Using virtual reality to assess age-related differences in driving behaviour

Simone Fontana[1], Stefania La Rocca[2], Alessio Facchin[2], Laura Vacchi[3] and Carlotta Lega[2]

[1]Università degli Studi di Milano - Bicocca, Dipartimento di Informatica, Sistemistica e Comunicazione, Milano, Italy
[2]Università degli Studi di Milano - Bicocca, Dipartimento di Psicologia, Milano, Italy
[3]Università degli Studi di Milano - Bicocca, Dipartimento di Medicina e Chirurgia, Milano, Italy

Abstract

Artificial intelligence can be used in a variety of ways to mitigate the cognitive and psychophysical decline that accompanies ageing. However, it is not always easy to assess this decline. Several laboratory tests have been developed, but ecological assessment is still an open problem in many areas. Driving is one of these areas. Evaluating driving behaviour in a real-world environment raises ethical, practical, and economic issues. Virtual reality (VR), on the other hand, is already being used in several areas as a diagnostic and therapeutic aid. There are previous attempts to assess attention while driving using VR, but they are less than ecological. In this work, we propose a protocol to assess and quantify attention while driving and its effect on driving behavior. The protocol does not require expensive instruments and is easy to apply. Since its main goal is to assess age-related cognitive decline, it can be used to evaluate possible intervention areas for artificial intelligence and to quantify the effectiveness of these techniques.

Keywords

virtual reality, driving assessment, brain stimulation, ageing, distractors evaluation

1. Introduction

Nowadays, Artificial Intelligence (AI) is able to provide a great help in mitigating cognitive and psychophysiological declines due to aging. AI techniques are used to personalize drug-based treatments, to maximize the beneficial effects, while, at the same time, reducing side-effects, for example in dementia [1]. AI can be used in conjunction with data from assisted living environments to prevent or detect age-related accidents, especially falls [2]. Moreover, AI can be used to predict, detect and mitigate the effects of cognitive decline [3, 4, 5]. Lastly, while robotic assistants are definitely not yet widespread, they are nevertheless promising and can provide a great help in assisting the elderly [6].

However, while mitigating or preventing decline is important, we believe it is also crucial to recognise it: to solve a problem, we need to know that it exists. Moreover, detecting the problem is not enough: quantifying it is essential. Indeed, quantifying the problem is necessary

Italian Workshop on Artificial Intelligence for an Ageing Society, 21st International Conference of the Italian Association for Artificial Intelligence, November 28th – December 2nd, 2022, University of Udine, Udine, Italy
simone.fontana@unimib.it (S. Fontana)
0000-0001-7823-8973 (S. Fontana); 0000-0002-8389-4665 (S. L. Rocca); 0000-0002-0604-5029 (A. Facchin); 0000-0002-6250-2976 (L. Vacchi); 0000-0001-7030-7639 (C. Lega)

to evaluate the mitigation techniques, that is, to detect whether the treatment (of whatever type) reduce the entity of the problem. Furthermore, quantifying the entity of the problem can be essential in designing the best treatment, or in deciding whether it is really necessary, a fundamental characteristic if the treatment has adverse effects, and necessary as a cost reduction strategy in public health.

While some declines associated to ageing are commonly recognized, they still need to be assessed in a scientific and quantitative way. One of such example is driving. Driving is a very complex activity, which requires a complex set of cognitive abilities, such as attention, memory and motor coordination. While driving, we are presented with a huge amount of stimuli. Some of them are not relevant to the activity, *e.g*. advertising, and must therefore be ignored. On the other hand, others are very relevant, such as signs or the presence of incoming traffic. Since the reduction of the ability to drive is associated with a decrease of the daily autonomy and quality of life, and with an increase of the danger for other road users, assessing it and developing mitigating strategies is desirable, especially considering the continued aging of the population. This is especially true for people living in rural areas, with less access to an efficient public transportation system.

AI is already being widely used to improve driving safety, *e.g*. with the widespread adoption of Advanced Driver-Assistance Systems (ADAS) that help drivers with various tasks, such as lane keeping or emergency braking, even tough they are not specifically targeted at the elderly population.

