Visual attention in naturalistic scenes across the lifespan

A thesis submitted in partial fulfilment of the requirements of Bournemouth University for the degree of Doctor of Philosophy

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Chapter 1

Ageing with maintained executive functioning abilities is associated with effective compensatory strategies in dynamic perceptual decisions

1.1 Introduction

Attentional control, the ability to limit information processing to that relevant for the task, is crucial to effective functioning in daily life. Attentional control declines with age (Treitz, Heyder, & Daum, 2007; Lustig & Jantz, 2015) and this decline has been linked to the deterioration of the prefrontal cortex with age (West, 1996, 2000; Salat et al., 2004; Raz et al., 1997, 2005; Fjell, McEvoy, Holland, Dale, & Walhovd, 2013) as well as micro- and macrostructural alterations in brain connectivity between the frontal areas and other parts of the brain (Fjell, Sneve, Grydeland, Storsve, & Walhovd, 2017; Hirsiger et al., 2017).

Two components of attentional control are commonly described, bottom-up and top-down control (Bundesen, 1990; Cave & Wolfe, 1990; Duncan & Humphreys, 1989; Eriksen & Hoffman, 1972; Koch & Ullman, 1985; Posner, 1980; Treisman & Gelade, 1980; Yantis & Jonides, 1984). Bottom-up attention is commonly typified as exogenous, stimulus-driven attention and is said to be based on the properties of the stimulus such as saliency or onset (Itti & Koch, 2001; Borji, Sihite, & Itti, 2013). In contrast, top-down attention is typically referred to as endogenous, goal-directed attention and is concerned with how our prior knowledge, intentions and goals control visual selection (Carrasco, 2011).

The bottom-up versus top-down distinction is important for characterizing the age-related changes observed in visual performance (Hartley, Kieley, & Mckenzie, 1992; Madden, Whiting, Provenzale, & Huettel, 2004). Top-down attentional processes may minimize or inhibit stimulus-driven attentional capture (e.g., Bacon & Egeth, 1994) and the ability to do so is arguably one of the most frequently tested phenomena in attention and ageing research. The Inhibitory Control Deficit theory (Hasher & Zacks, 1988) posits that the ability to inhibit the processing of task irrelevant information declines with older age. This theory states that once irrelevant information is attended to, it receives sustained attention at the expense of the processing of task relevant information. Accordingly, it has been suggested that ageing is associated with a selective inability to effectively use top-down suppression of neural activity associated with distracting information (Gazzaley & D'esposito, 2007), in connection with a decreased involvement of dorsolateral prefrontal and parietal regions (Milham et al., 2002) and a reduced ability to switch between targets (Hampshire, Gruszka, Fallon, & Owen, 2008). Even in multifactorial theories of cognitive decline in ageing, declining performance arises from a combination of declines in attentional and neural resources, processing speed, and inhibition (Park & Festini, 2017).

However, the pattern of results in studies on attentional control and ageing is not always unequivocal. In the Simon task for instance, older adults show a deficit in attentional control compared to younger adults (Pick & Proctor, 1999; Juncos-Rabadán, Pereiro, & Facal, 2008; Vu & Proctor, 2008), even after correcting for slower response times in the older adults (Van der Lubbe & Verleger, 2002; Castel, Balota, Hutchison, Logan, & Yap, 2007). Some studies show a modulation of the effect by complexity of the task (Kubo-Kawai & Kawai, 2010; Lee Salvatierra & Rosselli, 2011). Similarly, the reflexive or volitional orientation of attention towards peripheral cues show age-related effects only in specific conditions (Nobre, Nobre, & Kastner, 2014). Some studies even argued that the attentional control is preserved with advanced age (Lien, Gemperle, & Ruthruff, 2011).

The previous research on ageing and attentional control suggests that fine-grained and robust results obtained in well controlled experimental situations are also highly context dependent. Therefore, it is crucial to understand how the decline of attentional control impacts on day to day activities. Indeed, previous studies have linked declines in attentional control in older adults to problems in natural situations such as motor vehicle crash rates (Shinar, Zaidel, & Paarlberg, 1978), and the ability to adjust gait (Sparrow, Bradshaw, Lamoureux, & Tirosh, 2002). In order to increase generalisability, some studies on attentional control have used more complex stimuli and focused on visual attention in natural scenes. This research has shown that information selection is influenced by bottom-up processes sensitive to features, as well as top-down influences (Henderson, Weeks Jr, & Hollingworth, 1999; Loftus & Mackworth, 1978; Palmer, 1975) such as scene context (Castelhano & Pereira, 2018), semantic informativeness (Henderson, Brockmole, Castelhano, & Mack, 2007) or the observer's intention and understanding of a scene (Henderson, 2017). The age-related decline in attentional control might be linked to the change in the relative influence of top-down and bottom-up processes with age as bottom-up fixation selection loses strength or the role of top-down processes becomes more important (Açık, Sarwary, Schultze-Kraft, Onat, & König, 2010).

Understanding the decline in the control of visual attention with ageing is particularly relevant for pedestrian safety. Indeed, older adults (above 75y/o) have the highest rate of pedestrian accidents in Australia (BITRE, 2015), and in the EU older adults make up nearly half of all pedestrian fatalities (ERSO, 2018). Studies on pedestrian behaviour in older adults have pointed towards deficits in cognitive processes as factors that might explain the high number of older adults involved in accidents (Nagamatsu et al., 2011). Specifically, attentional control abilities such as attention switching (Dommes, Cavallo, & Oxley, 2013), and executive function abilities such as spatial planning (Geraghty, Holland, & Rochelle, 2016) have been linked to fewer safe crossing decisions. These studies link executive functioning to performance in realistic tasks. However, they do not provide a fine-grained understanding of how declines in attentional control affect the visual exploration of the environment which, in turn, might impact performance. To the best of our knowledge, only one study, Zito et al. (2015), has linked visual sampling, executive functions, and road crossing decisions with age. In this study, both older adults and younger adults looked mostly at the appearing point of the vehicles. However, older adults spent more time than younger adults looking at the ground in front of them. Moreover, older adults made more unsafe crossing decisions and showed a decline in executive function as measured by the trail making task and the Clock Drawing Test.

The studies performed by Dommes et al. (2013); Geraghty et al. (2016) and Zito et al. (2015) investigated the impacts of ageing and executive function on visual exploration and road crossing performance together but not separately. Therefore, it is impossible to dissociate the impacts of executive function ability on visual exploration and road crossing behaviour, from the impact of ageing on visual exploration and road crossing behaviour. Alternatively, ageing with maintained executive function may not impact on visual exploration or road crossing behaviour at all. Older adults that do not show a decline in executive function may perform as safely as younger adults, as they may be aware of physical declines such as slower walking speeds (Thomas, Donovan, Dewhurst, & Bampouras, 2018; Bohannon, 1997). Moreover, maintained executive function abilities may allow older adults to compensate for their physical declines. To determine whether there is an impact of ageing without declining executive functions on visual exploration and road crossing behaviour I recruited participants from the Bournemouth University Ageing and Dementia Research Centre participant pool and from the Bournemouth branch of the University of the Third Age. I recruited from these groups as they are typically very physically, and socially active which helps to maintain executive function ability as individuals age (Carlson et al., 2008; Ybarra et al., 2008). Therefore, these participants are likely to have similar executive function abilities to younger adults. The similarity in executive function abilities between older adults and younger adults allows assessing the impact of healthy ageing on attentional control, separately from executive functioning on decision making in a naturalistic task.

