conditions. A Wilcoxon signed rank test showed no difference between mean fixation time in ms (*p* = .29), percent (*p* = .26), fixation count (*p* = .2), or fixation duration (*p* = .58) between conditions (see Table 2). This supports the second hypothesis.

Table 2

Descriptive Statistics and Wilcoxon Signed Rank Test for Fixation Measures

	Control Condition (*N* = 10)				Experimental Condition (*N* = 10)				Wilcoxon Signed Rank Test	
	M	*SD*	min	max	*M*	*SD*	min	max	*Z*	*p*
Time spent (ms)	1885	2929	0	9521	1567	1314	0	3350	38	.29
Time spent (%)	3.1	4.89	0	16	2.7	2.21	0	6	32	.26
Count	12.7	20.75	0	67	12.5	10.48	0	31	40	.2
Duration	122	4	0	260	115	80	0	261	22	.58

Note. Time spent refers to total time spent fixating on the dashboard, measured once in milliseconds and once in percent of total time. Count means the number of fixations on the dashboard. Duration refers to the average length of a fixation on the dashboard in milliseconds.

Discussion

The goal of this study was to investigate the potential distraction posed by an eco-driving feedback gauge in an electric vehicle. This was operationalized in an experiment to see if drivers would look at the dashboard more often or longer when such a device was present, compared to when it was not. Our findings suggest that this was not the case. The results are discussed below.

Gaze measures

Contrary to expectations based on the findings of Birrell and Fowkes (2014), we did not see a significant increase in gazes to the dashboard when the feedback gauge was present. This is a strong indication that no distraction was taking place: since participants did not look at the dashboard more, it is unlikely that it received more of their attention and therefore it did not distract them. It is noteworthy that the overall time spent looking at the dashboard in both conditions was rather low, at 3.6% and 3.4% of recorded gaze time respectively. Following the rule of thumb that up to 40% of visual attention is spare in a routine driving scenario (Green & Shah, 2004), even if the feedback gauge was demanding additional attention, it would be well within capacity.

Fixation measures

There was also no significant difference found between experimental- and control condition in fixation measures. Note that Hayhoe (2004) states that the duration of a fixation correlates with the amount of perceived information from the fixated source. So, if participants show similar fixation durations in both conditions, we can conclude that they have likely taken in a similar amount of information from the dashboard. There are two possible explanations. Either taking in information from the feedback gauge is a low-complexity task, meaning that drivers can do it with so few glances that it did not show up significantly in our measures (Klauer et al., 2006). This would mean that the associated crash- and near-crash risk in the real world would not be increased. Or the feedback gauge was ignored altogether by drivers. There are again two possible reasons for that behaviour: Either the gauge did not present any useful information, or it did, but participants were not interested in the information. A possible reason for the lack of interest could be that participants did not experience any range anxiety (because in the present study, there were no consequences to stranding with an empty battery). It is described in the literature that the expected benefit of a secondary task is related to a driver's willingness to engage in it (Ranney, 2008). In a real-world situation, drivers that expect benefits from a feedback gauge might engage the gauge differently.

Findings in scientific Context

The present study investigated the prerequisite for distraction, namely the distribution of visual attention resources. We thereby examined the potential for distraction, as described by Ranney (2008). Finding no significant signs of visual distraction can be attributed, as stated above, to low secondary task complexity, which would mean that the investigated system is safe. However, there are more factors that contribute to the degree of distraction caused by any secondary task, other than its inherent complexity. These are characteristics of the driving situation and of the driver themselves. According to the findings of several studies included in the review by Ranney (2008), the complexity of the driving situation influences the distracting impact of secondary tasks. The effects of distraction (manifested in driving performance) are significantly greater in more complex driving scenarios. However, evidence shows that drivers can compensate for that, by engaging less in secondary tasks when the driving situation is complex and requires more attention (Young et al., 2007). For the present study, this means two things. The driving situation (urban, lots of turns and intersections, medium density traffic) was rather complex, meaning that any distracting properties of the secondary task were amplified, which makes it a worst-case study for assessing the distracting potential of the feedback system. A possible conclusion would be that, if the system is not distracting in a highly complex situation, it is not distracting at all. Alternatively, the high complexity situation might have led to the described coping strategy of engaging less (or not at all) with the secondary task, which would also explain our findings. As for driver characteristics, the literature shows that driver age and driving experience both influence secondary task engagement and distraction. A higher age (60+) was found to correlate with higher degrees of secondary task distraction, due to degradation in sensing- and cognitive capacities. At the same time, inexperienced drivers have significantly less spare attention to allocate to secondary tasks, because the driving task requires their full attention. This increases the distracting effects of any secondary task they engage in. (Young et al., 2007). Participants in the present study were relatively young and moderately experienced, which limits the generalizability of the findings. In conclusion, the findings of the present study can be explained by inherent properties of the investigated system, but driver and situational characteristics may have played a role as well.