Unfortunately, assessing the driving ability of a person involves practical, technical and ethical issues. On the one hand, the assessment should be as realistic as possible; on the other hand, an open world is a continuously changing environment, with stimuli that are substantially impossible to predict. Hence, developing a testing protocol that takes place in an open street and, at the same time, is reproducible, is almost impossible. We think that reproducibility is an essential requirement of any scientific assessment protocol. Testing the driving capabilities on a private track could be an option, but it has relevant drawbacks. First of all, it lacks realism. While some kind of stimulus could be reproduced, *e.g*. signs, recreating traffic is impractical. Moreover, it is a very costly option and not widely applicable.

Technical problems arise from the difficulty in accurately detecting stimuli in the real world and in measuring the driving behaviour, which indirectly involves measuring the trajectory and speed of the vehicle. While these operations are technically feasible, they are nevertheless hard, not always accurate, and require specific instrumentation installed on the vehicle.

Besides practical and technical issues, we think that ethical ones are as much important. Testing the driving capability of a person and, specifically, how they react to stimuli, involves presenting distractors. These could, and probably would, lead to unsafe driving behaviours and, hence, to crashes. We think that this is not ethically acceptable.

We think that, while these issues are not total impediment in the development of an assessing protocol in the real world, they all contribute to make it hard, tedious, costly and not widely applicable. On the other hand, we think that virtual reality (VR) is of great help in this field. VR has already been used extensively both as a diagnostic and therapeutic tool in the fields of neuroscience and psychology. For example, it has been used as a rehabilitation tool after a stroke [7, 8] or for patients with gait imbalance due to Parkinson diseases [9]. Simulators have also been used to study the effects of ageing on driving behaviour [10, 11, 12, 13, 14, 15].

Driving is a complex and multifaceted task that involves multiple cognitive domains, such as visuospatial attention, visuomotor and auditory skills, and multisensory processing of the environment [16]. One of the main sources of traffic accidents are distractions during driving, *i.e.*, performing a secondary task that diverts attentional resources from the main task. Despite the relevance and pervasiveness of auditory distractions, visual distractions have been shown to have a greater impact on driving behaviour [17]. This is due to the fact that most relevant stimuli while driving are visual. To improve driving safety and avoid distraction-related crashes, it is critical to suppress relevant and irrelevant attention-grabbing stimuli, a cognitive function known as visual selective attention [18, 19, 20, 21]. Consistently,there is consistent evidence that performance on tests of selective attention predicts better overall performance in safe driving [22].

With this work we propose a quantitative and easy to reproduce assessment of the driving behaviours with a specific focus on reaction times and distractor suppression, two characteristics essential in avoiding crashes. In particular, the protocol was developed in the context of a neuroscience experiment and is based on those of Karthaus et al. [15, 14]. The experiment was aimed at evaluating the effect of conventional transcranial Direct Current Stimulation (tDCS) or focal High-Definition transcranial Direct Current Stimulation (HD-tDCS) over the Frontal Eye Fields (FEF) on driving performance. However, it can be used to evaluate the effect on driving of different techniques and to assess driving-related cognitive declines.

Numerous functional imaging studies show that the dorsal frontoparietal attention network, whose core regions include the frontal eye field (FEF) and posterior parietal cortex (PPC), supports attention in the presence of distractors [23, 24, 25, 26, 21]. In addition, human brain imaging studies reported a correlation between neuronal activity in the frontal region and the extent of interference by distractors, indicating a prominent role of frontal regions in actively avoiding interference by irrelevant distractors [27, 28, 21]. Consistent evidence suggests that HD-tDCS, by optimising currents to the brain, improves focus on areas of interest by 80% and increases the precision of the cortical region to which the current is delivered [29, 30, 31, 32, 33, 34]. Using this approach, Choe et al. demonstrated that HD-tDCS improved performance during a flight simulation task [35].

Based on this premise, two groups of participants, one composed of younger (age<30) people, the other of elderly (age>65), attended three sessions of simulated driving. Before each session, they underwent a brain stimulation session, with either conventional tDCS, focal HD-tDCS or sham (placebo) stimulation. During the simulated driving, they had to respond to stimuli, while suppressing distractors and keeping the car in the center of the lane.Driving performances were measured in terms of the quality of the lane keeping, reaction times to stimuli and how many distractors were not correctly suppressed.

