Blind Driving III

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Abstract

To this day, driving still is the most used form of transportation. Therefore the risks that come with this responsibility stay a pressing issue. In this follow-up research the concept of a non-automated lane keeping assistance is further developed. In this system the driver himself steers with the help of auditory feedback. This feedback is based on the driver's position on the road as well as his steering angle. To improve the previous model, the curvature of the track as well as the curvature of the predicted path (based on steering angle) are taken into account. A new variable which represents the angle between these curvatures is introduced. The aim is not only to compare this concept with the method of error prediction used in Blind Driving 2, but mainly to see which type of feedback yields the best performance utilizing a new algorithm. Using the new prediction algorithm in combination with a directional, surround sound feedback system results in better lane keeping performance on straight parts of the track when looking at the root mean squared error (RMSE). This feedback system describes in which direction and how much the steering angle must be adjusted (auditive beacon). Overall it does not result in better lane keeping performance in comparison to a binary feedback system. In this system the auditive feedback plays either left or right of the driver and needs to be steered away from. The addition of corner support, indicating when entering or exiting a turn, as well as providing information regarding the sharpness of the corner, is no improvement to the system. Considering that there was no run without resets among the participants, the system is not optimal. A side experiment did show that with proper training a learning curve exists and can bring down the total amount of resets per run significantly.

Introduction

Driving is predominantly a visual task (Groeger, 2000). To be able to drive safely, a clear estimation of the position in relation to other road users and road boundaries is indispensable.(Groeger, 2000)(Macadam, 2003) However, visual information from the environment may be absent in case of darkness, fog or rain (Edwards, 1999) (K. Smith, 1982). Moreover, studies have shown that glare sensitivity and the loss of one's visual fields were significant predictors of crash involvement, as well as the decrease of the UFOV (useful field of view), which is a problem with elderly drivers (Rubin et al., 2007). Even in the case where visual information is present, one may not use it properly. It is estimated that 25% of traffic accidents are due to a distracted driver (Young & Regan, 2007).

Autonomous driving technologies are becoming more common. However, experts do state that fully automated driving will not be technologically feasible before 2075 (Shladover, 2015). Even when autonomous driving technologies are fully developed, it could still be necessary for a driver to take control. For example, in case of a malfunction or when the drivers prefer to drive themselves. Hence, much research still has to be conducted before implementing autonomous driving into society.

Previous studies have shown that auditory displays are promising when used to warn or support human operators because humans can receive auditory information from any direction, irrespective of the orientation of their head and eyes (Sanders & McCormick, 1987)(Stanton & Edworthy, n.d.). The benefit of using auditory displays has already been established by various research. Tactile and auditory collision warnings improve the braking response time in rear-end collision situations (Belz, Robinson, & Casali, 1999). A more recent study has shown that the use of auditory feedback together with combined auditory and visual feedback displays yielded improved performance in terms of response times, total number of correct turns and subjective workload in comparison to those using just visual feedback displays (Liu, 2010). Bazilinskyy et al (2015) found that without predictor feedback, a driver was more likely to deviate from the road than with predictor feedback. This feedback consisted of a beep on either side which needed to be steered away from. Lastly, a study using auditory feedback to influence the choice of speed found that participants who received less auditory feedback chose a higher velocity and were less accurate in estimating their speed (Horswill & Mckenna, 2000). Such a display can be designed in various ways. An example is the racing auditory display (RAD), developed by Smith and Nayar. This is an audio-based user interface that allows blind players to play the same racing games as sighted players, with a similar efficiency and sense of control. A 'sound slider' is utilized in RAD, which indicates the appearance of corners (B. A. Smith & Nayar, 2018).

As mentioned before, there is a need for assistive technologies that support the driver when visual information is degraded, when the driver fails to process the available visual information or when an autonomous system is not working. To gain knowledge on the feasibility of developing such a system, the extreme case is evaluated eliminating all visual input. The intent is not to actually assist visually impaired drivers. This paper presents a follow-up research aiming to improve the auditory feedback systems designed in Blind Driving I and Blind Driving II (Bazilinskyy et al., 2016)(Bazilinskyy et al., 2017). Hereafter, called 'BD1' and 'BD2', respectively. Instead, the intent is to focus on an error prediction algorithm which translates into useful feedback on straight parts of the track as well as in corners, since both BD1 and BD2 preformed significantly better on one or the other. As well as focusing on a more intuitive form of feedback resulting in less oscillating behaviour. More specifically, the focus is to test whether a directional, surround sound feedback system, hereafter referred to as 'beacon', yields better lane-keeping performance than linear graded binary feedback. This surround sound feedback system describes in which direction and how much the steering angle must be adjusted. Also will be validated whether a corner support system improves lane-keeping performance. The expectation is that both the beacon feedback and the corner support improve lane-keeping performance, all using an error prediction utilizing the curvature of the predicted path as well as the curvature of the track.