Contributions to science

As stated above, this study was a pilot. It served its role as a proof of concept, showing that this methodology for a quick and safe way of data collection in automotive research. Even with only one AOI, the gathered eye-tracking data allowed for some conclusions to be drawn: the findings of the present study suggest that an eco-driving feedback gauge does not lead to visual distraction in the driver. Increasing the quality of research possible with this setup is also straightforward, it only requires more time and manpower. This way, more AOIs and other measures can be employed, and more footage can be covered, in order to get a more complete picture of the gaze behaviour while driving an EV. In conclusion, the present study contributes both methodological and contentual findings to automotive research.

Limitations

The position of the present study as a pilot of a larger project, in addition to the limited timeframe it was conducted in, brought with it a set of technical and procedural difficulties that have some implications for its results.

Simulator

The simulator itself is a subject of ongoing development and had, at the time of the study, some problems. Discussed below is the single problematic feature with the largest impact on the results, the feedback gauge. Compared to its real-world counterparts, the simulated representation was of quite low fidelity. It worked by interpreting high differences in rpm over a short time as “inefficient”, but it did not track continuously. Instead, it could only be in one of three positions: green, yellow, red (high, medium and low efficiency, respectively) and it would jump between them. This readout was further complicated by the fact that the “electric vehicle” in the simulator was a model of a combustion engine car with the engine sound muted. This means it had a gearbox, so where in an EV’s rpm would climb continuously (proportional to acceleration), rpm in this car would jump whenever a shift up or down happened, without the driver’s knowledge. This caused the eco-feedback gauge to jump as well without any change in input from the driver. This might have led to the drivers discarding the readout of the gauge as unreliable or just noise. As stated above, driver’s willingness to engage in secondary tasks is related to the tasks associated benefits.

In this case, it could mean that while the feedback gauge simulated in this study did not cause any distraction, its real-world counterpart might have a bigger impact.

Motion Sickness

Motion sickness is not just a relevant factor for determining future sample sizes because of dropouts, where in the present study, a larger sample might have revealed statistically significant differences between conditions. Not every participant that experienced motion sickness quit the experiment, some reportedly “fought through”. There are, however, implications of the coping strategies some reported: They said to have driven slower and keep their gaze fixed straight ahead, which reduced the amount of apparent movement in the visual field and therefore helped mitigating the motion sickness. It is unknown how many participants engaged in this behaviour, but participants ignoring the dashboard altogether because of motion sickness could potentially be a factor masking possible differences in gazes and fixations to the dashboard between conditions.

Recommendations and future research

For future VR simulator research into the gaze behaviour of EV drivers and the effects of eco feedback devices, the present study has some implications. Firstly, when determining the sample size, to account for dropout rates due to motion sickness. Secondly, the validity of following work can be increased by increasing the quality of the simulation, specifically the eco-feedback gauge. Mentioned above were different reasons for why participants might have looked less to the gauge. Future research could account for these, by making sure that participants do use the system. For example, in order to incentivise actually looking at the gauge, range anxiety could be artificially raised in participants by promising a reward, which gets taken away should the participant run out of battery charge. Methodologically, the next steps in this project have already been outlined above. To reiterate: A useful next step would be to build on the methodology of the present study and analyse gaze behaviour in greater detail. This would mean to employ more AOI to track the areas mentioned by Birrell and Fowkes (2014) and to try to replicate their findings that gazes to areas critical to the driving tasks do not diminish in the presence of an eco-feedback system. Alternatively, saccadic behaviour could be analysed, as it has been shown that cognitively distracted drivers tend to spend more time looking centrally and less time scanning for hazards (in saccades) in the periphery (Harbluk et al., 2002). Another important step is to include other measures of distraction, specifically measures of driving performance. Papantoniou et al. (2017) prominently mention measures of car control for this purpose: Future research might investigate how headway (the distance kept to the leading vehicle) or deviation from lane centre relate to gazes directed at an eco-feedback gauge. Thereby, the actual distracting impact of the system can be tested, whereas the present study investigated merely the potential. Furthermore, car control measures can also show what kind of distraction, if any, is taking place. In the present study, we focussed on visual distraction, but there might be cognitive distraction taking place. Carsten and Brookhuis (2005) found that visual secondary tasks led to impaired lateral vehicle control (steering), whereas more cognitive secondary tasks led to decreased longitudinal vehicle control, following a leading vehicle in particular. Additional mental workload measurements like the NASA-TLX could also be employed to understand the cognitive impact of an eco-feedback gauge. A third possible approach would be to investigate changes of gazes to the feedback gauge in driving scenarios of varying complexity, as the present study took place in a mostly complex environment. Situational complexity is a known determining factor for how drivers interact with onboard technology (Kroon et al., 2014; Mueller, 2014).

Conclusion

This study tried to answer the question whether an eco-driving feedback gauge would cause drivers to look to the dashboard more and thereby potentially be distracted. By the means of a VR simulator experiment and within the confines of its generalizability, the conclusion we arrived at was that the potential for distraction is low. There was no significant increase in allocation of visual attention. Future research is required to determine possible effects of an eco-driving feedback gauge on driving performance.

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