Results show that there is a great discrepancy between the driving capabilities of the elder and younger group. For the younger group, the task was probably easy. On the other hand, the performances of the elder group were very dishomogeneus. While some elder people performed very similarly to the mean of the younger group, others performed very badly. This difference is noticeable with every kind of stimulation, including no stimulation.

2. Materials and Methods

2.1. Hardware and Software

The hardware of the simulation environment consists of a computer, three screens, a chair, driving pedals and a steering wheel.

The screens have been arranged to replicate as realistically as possible the field of view perceived while driving a real car. The arrangement of the displays is shown in figure 1. As can be seen, we were also able to realistically simulate the lateral field of view. We believe that, although the crucial part of the simulation is almost always seen in the centre of the screen, this is essential to give a realistic feel to the simulation.

The pedals, steering wheel, and gearshift of a car have been recreated using standard gaming equipment. Finally, for the seat, we simply used a standard chair. To enhance the participants' sense of immersion in the environment, a curtain panel separated them from the researcher conducting the session, and the lights were turned off while driving.

Before deciding on this setup, we carefully considered several alternatives. We are aware that the setup is relatively simple and not the most realistic given today's alternatives. Nevertheless, it has a very important advantage: it is cheap and easy to reproduce, and at the same time realistic enough for our purposes. We believe that these properties are essential to ensure that the protocol is reproducible and that the proposed approach is therefore generally applicable. Since our goal was to develop an assessment protocol, reproducibility is a fundamental property.

Regarding realism, the weakest component of our experimental setup is the seat, which is a standard fixed chair (without wheels and armrests). While there are much more realistic

Figure 1: The arrangement of the displays used for the simulation environment.

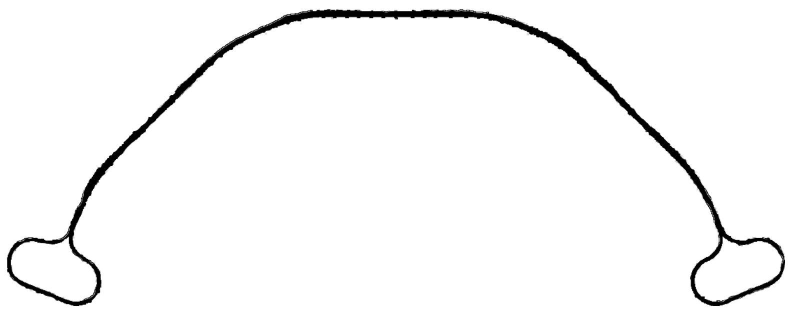

Figure 2: A schematic of the path followed by the participants.

solutions that replicate a real car seat (although they are often sports car seats), our proposal is much cheaper and widely available. However, if a more realistic seat, it can be used without any changes to the protocol or software.

Another component whose use we evaluated are the monitors. We could use a head mounted display, that is, a virtual reality visor, instead. While this type of device provides a very immersive experience, it can be, nevertheless, problematic. Specifically, motion sickness is not uncommon for first-time users [36]. Since our setup is aimed at testing elderly people, we cannot realistically expect them to have any prior experience with this kind of device, which is uncommon even among younger people. For this reason, we decided to use standard monitors arranged in a semi-circular way.

As simulation software, we used the CarnetSoft driving simulator. It is a well-known simulator that has already been used for several experiments in the field of neuroscience [15, 14].

2.2. The simulated environment

The simulation takes place on a highway surrounded by a countryside environment. The user has to drive along a predetermined path, which runs across a highway, takes an exit, and then reenters the highway again (figure 2). It is therefore a loop that, during a single session, is traveled several times. The path, therefore, includes large radius turns, sharp turns, and almost straight sections. The path is never exactly straight, however, for long sections, the curvature is not perceivable. The usage of a relatively complex path and environment differentiates us from previous attempts [15, 14], which mainly used long straight paths.

The simulation includes vehicular traffics, composed of cars, lorries, and motorbikes. Since we are driving in a highway environment, there is no pedestrian, bicycle, or crossing roads. The composition of the traffic, as well as its behavior, such as driving behind or overtaking the user, is randomized. The presence of traffic with realistic behavior is another characteristic that differentiates us from previous experiments [15, 14], which did not use any kind of traffic at all.