In the current study I assessed two main questions:

- Does ageing with maintained executive function abilities impact on crossing behaviour?
- Does ageing with maintained executive function abilities impact on visual exploration in a naturalistic dynamic scenario?

To answer these questions I presented older adults and younger adults with road traffic videos and recorded their road-crossing decisions and eye-movements. The videos contained distractors and a variety of traffic densities, as in Nicholls et al. (2019). I used automatic object detection techniques to measure, at each frame, the distance and the time to impact of the approaching vehicles. To confirm that our older adults showed similar executive function abilities to younger adults I tested their executive function abilities using the BADS zoo map test, and the Rogers and Monsell attention shift paradigm (RMA, Wilson, Alderman, Burgess, Emslie, & Evans, 1996; Rogers & Monsell, 1995). The BADS zoo map and the RMA tests were chosen as they had previously been linked to road crossing performance in older adults (Geraghty et al., 2016; Dommes et al., 2013).

1.2 Methods

1.2.1 Participants

64 participants were recruited, 31 older adults aged between 60 and 83 years old (y/o, mean=69.03, SE=1.38), and 33 younger adults aged between 18 and 35 y/o (mean=22.37, SE=0.91). All younger adults were recruited at Bournemouth University, UK. All participants had normal or corrected to normal vision. Participants

were screened for mild cognitive impairment using the MoCA (Nasreddine et al., 2005). One older adult was excluded based on a cut-off score of 23 (Luis, Keegan, & Mullan, 2009). Therefore 30 older adults and 33 younger adults were included in the final analyses. The study was approved by Bournemouth University's ethics committee. Informed consent was obtained from participants prior to taking part. Participants took part in exchange for course credits or monetary compensation for their time. This study was performed in accordance with all appropriate institutional and international guidelines and regulations, in line with the principles of the Helsinki Declaration.

1.2.2 Apparatus

During the experiment participants' eye movements were recorded at a sampling rate of 1000Hz with the SR-Research EyeLink 1000 (with a chin and forehead rest), which has an average gaze position error of about 0.25° and a spatial resolution of 0.01°. Only the dominant eye was tracked. Stimuli were presented on an HP monitor with a screen resolution of 1920 by 1080 pixels, a width of 534mm and a height of 300mm, a horizontal viewing angle of 46.9° and a vertical viewing angle of 27.4° at a distance of 740mm. The experiment was coded in Matlab (MATLAB, 2016) using the Psychophysics toolbox, PTB-3 (Brainard, 1997) and EyeLink Toolbox extensions (Cornelissen, Peters, & Palmer, 2002). Calibrations for eye fixations were conducted at the beginning of the experiment using a nine-point fixation procedure as implemented in the EyeLink API (see EyeLink Manual) and using Matlab software. Calibrations were then validated with EyeLink software and repeated until there was less than 1° of error for every calibration point.

Executive Function Tests

To assess the participants' executive function abilities, participants completed the BADS zoo map test (Wilson et al., 1996), and the Rogers and Monsell attention shift paradigm (RMA; Rogers & Monsell, 1995). The BADS zoo map test assessed the participants' spatial planning ability by assessing participants' ability to plan a route around a zoo. In the first trial participants were given a map of a zoo and instructed to plan a route around a zoo, starting at the entrance and finishing with a picnic. Along the route participants had to visit specified locations in any order while following set rules, such as only using specific paths twice and not visiting unspecified locations. Participants' planning time and time to complete the task was recorded. In the second trial participants had to plan a route around the same zoo, following the same rules, and visiting the same locations but in a specified order. Again, the participants' planning time and time to complete the task were recorded. Participants were scored based on visiting the correct locations and points were deducted when participants break the rules and exceed time limits for planning on the second trial. There was only one correct route in both trials, therefore, if participants did the task correctly their route for trial one would mostly match the route for trial two. The only exception being the order in which they went around a loop section of the map.

The RMA assessed participants' attentional control by getting participants to switch between two similar tasks. Participants were presented with number letter pairs (e.g., 9E) and depending on the position of the stimulus on the screen they either had to identify whether the number was odd or even or whether the letter was a vowel or consonant. For the RMA task I extracted the global and local switch costs as done by Rogers and Monsell (1995). The global switch costs refer to the difference in performance between a block where participants perform the same task and a block where participants are switching between tasks. Local switch costs refer to the differences in performance between switch and non-switch trials. These tests have previously been linked to road crossing ability (Dommes et al., 2013; Geraghty et al., 2016) and were designed to assess participants' spatial planning and attention shifting abilities.

1.2.3 Experimental Procedure

I used the same video stimulus and design as in Nicholls et al. (2019). At the beginning of the experiment participants were informed that they would be presented with a series of videos of road crossing situations on screen and that they would have to indicate by pressing the spacebar on a keyboard when they could cross the road and hold the button pressed for as long as they thought it was safe to cross. Participants were instructed to focus on approaching vehicles on the side of the road closest to them but vehicles did travel on both sides of the road (see Figure 1.1A for a capture of the scene). Vehicles travelled at an average velocity of 50 km/h. Each trial started with the presentation of a central fixation cross. Once the participants had fixated on the cross a blank screen was presented for 500 ms and then the video clip for the trial was presented (see Figure 1.1A). Each trial was followed by another blank screen for 500 ms and the next trial started with the central cross. One hundred trials were presented to the participants each with a different video clip, each lasting 10 seconds. All video clips were filmed at a real road crossing in Fribourg with a variety of traffic densities, with or without pedestrians and cyclists (distractors). The videos were completely natural, and no aspects of the videos were staged and they were not edited to control when the cars emerged. Thirty-five of the videos contained pedestrians. The camera was always fixed in the same location, at a height in between the average adult and the average child's height. All video clips were mirrored so as to simulate a road crossing in the UK. Critically, registration numbers were not identifiable and the visual scenes did not include any information allowing participants to identify where they were filmed. Prior to the experiment, 10 British drivers were asked where the video clips were located, all of whom responded with a location in the UK. Number of presses for each trial were collected and analysed for the purpose of the present experiment.

1.2.4 Statistical Analyses

All statistical analyses and figures were performed and created using Matlab 2016a (MATLAB, 2016) and R (R Core Team, 2016).

Crossing decisions

For the sake of simplicity, I defined "time to impact" as the time that it would take for the closest approaching vehicle to reach the participants, from the moment when the participants stopped indicating that crossing was safe (i.e. when they released the spacebar indicating that it was no longer safe to cross). This is illustrated in Figure 1.1D.

The number, and duration of crossing decisions, and time to impact were analysed with linear mixed models. Each of the models had fixed effects of age group (above or below 60y/o), traffic density, distractors, and zoo map score. Each of the models included two interactions one between age group and traffic density, and one between age group and distractors. The model for time to impact and number of crossing decisions also included random intercepts for each participant and video and random slopes for zoo map score. The model of button press duration only included random intercepts for each participant and each video. To begin with, each of the models contained random slopes for each fixed factor and interaction but the model did not converge so the random effects structure was pruned using the procedure proposed by Bates, Mächler, Bolker, and Walker (2015). Initially the model contained additional fixed effects of MoCA score, response time on the RMA, local switch cost on accuracy score of the RMA, the local switch cost on response time on the RMA, global switch cost on accuracy of the RMA, and global switch cost on response time on the RMA. This model did not converge so a lasso regression was used to determine which fixed effects could be removed (Tibshirani, 1996). Lasso regression is used for variable selection and functions similarly to ridge regression by shrinking large regression coefficients to reduce overfitting. This is achieved by forcing the sum of the absolute value of regression coefficients to be less than a fixed value. The difference between ridge regression and lasso regression is that this shrinking process forces some coefficients to be set to zero in the lasso regression but not in the ridge regression. Forcing these coefficients to be set to zero is the equivalent of removing these coefficients from the regression (Tibshirani, 1996).