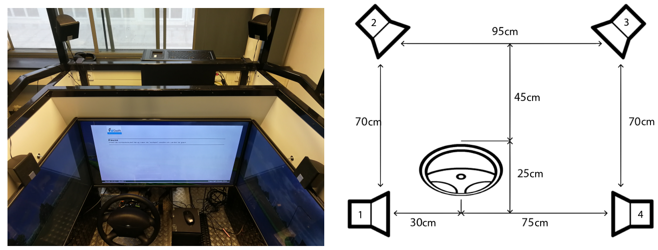
Method

Apparatus

For this research, a fixed-base driving simulator (figure 1, Green Dino) was used. An interface was programmed in MATLAB/Simulink r2016b to retrieve data from the simulator and to generate output via the driving simulators 4.0 integrated speaker system. This sound system was adapted so that the four front speakers were placed in front of and above the driver's seat. The speed of the car was predetermined, so the driver does not use the gas pedal. Also, the car is automatic, so it is not necessary for the participants to shift gears. In figure 1 the setup and the dimensions are shown. The schematic figure show the top down dimensions. The distance in height between the side speakers and the steering wheel is 55cm and distance in height of the front two speakers is 100cm. The speaker we used is a creative inspire 4.1 4400 without the sub-woofer.

Track

To compare results between BD1, BD2 and BD 3 it was decided that the same track was used as in BD1 and BD2. This track was a two-lane 7.5-km road without intersections and without other road users. It contained straight segments, 180-degree corners, sharp 90-degree corners, most of which had a radius of about 20 m. The lane width was 5 m. There were four starting points, yielding four different segments



(a) (b)

Figure 1. (a)Setup of driving simulator (b)Schematic top-down view

(Fig. 2). In each trial, the participant drove for 3 minutes. The track, including starting points are displayed in Fig. 2. The ending points are variable, since the experiment is limited by a 3 minutes driving time and not a predetermined distance.

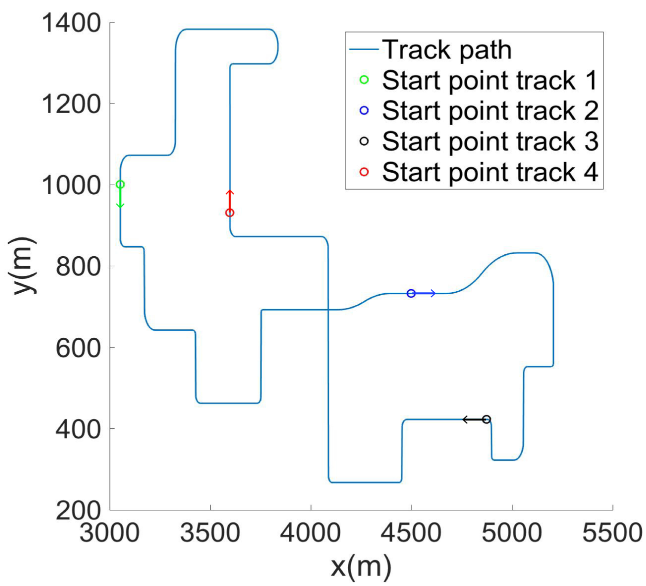


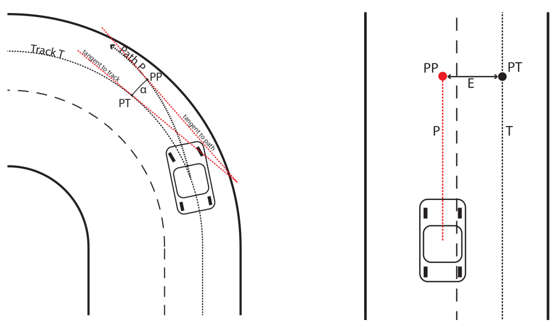
Figure 2. Track with 4 starting points

Error prediction

To be able to give useful auditory feedback a method was developed to give a value to the predicted error of the vehicle. A conceptual representation is given in figure 3. To determine this predicted error that must be corrected the curvature of the predetermined track (T) as well as the curvature of the prediction line (P) are taken into account. Using the steering angle and velocity to determine an expected path for the vehicle, a prediction point (PP) is established mapping the vehicle's expected point in 2 seconds. A representation of the distance between the car and PP following the line P on the track T will determine a predicted point on the track

(PT). Angle alpha indicates the angle between the tangent lines to both PT and PP. The magnitude as well as the sign of this alpha is the representation of the predicted error and will then be translated to a certain amount of auditory feedback explained in section Auditory feedback.