2.3. Methodology

The participant cannot drive the car freely. To keep the variability in the simulation low and thus ensure reproducibility, the path of the car is forced. Specifically, the participant's car automatically follows a car ahead and regulates its speed to keep the distance between the two cars constant. The participant has control of the steering wheel and therefore must keep the car in the middle of its lane. In addition to keeping the car in its lane, the participant must respond to certain stimuli while suppressing others. There are two types of stimuli: the braking of the vehicle ahead (figure 3) and signs. The participant must respond to the brake lights of the vehicle ahead by using the brake pedal. The road signs were designed to mimic those on a highway and can represent either cities or countries. The participant must respond to only one of the two types of signs; the type is randomly selected before the simulation begins. The participant reacts to signs by activating a lever on the steering wheel. Signs and brake light stimuli can also occur simultaneously (figure 4).

A single simulation session lasts approximately 25 minutes, plus 5 minutes for practicing before the first session. During the simulation, the participant is presented with:

- 72 braking stimuli;
- 72 sign stimuli, of which 50% are "go" stimuli (*i.e.*, the participant must respond to them), and 50% are "no-go";
- 72 complex stimuli consisting of a braking and a sign; the signs are divided into 50% "go"and 50% "no-go".

Figure 3: An example of braking stimulus. Notice the braking lights of the car ahead.

Figure 4: An example of combined stimulus: the car ahead is braking while a sign is shown.

The time interval between two stimuli is drawn from a random uniform distribution between 6 and 8 seconds.

Participants in the younger group had ages between 21 and 30, with a mean of 24.7 and a standard deviation of 2.6. Furthermore, it was composed of 14 females and 13 males. The inclusion criteria were:

- age between 20 and 35 years old;
- having a driving license for at least two years;
- normal or corrected-to-normal vision and normal hearing;

Participants with a present or history of neurological or psychiatric disorders, epileptic seizures, intracranial metallic implants, cardiac diseases, substance abuse, or dependence had been excluded. The exclusion criteria are due to the usage of brain stimulation and are not related to the simulation.

The experimentation with the older group is still going on, therefore complete statistics are not available yet. Anyway, the inclusion criteria are the same of the younger group, besides the age, which has to be equal to or greater than 65. Moreover we administered the Montreal Cognitive Assessment (MoCA) test to exclude participants with possible cognitive impairments [37].

Participants underwent three sessions of simulations that took place on different days. The three sessions correspond to the two different kinds of tDCS and one to sham stimulation.

We use three different indicators to measure driving performances: task accuracy, response time, and lane keeping accuracy. *Task accuracy* measures how the participant responds to the stimuli. In particular, we measure the number of missed stimuli for the three different kinds, that is, braking, road signs, and braking combined with road signs. *Response times* are strictly related to the previous measure since they represent the time interval between a stimulus and the corresponding response (if it took place). *Lane keeping*, instead, measure how much the participant's car diverged from the center of the lane, while they were subject to stimuli and distractors. It is measured using two different average lateral deviations, called SLDP1 and SLDP2. SLDP1 is the average distance from the center of the lane, measured in the time interval between a stimulus and the corresponding response (after a maximum of 2.5 seconds). SLDP2, instead, is measured between the response and 1.5 seconds after.

3. Results

The data collection is not yet completed. Therefore, we present only partial results, which, however, we believe are relevant. In particular, the experiment with the younger group has been completed, while with the elderly we have tested only 11 participants out of 27.

The focus of this paper is on comparing the performance of young and elder participants, not on comparing the effect of different types of tDCS. Therefore, we present only the results of the "sham" sessions, *i.e.*, without any type of stimulation. Tables 1 and 2 show descriptive statistics of task accuracy scores for the young and elderly groups. We can see that there is a large difference in performance between the two groups in terms of braking accuracy. On average, an older participant missed 45 brakings per session (a session contains 144 braking stimuli composed of 72 braking stimuli solely and 72 braking stimuli combined with a sign), which is a large difference from the young average of 6.14. However, we can see that the standard deviation for the elder group is also very high; thus, there is a large variability in performance. This becomes even more apparent when we look at the best and worst participants in the elder group: the best participant missed 4 brakings, while the worst participant missed 129, *i.e.*, almost every braking. In contrast, there is much less variability between participants in the young group. As expected, the combined task, *i.e.*, responding to a braking and to a sign, is much more difficult than the single task. With an average of 1.29 missed brakings solely, the young group performed almost perfectly on the task. The performance on the combined task is worse, but still quite good. On the other hand, the combined task seems to be very difficult for the elder group, with an average missing rate of 38.27 and a median of 45 over 72 combined stimuli. The results related to missed signs seems to be not relevant, as the two groups performed very similarly, missing on average less than one stimulus per session. This is probably due to the fact that the "sign stimulus" is much larger on the screen compared to the stop lights and is therefore easier to see.