Linear mixed models were chosen as they have a number of advantages over non-mixed methods as well as mixed-ANOVAS. For example, linear mixed models allow researchers to simultaneously consider all factors which potentially contribute to the understanding of data, including fixed and random effects (Baayen, Davidson, & Bates, 2008). Linear mixed models have more power than mixed ANOVAs because linear mixed models are able to simultaneously accommodate by item and by participant subject variation (Barr, Levy, Scheepers, & Tily, 2013). Linear mixed models are also well suited to naturalistic experiments as they are able to take into account large unbalanced data sets and missing data (Baayen et al., 2008).

For each video clip the presence of a human distractor was encoded in a dichotomous way (1 for one or more human distractors present in the trial, 0 for no human distractors in the trial). The number of vehicles and vehicle locations at each video frame were determined using a custom automatic car detection algorithm. The vehicle locations were used to calculate the time to impact. Our method combines a Matlab car detection algorithm using Gaussian mixture models (Kingdom, 2017) and a Kalman filter (Kingdom, 2019). The car detection algorithm detects and counts cars using a foreground detector via Gaussian mixture models and then performs a Blob Analysis on the detected foreground objects. I applied the Kalman filter to reduce the number of times the objects were lost (Figure 1.1A). To further improve the performance of the foreground detector I created difference videos from the stimuli videos. In the difference videos, each frame was created by subtracting the previous frame in the original video from the current one (Figure 1.1B). Moreover, the motion in each difference video was enhanced using the Eulerian magnification toolbox (Wu et al., 2012). I amplified the motion so that the vehicles blurred into one very bright object – including larger vehicles (such as trucks) which would often be detected as two objects by the car detection algorithm (Figure 1.1C; I used a bandpass between 0.4 and 3Hz, α=40, λ=80). A marker was then placed in the video at known distances along the road and the time at which the car passed over these markers was calculated (Figure 1.1A). Location and time were used to calculate how long it would take the vehicles to reach the participants from the time the key was released indicating safe crossing; i.e. the time to impact when the crossing was considered unsafe. A large value would indicate an early and safe decision.

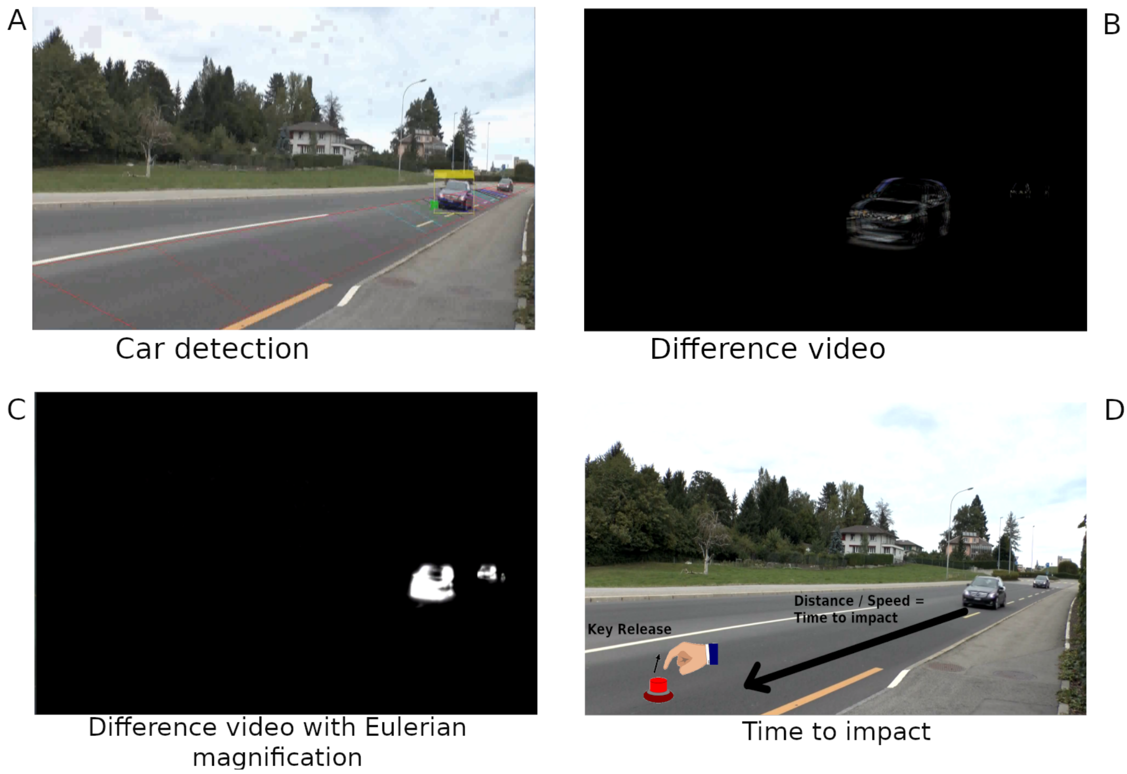
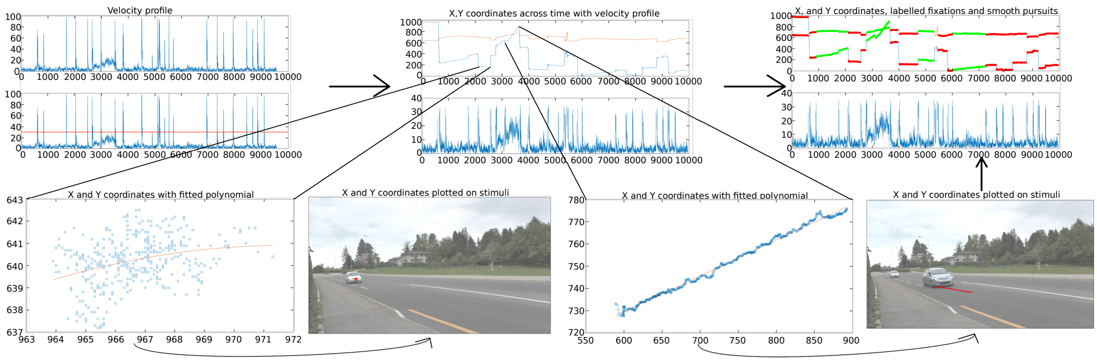


Figure 1.1: Illustration of the car detection algorithm. (A) Screenshot of the car detection algorithm on original stimuli. Coloured markers on the road indicate where car distance is calculated. (B) Difference video. (C) Difference video features magnified by the Eulerian magnification (see Methods for magnification procedure). (D) Illustration of the time to impact measure (see Methods for calculation).

Executive function tests

Differences between older adults and younger adults on all measures were determined using a bootstrap t-test with a one step M-estimator. Multiple comparisons were corrected using the Hochberg method. I used bootstrap t-tests as they handle skewed distributions and outliers better than the Student's t-test. They are able to do this by creating t-distributions that are closer in shape to the sample distribution and can be used with any estimate of central tendency, creating better confidence interval estimates. (Rousselet, Pernet, & Wilcox, 2019). Bayes factors were also calculated using the BayesFactor package in R (Morey & Rouder, 2018), after outliers were removed using the median absolute deviation rule.