One issue with this error prediction is the case implied in figure 3b. Angle alpha in this case will be undefined and therefore give positive feedback, while the vehicle is not yet on the desired track. To avoid this the expected lateral error (E), a representation of the shortest distance of PP to T, is taken in taken into account when angle Alpha is between a certain bandwidth. In this case the amount of feedback is decided using both angle alpha as well as the magnitude of this lateral error.



(a) Corner (b) Straight

Figure 3. Error prediction on straight parts and in corners

Figure 4 shows the comparison between the prediction methods of BD1, BD2 and BD3. The error prediction in BD1 and BD2 is represented by the lateral error. BD1 takes a linear velocity vector to describe the vehicle's predicted path. In BD2 the steering angle is also taken into account to evaluate the predicted path. As described before BD3 utilizes the angle between the tangent line of track and the tangent line of the predicted path represented by the yellow and black lines respectively.

Auditory feedback

Binary. In the binary feedback mode, sound either comes from the right or the left. The aim is to steer away from the sound and to minimize the volume, as an increase in volume indicates an increase in predicted error. Strictly speaking, the feedback is not purely binary, but in this research, this is the terminology used. No auditory feedback means the participant is on the desired track or within an allowable bandwidth of 3 degrees and a lateral allowable bandwidth of 0.5 m. The volume relates to the extent of steering necessary to correct the predicted error. The sound used for all the experiments is an interrupted tone with a constant frequency of 463 Hz and a constant interval of 0.2 second sound on and 0.2 second sound off, while the engine sound has a

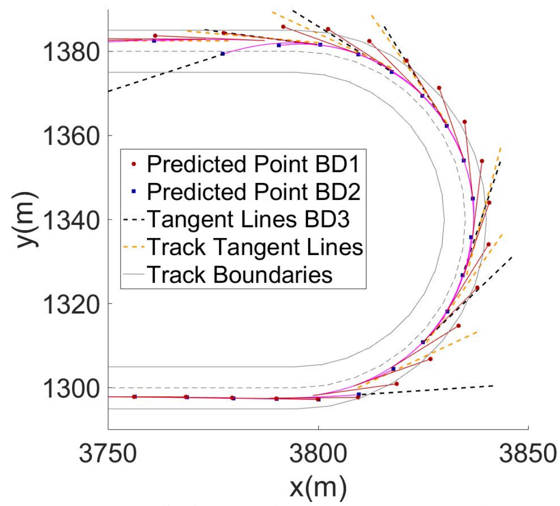


Figure 4. Prediction methods BD1, BD2 and BD3

frequency between 90 and 105 Hz.

Beacon. The beacon feedback mode utilizes a fundamentally different type of feedback. In this type of auditory feedback the source of the sound is mapped using 4 speakers placed in front of the driver in the formation represented in figure 1b. The predicted error is mapped along these 4 speakers, using a division of volume between these speakers to mimic a shifting sound location in front of the driver which the driver aims to follow. When angle alpha is between -20 and 20 degrees the sound is divided along speakers 2 and 3. An error with a value between 20 and 40 degrees is mapped along speakers 3 and 4 and lastly a value between -20 and -40 by speaker 1 and 2. An angle exceeding this bandwidth is represented by either 1 and 4. In this form of feedback, no audio signal also indicates the driver is on the desired track in the same manner as for binary feedback.

Corner support

To clarify when a turn starts or ends, corner support was implemented. Before a corner starts, the driver hears a set of tones on the side in which direction the car needs to be steered away from. The sound is played once, twice or thrice, depending on how sharp the curve is (with 926 Hz and interval of 0.01 seconds on and 0.01 seconds off). The degree of sharpness directly links to the needed steering angle. For a wide curve, corresponding to a steering angle between 0 and 90 degrees, the sound plays thrice. The tone plays twice for an angle varying from 90 to 180, and once for a range of 180 to 270, which corresponds to the sharpest type of curve. When exiting a turn, the driver hears the same sound on both sides for 1 second.