The statistics for reaction times show no significant difference between the two groups. The sign response times are almost identical, while there is a difference of 0.1 seconds between the braking response times. This difference is too small to be relevant, especially considering the standard deviation of the two groups. The same is true for the lane keeping capabilities too. In summary, we found a large difference in driving performance between the groups of young and elder participants. This difference mainly concerns the ability to respond to the braking of another car. As expected, participants missed more brakings when the stimulus was presented in conjunction with another stimulus or distractor. This is significant because in real-world road traffic there is a large number of visual stimuli, many of which should be suppressed to maintain attention on the main task. In addition, timely braking is essential for safe driving. Therefore, it should be used as a measure of a person's driving ability.

Table 1
Task accuracy of the young group: number of missed brakings (br) during braking only stimuli (br. solely), combined stimuli (br. comb,) and total. The same nomenclature is used for sign stimuli (si) too.

	Missed br.	Missed br. solely	Missed br comb.	Missed si.	Missed si. solely	Missed si. comb.
mean	6.14	1.29	4.86	0.79	0.39	0.39
std	7.22	1.94	5.87	0.99	0.69	0.63
min	0.00	0.00	0.00	0.00	0.00	0.00
median	3.50	1.00	3.00	0.50	0.00	0.00
max	23.00	8.00	21.00	3.00	2.00	2.00

Table 2
Task accuracy of the elder group: number of missed brakings (br) during braking only stimuli (br. solely), combined stimuli (br. comb,) and total. The same nomenclature is used for sign stimuli (si) too.

	Missed br.	Missed br. solely	Missed br. comb.	Missed si.	Missed si. solely	Missed si. comb.
mean	45.00	6.73	38.27	0.91	0.27	0.64
std	34.53	18.47	21.83	1.22	0.47	0.92
min	4.00	0.00	4.00	0.00	0.00	0.00
median	49.00	0.00	45.00	1.00	0.00	0.00
max	129.00	62.00	67.00	4.00	1.00	3.00

Table 3
Response times (rt) and lane keeping performances of the young group.

	Braking rt (s)	Secondary rt (s)	sdlp1 (m)	sdlp2 (m)
mean	0.73	0.89	0.06	0.06
std	0.22	0.19	0.09	0.08
min	0.35	0.49	0.00	0.00
median	0.69	0.86	0.03	0.05
max	1.95	2.49	1.75	1.75

4. Conclusions

We propose a protocol for assessing driving capabilities using a simulator. The protocol is designed to be widely applicable, easily reproducible, and cost-effective. Given these requirements, we believe that the use of virtual reality is essential and offers several advantages over a real driving activity. We used the protocol to quantify age-related differences in driving

Table 4
Response times (rt) and lane keeping performances of the elder group.

	Braking rt (s)	Secondary rt (s)	sdlp1 (m)	sdlp2 (m)
mean	0.83	0.91	0.07	0.07
std	0.30	0.21	0.11	0.10
min	0.41	0.62	0.00	0.00
median	0.75	0.86	0.04	0.05
max	2.32	2.35	1.73	1.82

performance and to test the effectiveness of different types of non-invasive neuromodulation. The number of missed responses to stimuli appears to be the main performance affected by aging. In contrast, we found no relevant difference in reaction times. Nevertheless, within our framework, additional measures can be easily implemented if needed. Moreover, different types of environments and traffic models can be used, as well as different types of distractors, *e.g.* auditory distractors. With this work, we aim to show the effectiveness of virtual reality environments in assessing age-related differences in driving behavior. Assessing a decline is the first step towards mitigating it, an area where AI techniques have achieved great success in recent years. However, real-life assessment can be problematic for some activities and therefore may hinder progress in this area. For this reason, we believe that virtual reality can be of great help in this context. On the other hand, we recognize that there may be differences in driver behavior between virtual reality and real-world driving activities. We believe that this difference needs to be assessed and quantified to further advance the use of virtual reality in the assessment of real-life activities.