Parsing of eye movements



(a) Illustration of the eye movement parser algorithm

Figure 1.2: Illustration of eye movement parser algorithm. Top left – velocity threshold to extract saccades (bottom panel). Velocity of eye movement samples (top panel). Top centre – plotting X and Y coordinates of eye movement samples across whole trial (top panel). Bottom left and right – extraction of segments of eye movement samples maintaining a velocity of 30 deg/s for at least 100 ms with a polynomial fitted to the segments. Beside these are X and Y coordinates of the segments plotted on matching frames of the experiment stimuli. Top right – completed labelling of eye movements as fixations (red lines), smooth pursuits (green lines), and saccades (blue lines) for a whole trial.

Eye movements were parsed into fixations, saccades and smooth pursuits using a custom algorithm (see Nicholls et al., 2019). Previous studies examining properties of smooth pursuit eye movements have typically calculated smooth pursuit gain, which is the ratio between eye velocity and target velocity (e.g. Stubbs, Corrow, Kiang, Panenka, & Barton, 2018; Maruta, Suh, Niogi, Mukherjee, & Ghajar, 2010). This requires knowledge of the target velocity and in realistic videos, the target changes and it requires sophisticated image analysis to determine the velocity of cars from videos. Other techniques for parsing smooth pursuit eye movements from fixations and saccades which do not require knowledge of the target have been developed. These are based on dual velocity thresholds, velocity and dispersion, and principal component analysis, with and without binocular eye tracking (Komogortsev & Karpov, 2013; Larsson, Nyström, Andersson, & Stridh, 2015; Larsson, Nyström, Ardö, Åström, & Stridh, 2016). The algorithm combining velocity, and dispersion information works very effectively for moving dot and image stimuli but they did not work very effectively for realistic videos (Larsson et al., 2016). Another approach using machine learning was also shown to be effective on moving dot stimuli (Vidal, Bulling, & Gellersen, 2012), however, it has not been tested on realistic video stimuli and it requires the development of a training set. To my knowledge there is no algorithm that separates out smooth pursuits from fixations effectively for realistic video stimuli, therefore, I created my own. The advantages of this algorithm are that it effectively labels saccades, fixations, and smooth pursuits from data recorded when participants gazed at a realistic stimuli, without knowing the velocity of the cars, and only needing monocular tracking data. Below I describe how the custom algorithm works.

Saccades were extracted using a manually set velocity threshold starting with a threshold at 30°/s to match the EyeLink Manual, increasing to a maximum of 80°/s, if the first threshold was too low for the a given participant. I changed the velocities manually at an individual level to adapt to the differing levels of noise present in different participants. Noise might be caused by factors related to the stability of the participant's eye which vary with age and any medication used. Noise can also be caused by factors related to the stability of the recorded eye movement signal such as dryness of the eye, makeup, occlusion due to the eyelid, reflections from glasses, etc. The Eyelink setting is acceptable on average but can sometimes lead to misrepresentations at an individual level which can bias the sample distribution. If the majority of samples in the trial were above the maximum velocity threshold then the trial was removed and if more than 50% of the trials were removed then the participant was excluded. In total, 77 trials were removed, and two participants were excluded for noisy recording.

Potential smooth pursuit segments were first isolated as segments for which velocity was maintained below or equal to 30°/s for a minimum of 100ms. From this initial extraction, smooth pursuit segments were identified using a dispersion threshold, based on the following algorithm. A polynomial was fitted to the X and Y coordinates of the gaze samples in each smooth eye movement segment, after having removed outliers using the Corr v2 toolbox (Pernet, Wilcox, & Rousselet, 2013). The root-mean square error of the polynomial fit was then calculated and divided by the exponential of the arc length (calculated using the arclength toolbox, D'Errico,

2010) of the polynomial. A threshold was set at $1\text{x}10^{-9}$ and samples below that threshold were considered as smooth pursuit, while samples above were considered as part of a fixation. This algorithm is summarized in Figure 1.2 and the following equation:

$$P_{RMSE}/\exp(A)$$

P_{RMSE} is the root mean square error of the polynomial line, A is the arc length of the polynomial line.

Statistical analysis of eye movements

Gaze samples were analysed using gaze similarity matrices. Gaze similarity matrices were computed by creating smoothed (Gaussian kernel = 4° of visual angle) Z-scored maps of the gaze positions. The Fisher transformed correlations between the gaze map on a single trial and the gaze maps for all other trials were calculated (Figures 1.4A,B). The mean similarity between the gaze map on a single trial and all the other maps was then computed for each age group with the bootstrap confidence intervals (Figure 1.4C). Statistical maps were calculated using the iMap toolbox, version 4 (Lao, Miellet, Pernet, Sokhn, & Caldara, 2017). iMap computes pixel-wise linear mixed models (LMMs) across participants and trials on each z-score gaze map. The z-score gaze map is created by pooling together fixation, and smooth pursuit gaze positions. The gaze maps pool the gaze positions across the entire video duration. The gaze maps are then z-scored. After the pixel-wise LMM is computed iMap uses a universal bootstrap clustering test to resolve biases in parameter estimation and problems arising from multiple comparisons (Pernet, Chauveau, Gaspar, & Rousselet, 2011; Pernet, Latinus, Nichols, & Rousselet, 2015). The bootstrap clustering works in the following way. For each pixel in the image an LMM is computed with pixel intensity (combined gaze frequency and duration) as the response variable for each pixel in the gaze map to produce a statistical gaze map. IMap also computes the F and p values for each of the LMMs. The outputted statistical map is thresholded at $p < 0.05$. From the thresholded map iMap records the maximum cluster characteristic across all significant clusters in the statistic map. IMap then randomly shuffles the response variable and randomly draws with replacement new values for the response variable, the predictor variable, and the error. Another LMM is calculated and again the resulting statistic maps are thresholded and the maximum cluster characteristics are recorded. This process is repeated a large number of times to get a distribution of the cluster characteristic under the null hypothesis. The original statistic map calculated by iMap is then thresholded at $p<0.05$ and iMap compares the selected cluster characteristic with the value of the null distribution corresponding to the 95th percentile. Any cluster with the chosen cluster characteristic larger than this threshold is considered significant.

The linear mixed model used for iMap had the same fixed effects structure as the model used with the time to impact data. This model only included random intercepts for each participant and each video but no random slopes. This model started with random slopes for each fixed factor and interaction but did not converge. The same pruning procedure I used for the time to impact data was used for the iMap linear mixed model. The aim in using iMap was to determine where participants looked during the videos, how this changes depending on changes in the scene such as the presence of pedestrians or changes in traffic density, and how this changes across the lifespan.

1.3 Results

Executive functions

Older adults performed to the same level as younger adults on the MoCA ($t=0.11$, $df=34.10$, $p=0.985$, $d=0.02$, Bayes factor(BF)=0.26, Figure A.1A in Appendix B), BADS zoo map ($t=0.07$, $df=34.70$, $p=0.928$, $d=0.05$, BF=0.27, Figure A.1B), RMA local switch cost ($t=0.003$, $df=31.53$, $p=0.944$, $d=0.1$, BF=0.62, Figure A.1C), and RMA global switch cost ($t=0.18$, $df=28.84$, $p=0.062$, $d=0.54$, BF=2.91, Figure A.1D). In contrast, the overall latencies on the RMA were longer for older adults than younger adults ($t=3.84$, $df=22.14$, $p<0.05$, $d=0.88$, BF=4852.99 Figure A.1E).