Experiment design

Participants. Twenty people, aged 19 to 26 with a mean age of 22.9 years, participated in the experiments. Out of these participants, 15 were male and 5 were female. Each participant possessed a driver's license; the average amount of driving experience was 4.5 years.

Form. Three different feedback systems were tested: binary, beacon and binary including corner support. All these systems operated with the new error prediction algorithm.

Each participant tested all three feedback systems. Before participating in each feedback system, clear instructions were given about the particular system. In addition, a one-minute sighted test drive was conducted to increase familiarity with the system. After each session, a questionnaire was administered. This, the NASA Task Load Index (TLX), assess the perceived workload.

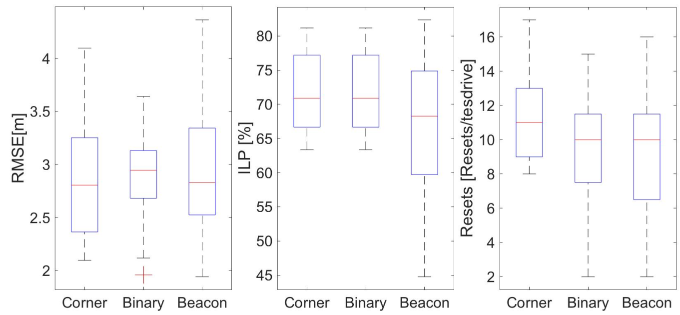
The order of test sessions was alternated among the participants, to take into account a learning effect that could occur. Half of the participants started testing the binary feedback system, after which they tested the binary feedback system including corner support and lastly the beacon feedback system. The other group performed the test in opposite order. Every test drive had a duration of one minute and every session a duration of three minutes.

During the test session, MATLAB and Simulink were used to store the required data to evaluate the test drive.

Learning Curve. To show the effect of a possible learning curve two participants conducted the session a total of 9 times. 5 of which were on the same track alternated with 4 sessions on a different track. Between each session these participants got clear instructions and feedback from one of the researchers on how to use the feedback system to their advance. One participant tested binary, and the second participant tested beacon. To evaluate if a learning curve occurs the 5 sessions driven on the same track are compared, since the difference in tracks might influence the results.

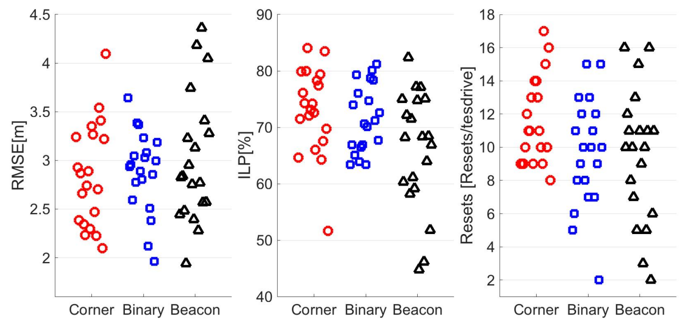
Results

To compare the three feedback systems, three main aspects were looked at. Root mean square error (RMSE), In lane percentage (ILP) and the amount of resets. As can be seen in figure 5 the average RMSE for binary feedback including corner support is the lowest (2.85 m) and the ILP the highest (73.0%). The average amount of resets (11.4) is also the highest. Beacon based feedback results in the highest RMSE (3.01 m) and the lowest ILP (66.1%), but does also has the lowest amount of resets (9). Looking at the standard deviation beacon shows the highest values for all aspects, while binary has very little spread. This is also visible in figure figure 6 showing RMSE, ILP and amount of resets per participant.



(a) (b) (c)

Figure 5. Boxplots of (a)Root mean squared error per participant (b)Average in lane percentage per participant (c)Total number of resets per participant



(a) (b) (c)

Figure 6. (a)Root mean squared error per participant (b)Average in lane percentage per participant (c)Total number of resets per participant