5. Citations and Bibliographies

References

[1] Q. Liu, N. Vaci, I. Koychev, A. Kormilitzin, Z. Li, A. Cipriani, A. Nevado-Holgado, Personalised treatment for cognitive impairment in dementia: development and validation of an artificial intelligence model, BMC medicine 20 (2022) 1–12.

[2] X. Wang, J. Ellul, G. Azzopardi, Elderly fall detection systems: A literature survey, Frontiers in Robotics and AI 7 (2020) 71.

[3] S. A. Graham, E. E. Lee, D. V. Jeste, R. Van Patten, E. W. Twamley, C. Nebeker, Y. Yamada, H.-C. Kim, C. A. Depp, Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review, Psychiatry research 284 (2020) 112732.

[4] M. E. Pollack, Intelligent technology for an aging population: The use of ai to assist elders with cognitive impairment, AI magazine 26 (2005) 9–9.

[5] E. Khodabandehloo, D. Riboni, A. Alimohammadi, Healthxai: Collaborative and explainable ai for supporting early diagnosis of cognitive decline, Future Generation Computer Systems 116 (2021) 168–189.

[6] A. A. Vogan, F. Alnajjar, M. Gochoo, S. Khalid, Robots, ai, and cognitive training in an era of mass age-related cognitive decline: a systematic review, IEEE Access 8 (2020) 18284–18304.
[7] S. Mugisha, M. Job, M. Zoppi, M. Testa, R. Molfino, Computer-mediated therapies for stroke rehabilitation: A systematic review and meta-analysis, Journal of Stroke and Cerebrovascular Diseases 31 (2022) 106454.
[8] S. Viñas-Diz, M. Sobrido-Prieto, Virtual reality for therapeutic purposes in stroke: A systematic review, Neurología (English Edition) 31 (2016) 255–277.
[9] C. G. Canning, N. E. Allen, E. Nackaerts, S. S. Paul, A. Nieuwboer, M. Gilat, Virtual reality in research and rehabilitation of gait and balance in parkinson disease, Nature Reviews Neurology 16 (2020) 409–425.
[10] T. Chen, N. Sze, L. Bai, Safety of professional drivers in an ageing society–a driving simulator study, Transportation research part F: traffic psychology and behaviour 67 (2019) 101–112.
[11] J. S. Leversen, B. Hopkins, H. Sigmundsson, Ageing and driving: examining the effects of visual processing demands, Transportation research part F: traffic psychology and behaviour 17 (2013) 1–4.
[12] W. C. Quillian, D. J. Cox, B. P. Kovatchev, C. Phillips, The effects of age and alcohol intoxication on simulated driving performance, awareness and self-restraint., Age and ageing 28 (1999) 59–66.
[13] A. Devlin, J. McGillivray, J. Charlton, G. Lowndes, V. Etienne, Investigating driving behaviour of older drivers with mild cognitive impairment using a portable driving simulator, Accident Analysis & Prevention 49 (2012) 300–307.
[14] M. Karthaus, E. Wascher, M. Falkenstein, S. Getzmann, The ability of young, middle-aged and older drivers to inhibit visual and auditory distraction in a driving simulator task, Transportation research part F: traffic psychology and behaviour 68 (2020) 272–284.
[15] M. Karthaus, E. Wascher, S. Getzmann, Effects of visual and acoustic distraction on driving behavior and eeg in young and older car drivers: a driving simulation study, Frontiers in aging neuroscience 10 (2018) 420.
[16] F. X. Graydon, R. Young, M. D. Benton, R. J. Genik II, S. Posse, L. Hsieh, C. Green, Visual event detection during simulated driving: Identifying the neural correlates with functional neuroimaging, Transportation Research Part F: Traffic Psychology and Behaviour 7 (2004) 271–286.
[17] J. Sodnik, C. Dicke, S. Tomažič, M. Billinghurst, A user study of auditory versus visual interfaces for use while driving, International journal of human-computer studies 66 (2008) 318–332.
[18] S. Forster, N. Lavie, Attentional capture by entirely irrelevant distractors, Visual cognition 16 (2008) 200–214.
[19] J. Jonides, S. Yantis, Uniqueness of abrupt visual onset in capturing attention, Perception & psychophysics 43 (1988) 346–354.
[20] J. Jonides, S. Yantis, " uniqueness of abrupt visual onset in capturing attention": Erratum. (1990).
[21] F. Marini, E. Demeter, K. C. Roberts, L. Chelazzi, M. G. Woldorff, Orchestrating proactive and reactive mechanisms for filtering distracting information: Brain-behavior relationships revealed by a mixed-design fmri study, Journal of Neuroscience 36 (2016) 988–1000.