1.3.1 Crossing decisions

To assess how risky or conservative the crossing strategies were, I measured the time to impact. In other words, I measured how long it would take for the moving vehicle to reach the participant (how far away the vehicle was) when the participant judged that crossing was no longer safe (released the crossing key). I then assessed how the time to impact was influenced by traffic density, distractors, age group, and executive functioning. Linear mixed model results showed a significant interaction between age group and traffic density on the time to impact of the car (β=61.29, SE=25.09, t=2.44, p=0.015, Figure 1.3D). The difference in time to impact between older adults and younger adults was larger for high traffic density. See Tables A.1-A.3 for full linear mixed model results. Across all traffic densities, older adults had larger time to impact than younger adults (bootstrapped t-test: t=10.18, df=852.91, p<0.05, d=0.35 Figure 1.3C), suggesting more conservative crossing strategies for older adults. This difference increased with increasing traffic density – one car on the road (t=-0.92, df=33.72, p=0.355, d=0.17, Figure 1.3D), four cars on the road (t=-4.24, df=203.69, p<0.05, d=0.29, Figure 1.3D), and seven cars on the road (t=-2.87, df=26.92. p<0.05, d=0.57, Figure 1.3D). In line with the results on time to impact, older adults decided to cross the road less often than younger adults (t=8.4971,df=2424.67,p<0.05, d=0.2, Figure 1.3A). The duration of the mean key presses per participant was not significantly different between age groups (t=0.97, df=2382.30, p=0.31, d=0.02, Figure 1.3B). This implies that on average younger adults decided to cross the road for a longer total time (number of crossing decisions x average key press duration), thus adopting a riskier crossing strategy. There was no effect of distractors or BADS scores on the time to impact and number of crossing decisions (See Appendix B).

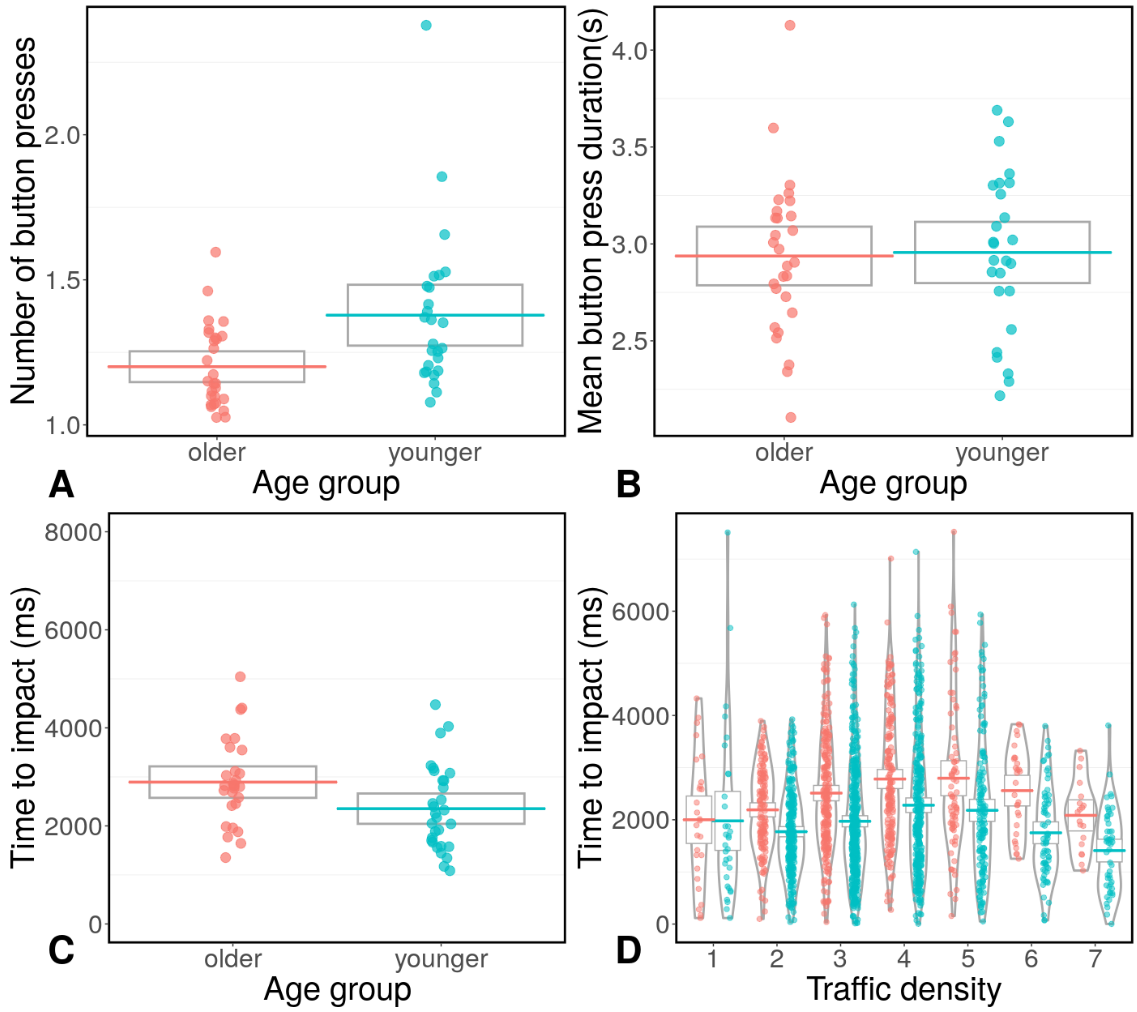


Figure 1.3: Crossing decisions for older adults and younger adults. (A) Mean number of crossing decisions. (B) Mean duration of button presses. (C) Mean time to impact, (D) time to impact at different traffic densities. In all panels, older adults are shown with red points and younger adults with blue points.

1.3.2 Eye movement results

Gaze similarity

I investigated the variability in gaze patterns across trials and age groups through gaze similarity matrices. Gaze similarity matrices are based on pairwise correlations between the trials' smoothed gaze maps. Thus, gaze similarity matrices reveal the consistency in gaze locations through the experiment (across trials). Figure 1.4C shows, for each of the 100 trials, the sorted average correlations between their gaze maps and the gaze maps generated by the other 99 trials. The shaded areas represent bootstrap confidence intervals across participants. Older adults and younger adults show similar levels of gaze variability across the experiment (Figures 1.4A,B) which is highlighted by the overlapping confidence intervals (Figure 1.4C).