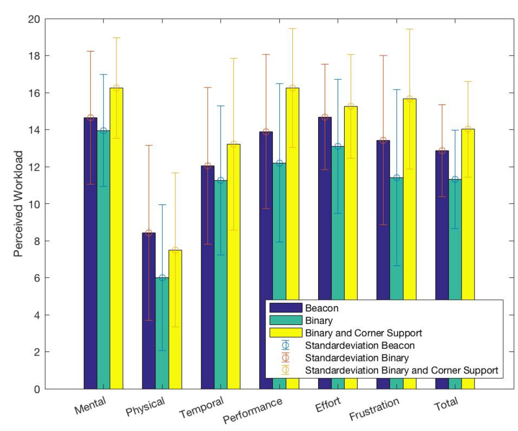
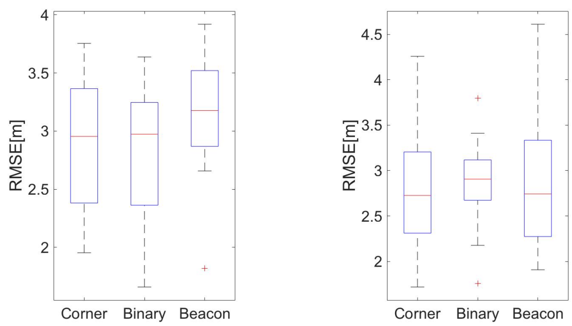


Figure 7. Results NASA TLX

The outcome of the NASA TLX (Figure 7) show that binary is perceived to require the least amount of workload. Binary including corner support on the other hand is seen as the system requiring the most amount of workload and sensed as highly frustrating.

The performance of the three systems in a corner is not addressed by these figures. Figure 8 shows the boxplots for the RMSE in corners as well as on straight parts of the track to be able to compare the systems. Beacon has a much lower RMSE for straight parts (2.89 m vs 3.18 m), while binary performs the best in corners.



(a) (b)

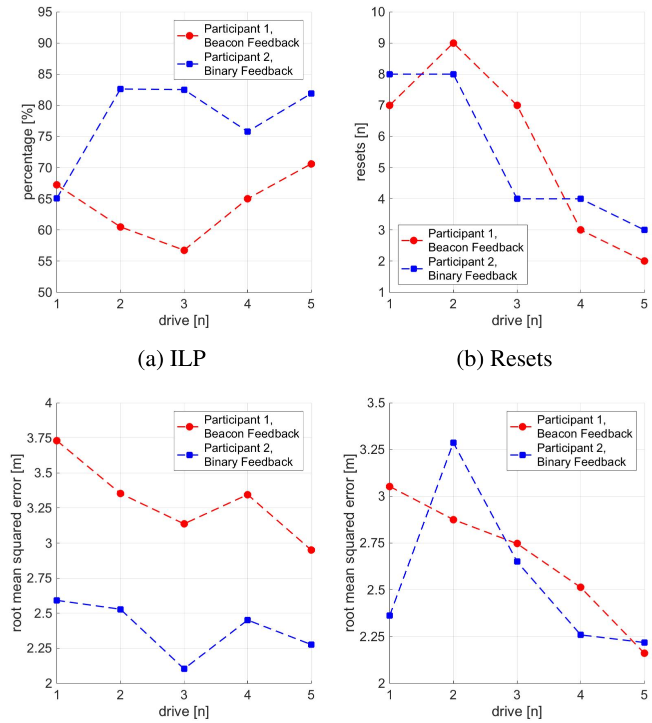
Figure 8. Boxplots of (a)Root mean squared error in corners per participant (b)Root mean squared error on straight parts per participant

To analyze the results from the learning curve experiments, the same aspects are used as in the main experiment. Figure 9 shows that the most notable difference is in the number of resets during the experiment.

Discussion

This study was aimed to use the benefits of auditory feedback as mentioned in the introduction to assist a driver in certain scenarios. In particular when visual information is degraded, when the driver fails to process the available visual information or when an autonomous system is not working. We do think the use of this concept can be useful when further developed. BD3 is not optimized enough yet to use in real life situations.

It can be derived from these results that, while using the new prediction method algorithm, beacon feedback only yields better lane keeping performance on straight parts of the track when looking at the RMSE. Overall it does not result in better lane keeping performances. The spread in results, which is very visible for the beacon support implies that beacon might be a hard system to master but is not necessary a faulty system. Binary seems to be easier to comprehend, since it does not show a spread as significant and is found the least demanding. Looking at the RMSE and ILP, the corner support scores very similar to both beacon and binary. This could be due to the fact that the corner support was always tested after binary and therefore the participants were not completely inexperienced anymore. The amount of resets is significantly higher, which complies with the high workload the participants experienced. The contradiction between the high amount of resets, the high ILP and the low RMSE presumably comes from the fact that after a reset the participant is placed back exactly on track. This benefits the average of these aspects. It seems the corner support is confusing and distracts the participants from focusing on the feedback. In conclusion, binary feedback yields better results than a beacon feedback system. Also the addition of a corner support is no improvement to the system.