[22] S. Depestele, V. Ross, S. Verstraelen, K. Brijs, T. Brijs, K. van Dun, R. Meesen, The impact of cognitive functioning on driving performance of older persons in comparison to younger age groups: A systematic review, Transportation research part F: traffic psychology and behaviour 73 (2020) 433–452.
[23] M. Corbetta, G. L. Shulman, Control of goal-directed and stimulus-driven attention in the brain, Nature reviews neuroscience 3 (2002) 201–215.
[24] N. E. DiQuattro, R. Sawaki, J. J. Geng, Effective connectivity during feature-based attentional capture: evidence against the attentional reorienting hypothesis of tpj, Cerebral Cortex 24 (2014) 3131–3141.
[25] A. B. Leber, Neural predictors of within-subject fluctuations in attentional control, Journal of Neuroscience 30 (2010) 11458–11465.
[26] J. Lee, J. J. Geng, Idiosyncratic patterns of representational similarity in prefrontal cortex predict attentional performance, Journal of Neuroscience 37 (2017) 1257–1268.
[27] J. De Fockert, G. Rees, C. Frith, N. Lavie, Neural correlates of attentional capture in visual search, Journal of cognitive neuroscience 16 (2004) 751–759.
[28] J. W. de Fockert, J. Theeuwes, Role of frontal cortex in attentional capture by singleton distractors, Brain and cognition 80 (2012) 367–373.
[29] A. Datta, J. M. Baker, M. Bikson, J. Fridriksson, Individualized model predicts brain current flow during transcranial direct-current stimulation treatment in responsive stroke patient, Brain stimulation 4 (2011) 169–174.
[30] A. Datta, D. Truong, P. Minhas, L. C. Parra, M. Bikson, Inter-individual variation during transcranial direct current stimulation and normalization of dose using mri-derived computational models, Frontiers in psychiatry 3 (2012) 91.
[31] J. P. Dmochowski, A. Datta, M. Bikson, Y. Su, L. C. Parra, Optimized multi-electrode stimulation increases focality and intensity at target, Journal of neural engineering 8 (2011) 046011.
[32] D. Edwards, M. Cortes, A. Datta, P. Minhas, E. M. Wassermann, M. Bikson, Physiological and modeling evidence for focal transcranial electrical brain stimulation in humans: a basis for high-definition tdcs, Neuroimage 74 (2013) 266–275.
[33] P. Faria, M. Hallett, P. C. Miranda, A finite element analysis of the effect of electrode area and inter-electrode distance on the spatial distribution of the current density in tdcs, Journal of neural engineering 8 (2011) 066017.
[34] H.-I. Kuo, M. Bikson, A. Datta, P. Minhas, W. Paulus, M.-F. Kuo, M. A. Nitsche, Comparing cortical plasticity induced by conventional and high-definition 4× 1 ring tdcs: a neurophysiological study, Brain stimulation 6 (2013) 644–648.
[35] J. Choe, B. A. Coffman, D. T. Bergstedt, M. D. Ziegler, M. E. Phillips, Transcranial direct current stimulation modulates neuronal activity and learning in pilot training, Frontiers in human neuroscience 10 (2016) 34.
[36] L. J. Hettinger, G. E. Riccio, Visually induced motion sickness in virtual environments, Presence: Teleoperators & Virtual Environments 1 (1992) 306–310.
[37] S. Conti, S. Bonazzi, M. Laiacona, M. Masina, M. V. Coralli, Montreal cognitive assessment (moca)-italian version: regression based norms and equivalent scores, Neurological Sciences 36 (2015) 209–214.