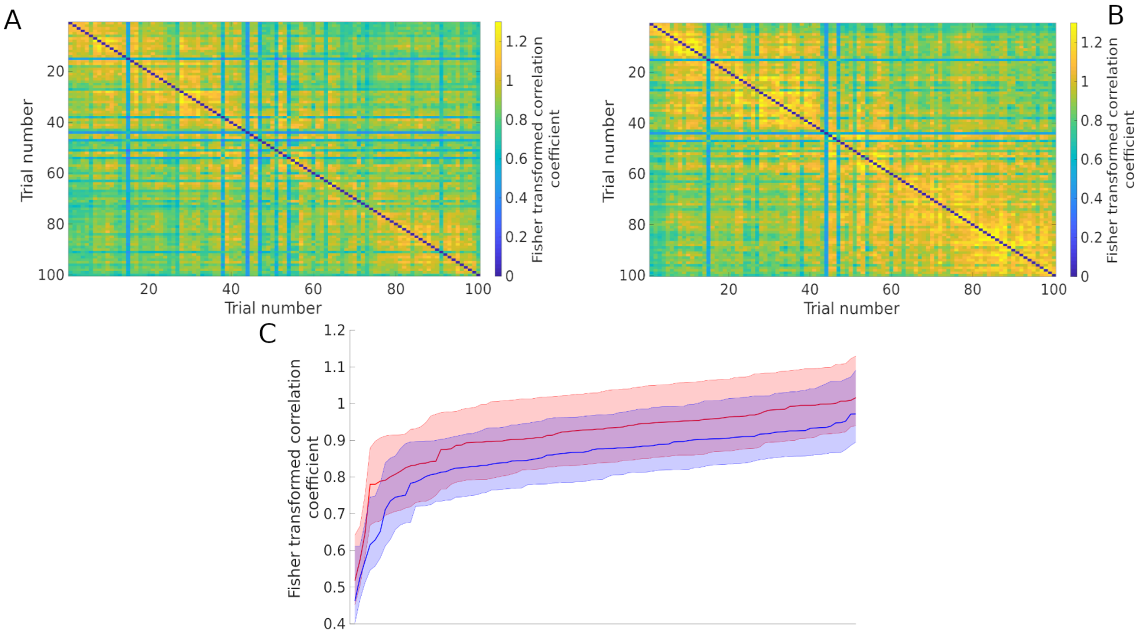


Figure 1.4: Gaze similarity matrices for younger adults (A) and older adults (B). Panel (C) shows the bootstrap means and confidence intervals for each group. Older adults are shown in red and younger adults are shown in blue

Statistical gaze maps

The iMap analysis with fixed effects of age, distractors, task difficulty, and BADS scores, showed that both older adults and younger adults looked mainly at the appearing point of the cars (Figure 1.5A,B). The appearing point might be the optimal viewing location for the task. However, younger adults explore the stimulus space slightly more than older adults (larger significant gaze area) pooled across time. As interactive effects are difficult to interpret in statistical maps, I tested the simple effects of distractors and traffic density for each age group. When pedestrian distractors were present in the scene, older adults' gaze was drawn to the sidewalk where pedestrians appear from (Figure 1.5C). Younger adults' gaze was not significantly impacted by the presence of distractors (Figure 1.5D). Older and younger adults' gaze was not significantly impacted by traffic density or their BADS zoo map scores.

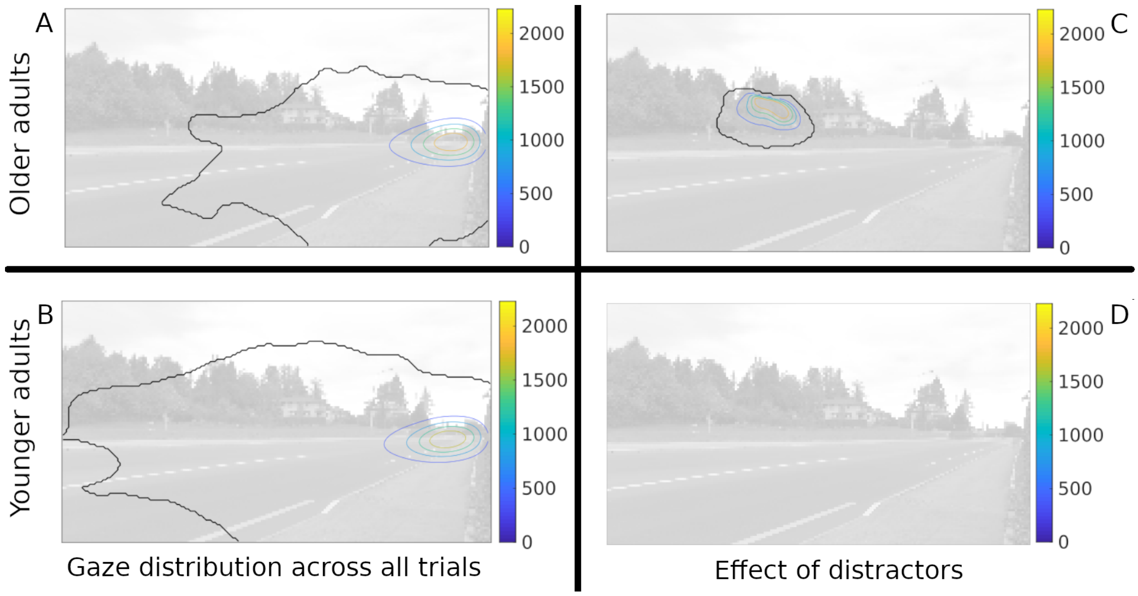


Figure 1.5: Statistical gaze maps. Gaze density contours are only plotted within significant areas. Black contour lines encircle significant areas. For all panels the larger the beta values and the brighter the contour lines the more participants gaze in those locations. The scales are determined by taking the maximum and minimum beta coefficient across all the statistical gaze maps for a particular LMM result. Beta maps for older adults (A) and younger adults (B). Beta maps for each age group were produced by running a one-sample t-test of the group gaze map against the mean gaze map for all trials and participants. The simple effect of distractors on older adults' (C) and younger adults' (D) gaze locations.

1.4 Discussion

I recorded eye movements of older adults and younger adults while they watched videos of road traffic and indicated when they could cross the road. I also measured some executive subcomponents to dissociate the impact of executive functioning from the impact of healthy ageing on visual exploration and crossing behaviour. In this study, the healthy older adults and the younger adults showed similar performance on our executive function measures (spatial planning and attention switching). Although the switching cost was similar for both age groups, older adults were generally slower than younger adults during the switching task. Eye movement data revealed that both older adults and younger adults look mainly at the appearing point of the cars. However, pedestrian distractors attracted older adults' overt attention, which was not the case for younger adults. Older adults typically made fewer and safer (larger time to impact) crossing decisions compared to the younger adults.

As mentioned in the introduction I recruited older adults from the Ageing and Dementia Research Centre participant pool and the local University of the 3rd age branch. These older adults tend to be very physically, and socially active, which can play a role in maintaining their executive function ability (Carlson et al., 2008; Ybarra et al., 2008). Indeed, I found that these older adults had similar executive function abilities to younger adults. As this older adult population showed no decline in executive function abilities this afforded us a rare opportunity to determine if ageing with maintained executive function impacted on visual exploration and road crossing behaviour.

1.4.1 Does ageing with maintained executive function abilities impact on crossing behaviour?

Older adults typically made fewer crossing decisions and had a larger time to impact than younger adults. This suggests that older adults show different crossing behaviour to younger adults. Although the crossing behaviour was different between the two age groups, for older adults this was a positive difference. Making fewer crossing decisions reduces the likelihood of an accident through exposure (Keall, 1995). A larger time to impact would allow participants longer to cross at a real road crossing. Longer times to cross would allow older adults to compensate for potentially slower walking speeds (Thomas et al., 2018; Bohannon, 1997) or reaction times as suggested by Lobjois and Cavallo (2007). Similarly, it is possible that the older adults in our study took into account their cognitive slowing when making crossing decisions. It has also been suggested that older adults can recruit additional neural resources in the frontal lobes in order to perform at the same level as younger adults, at least in simplistic scenarios like the one-way road in our experiment. However, on tasks that are more complex the resource ceiling is reached and older adults are no longer able to perform at the same level as younger adults (Reuter-Lorenz & Cappell, 2008). Therefore, it will be critical that future studies determine if compensatory strategies are still effective in more complex environments that are more taxing for older adults executive functioning.

Overall I find that so long as older adults are able to remain healthy and maintain their executive function abilities, they are able to make safe crossing decisions later in life.

1.4.2 Does ageing with maintained executive function abilities impact on visual exploration in a naturalistic dynamic scenario?