(a) ILP (b) Resets

(c) RMSE (d) RMSE in Corners

Figure 9. Results Learning Curve Experiment

Since driving a car with visual feedback usually takes people months to master, it can also be expected that it will take some time to develop the skills to drive with auditory feedback only. BD2 performed elaborate testing with the developers of the system, the results of the main experiment from BD3, performed by unbiased participants, does not show a significant improvement over BD2. This is arguably caused by the lack of experience of the participants. Since the participants of the experiments of BD3 only executed every feedback system once, it is impossible to determine any learning curve in BD3. To investigate the possibility of a learning curve, another experiment was conducted. The results of this experiment imply that there is indeed a learning curve when trained in these feedback systems, but further research is required to confirm this hypothesis.

Furthermore, BD2 has a fair amount of oscillation after a curve before stabilizing again. In BD3 this oscillation is observed to be much less. This might come due to the fact that BD3 uses a derivative (namely the tangent line) in contrast to BD2. In comparison to BD2 no significant improvement is achieved. One important factor to take into account while comparing these results is that the five participants in BD2 all conducted the experiment various times and were involved with the implementation of the system. The participants of BD3 were all unbiased and inexperienced in driving in this particular driving simulator.

Future studies may build on the methods presented in this paper, and focus on the development of the auditory feedback. In particular, the beacon feedback could be improved. In addition, the algorithm that combines the lateral error prediction with the angle between the predicted curve and track should be further developed. The collaboration between both errors is not optimized yet. A proposed direction of research is to examine whether Head Related Transfer Functions (HTRFs) give a realistic sound location as they represent the physical sound source by mimicking this virtually. Another possible improvement might be to apply an arch shaped rail, on which the speakers can move so that the precise location of the sound source is more clearly indicated. Also, this method of prediction indicates an angle, which is hard to translate to a directional beacon. Future studies might focus on a beep that indicates direction instead of an angle.

Supplementary Material

Example test drives of the three feedback systems:

- Beacon: `https://youtu.be/PyGILpMZ26U`
- Binary: `https://youtu.be/T7kBxnoMQbU`
- Corner Support: `https://youtu.be/xFMQJa8nSmU`

Folder with all the MATLAB and Simulink algorithms: `https://drive.google.com/open?id=1l6FrG0XTp8jSwt_M9VKxVxpxKzccjj4r`

References

Bazilinskyy, P., Beaumont, C., van der Geest, X., de Jonge, R., van der Kroft, K., & de Winter, J. (2017). Blind driving by means of a steering-based predictor algorithm.

Bazilinskyy, P., van der Geest, L., van Leeuwen, S., Numan, B., Pijnacker, J., & de Winter, J. (2016). Blind driving by means of auditory feedback.

Belz, S. M., Robinson, G. S., & Casali, J. G. (1999). A new class of auditory warning signals for complex systems: Auditory icons.

Edwards, J. (1999). The relationship between road accident severity and recorded weather. *Journal of Safety Research, 29(4)*, 249-262.

Groeger, J. A. (2000). Understanding driving: Applying cognitive psychology to a complex everyday task.

Horswill, M. S., & Mckenna, F. P. (2000). The development, validation, and application of a video-based technique for measuring an everyday risk-taking behavior: Drivers' speed choice.

Liu, Y.-C. (2010). Comparative study of the effects of auditory, visual and multimodality displays on drivers' performance in advanced traveller information systems.

Macadam, C. (2003). Understanding and modeling the human driver. *Vehicle System Dynamics, 40(1-3)*, 101-134.

Rubin, G. S., Ng, E. S. W., Bandeen-Roche, K., Keyl, P. M., Freeman, E. E., West, S. K., & the SEE Project Team. (2007). A prospective, population-based study of the role of visual impairment in motor vehicle crashes among older drivers: The see study.

Sanders, M., & McCormick, E. (1987). Human factors in engineering and design.

Shladover, S. (2015). Road vehicle automation history, opportunities and challenges [presentation]. *Mini seminar 'developments self driving vehicles in USA'*.

Smith, B. A., & Nayar, S. K. (2018). The rad: Making racing games equivalently accessible to people who are blind.

Smith, K. (1982). How seasonal and weather conditions influence road accidents in glasgow. *The Scottish Geographical Magazine, 98(2)*, 103-114.

Stanton, N., & Edworthy, J. (n.d.). Auditory warnings and displays. *Human factors in auditory warnings.*.

Young, K., & Regan, M. (2007). Driver distraction: A review of the literature. *Australasian College of Road Safety*, 379-405.