For both age groups, the appearing point of the vehicles was the preferred viewing location as overt visual attention was principally oriented towards it. This suggests that the appearing point is an optimal location to sample diagnostic information for the crossing task. Despite their good performance in the executive function tasks, the older adults overt attention was attracted by distractors, away from the otherwise preferred viewing location. younger adults did not show this attentional bias. This suggests that older adults were less able to inhibit attentional capture towards task-irrelevant distractors than younger adults, which is consistent with previous research (Olincy, Ross, Youngd, & Freedman, 1997; Crawford et al., 2013; Milham et al., 2002). The finding that for the most part older adults focus on the appearing point is consistent with a recent finding showing that older adults can modulate their attention in the same way as younger adults (Hilton, Miellet, Slattery, & Wiener, 2019).

Even though older adults' overt attention was captured by pedestrian distractors they were still able to make safe crossing decisions. Therefore, I cannot rule out an alternate explanation for the eye tracking results. As older adults made fewer crossing decisions and released the button earlier than younger adults they have more time to look at pedestrians in the scene. Therefore, older adults may voluntarily focus their overt attention on pedestrian distractors. To avoid missing new cars entering the road older adults might simultaneously employ their covert attention to attend to the appearing point. To determine whether older adults attention is captured by pedestrian distractors due to a decline in inhibitory control or whether older adults voluntarily gaze at pedestrian distractors and covertly attend to cars, the roles of covert and overt attention would need to be investigated. I intend to investigate the use of overt and covert attention in older adults and younger adults in road crossing situations. To this aim, I will use an approach that I recently developed and which is based on eye-tracking and Steady State Visual Evoked Potentials (de Lissa, Caldara, Nicholls, & Miellet, 2020). In this study, I showed that covert shifts of attention may reduce visual processing of objects even when they are directly tracked with the eyes.

Overall our results point towards providing support for the predictions made in the Inhbitory Control Deficit Theory, that participants' top-down inhibition over stimulus-driven attentional capture decreases with age. However, I cannot rule out the possibility that older adults voluntarily gaze at pedestrians.

1.4.3 Conclusion

In summary, while in this study older adults showed a general cognitive slowing and had their visual attention captured by distractors, they were able to make safe crossing decisions. This was achieved by adopting a conservative strategy of crossing less often and choosing larger crossing gaps (larger time to impact). This finding is important as it helps eliminate healthily ageing older adults as a group that requires intervention to improve the safety of their crossing behaviour on one-way roads. Therefore, training methods or infrastructure changes should be focused on assisting older adults that show declines in executive function to make safe crossing decisions on one-way roads.

In a more complex situation, such as a two-way street crossing, healthily ageing older adults may have more difficulties. It has been suggested that older adults can recruit additional neural resources in the frontal lobes in order to perform at the same level as younger adults. However, on tasks that are more complex the resource ceiling is reached and older adults are no longer able to perform at the same level as younger adults (Reuter-Lorenz & Cappell, 2008). Considering that the current study used an environment with a single lane of traffic, it will be critical that future studies determine if compensatory strategies are still effective in more complex environments that are more taxing on older adults executive functioning. Using virtual reality, I will systematically manipulate the number of driving directions and lanes in future studies in order to formally address this question and to explore how the situation complexity interacts with executive function to impact visual exploration, attentional control and decision making for pedestrians.

Appendix A

Supplementary materials for chapter 3

A.1 Supplementary Figures

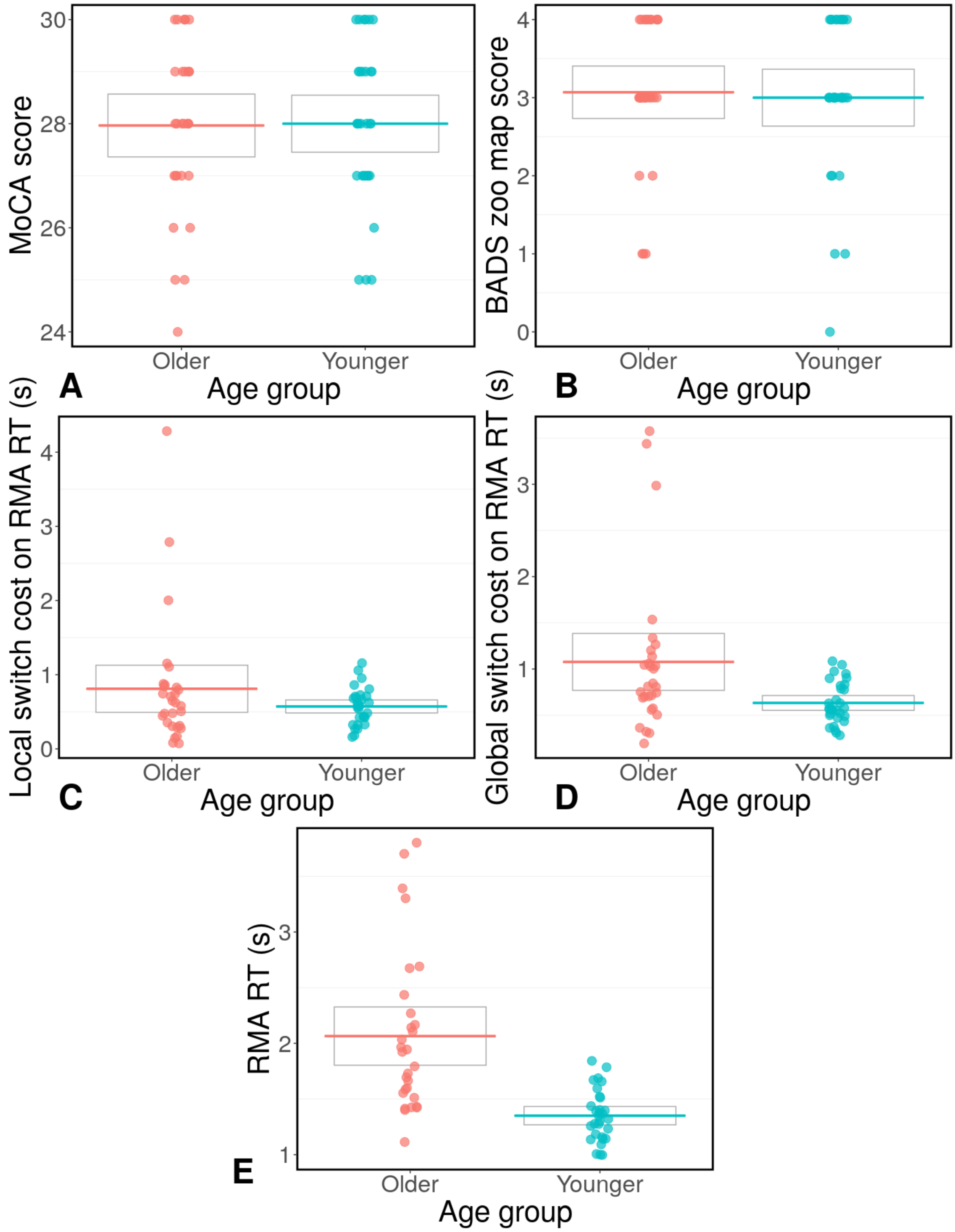


Figure A.1: Results for each executive function measure. (A) MoCA score. (B) BADS zoo map score. (C) Local switch cost on response time of RMA. (D) Global switch cost on response time of RMA. (E) Reaction times across all blocks of RMA. See Methods for how global and local switch costs were calculated.

A.2 Supplementary Tables

	β	*Standard Error*	*T-value*	*P-value*
Age group	442.47	267.76	1.65	0.103
Traffic Density	20.07	54.45	0.37	0.713
Pedestrian presence	-189.93	158.44	-1.20	0.234
BADS zoo map score	-92.85	158.18	-0.59	0.565
Age group * traffic density	61.29	25.09	2.44	0.015
Age group * pedestrian presence	-64.33	67.28	-0.96	0.339

Table A.1: Results from the linear mixed model on time to impact. Significant results are highlighted in blue. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Traffic Density	102.13	77.15	1.32	0.191
Pedestrian presence	-332.07	58.86	-1.51	0.137
BADS zoo map score	52.30	219.15	0.24	0.813

Table A.2: Results from the simple effects linear mixed model on time to impact for older adults. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Traffic Density	11.88	52.10	0.23	0.820
Pedestrian presence	-140.95	82.53	-0.93	0.357
BADS zoo map score	-241.19	177.33	-1.36	0.185

Table A.3: Results from the simple effects linear mixed model on time to impact for younger adults. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Age group	-0.13	0.08	-1.68	0.096
Traffic Density	0.001	0.02	0.08	0.938
Pedestrian presence	0.04	0.05	0.01	0.463
BADS zoo map score	0.01	0.04	0.28	0.781
Age group * traffic density	-0.01	0.01	-1.13	0.259
Age group * pedestrian presence	-0.05	0.03	-1.60	0.110

Table A.4: Results from the linear mixed model on number of crossing decisions. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Traffic Density	-0.02	0.02	-1.04	0.300
Pedestrian presence	0.006	0.05	0.12	0.907
BADS zoo map score	0.02	0.03	0.56	0.579

Table A.5: Results from the simple effects linear mixed model on number of crossing decisions for older adults. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Age group	-0.19	0.16	-1.25	0.215
Traffic Density	0.09	0.09	1.02	0.311
Pedestrian presence	-0.13	0.28	-0.46	0.648
BADS zoo map score	0.03	0.08	0.32	0.750
Age group * traffic density	-0.02	0.02	-0.76	0.446
Age group * pedestrian presence	0.04	0.06	0.71	0.477

Table A.6: Results from the linear mixed model on the duration of button presses. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Traffic Density	0.07	0.09	0.77	0.444
Pedestrian presence	-0.15	0.30	-0.52	0.605
BADS zoo map score	-0.03	0.11	-0.26	0.800

Table A.7: Results from the simple effects linear mixed model on the duration of button presses for older adults. See Methods for the model that was run.

	β	*Standard Error*	*T-value*	*P-value*
Traffic Density	0.09	0.09	1.02	0.312
Pedestrian presence	-0.11	0.29	-0.39	0.699
BADS zoo map score	0.11	0.12	0.88	0.387

Table A.8: Results from the simple effects linear mixed model on the duration of button presses for younger adults. See Methods for the model that was run.

A.3 Response to Examiners Comments

A.3.1 Response to external examiners comments

In general several of the comments from Chapter 2 apply here

I have applied the same changes made in response to the comments from Chapter 2, to Chapter 3. I have updated the description of the video task to match that in Chapter 2. I have added more information about the eye parser algorithm and iMap, and how to interpret the iMap results.

The F maps are not presented in the same way as in Chapter 2

Figure 1.5A and B are presented in the same way as for Figure **??** row B. The higher the numbers the more participants gaze in those locations for both beta coefficients and F values. The scale was determined by taking the maximum F value across all the statistical gaze maps for a particular LMM result. In all panels the black contour encircles areas of the video where participants look significantly. Figure 1.5 C is presented similarly to Figure **??** (j). However, instead of the interaction between age group and distractors it is the simple effect of distractors on older adults' gaze locations. I chose to present the simple effect rather than the interaction here as it is easier to interpret than the interaction. In Figure 1.5 D I wanted to highlight that distractors did not have a significant impact on gaze locations for younger adults, which is why the image shows no gaze data.

Moreover, the experiment in Chapter 3 was run two years after the experiment in Chapter 2. Visual representations produced with iMap, as is the case with SPM (fMRI), Fieldtrip (MEG) or EEGlab (EEG), might differ slightly between studies published several years apart. This is because these types of analyses are in constant development which allows them to be improved as soon as new statistical knowledge is produced.

Importantly, although the method suggests that older adult and younger adult have a similar spatial distribution, because it ignores time it could be that the two groups look at cars/people at a different time

As iMap pools the data over time older adults and younger adults could have looked at cars and people at different times. However, if younger adults looked at pedestrians as often as older adults, even at different times than older adults, then iMap would have shown a significant effect of distractors for younger adults. Our results do not show this therefore I can still conclude that younger adults do not look at distractors significantly often. In other words, as our conclusions are based on the differences in spatial gaze distributions, investigating the distributions at each time point should not change our conclusions compared to pooling gaze distributions across time. I have updated the text in the results and methods section of Chapter 3 to make it more explicit that the results show differences and similarities in spatial distributions but not over time.

Why was TTI investigated here but not in Chapter 2? This could be explained

The experiment in Chapter 3 was performed two years after the experiment in Chapter 2. Based on the results in Chapter 2 I noticed a need for a finer grained measure of road crossing. Therefore, I had not yet modified the automatic car detection algorithm to calculate time to impact before the experiment in Chapter 3. In Chapter 2 I wanted to have a simple measure of road crossing performance which would give me a baseline indication of crossing behaviour. I could then use this measure again in a follow up study, which I performed in Chapter 3 but in Chapter 3 I wanted to develop this measure further so I adapted the automatic car detection algorithm to calculate the time to impact.

It says here that the maps used a 4deg kernel which is different from in Chapter 2, why?

The gaze maps for older adults were noisier than for the participants in Chapter 2. I decided to increase the smoothing to reduce the impact of the noise. The choice of smoothing is a trade off between the spatial granularity of the analysis and robustness. Smoothing can reduce noise which helps to prevent false positives. This improves the robustness and statistical power of the analyses. However, too much smoothing would prevent the detection of subtle effects. As with neuroimaging techniques there is no standardised way to select the level or type of smoothing. This depends on scientific questions, preliminary results, expectations from literature, design, and the quality of the data. In Chapter 3, different age groups had different levels of noise in their oculomotor recordings, so I increased the smoothing to account for this. The question of the optimal smoothing is still debated in the literature (see Mikl et al., 2008) and is beyond the scope of this thesis.

A.3.2 Response to internal examiners comments

The number of abbreviations and their frequency of use is an undesirable feature of chapter 3

The number of abbreviations in the text have been reduced such that the only remaining abbreviations in Chapter 3 are: EU, UK, ANOVA, MoCA, BADS, RMA, and y/o.

In the BADS what happens if participants route in trial 1 meets the specified order required in trial 2?

If the participant's route on trial 1 of the BADS test matches the order required in trial 2, they will receive full marks for trial 1. There is only one solution to the zoo map test and if participants perform the test correctly their order on trial 1 will match that of trial 2. There is a loop section in the correct route of the zoo map test which participants could go round in a different order on trial 1 compared to trial 2, however, this would not alter their score. I have altered the paragraph starting "To assess the participants' executive functioning abilities" in the executive function tests subsection of the Methods for Chapter 2 to the following:

"To assess the participants' executive function abilities, participants completed the BADS zoo map test (Wilson et al., 1996), and the Rogers and Monsell attention shift paradigm (RMA; Rogers & Monsell, 1995). The BADS zoo map test assessed the participants' spatial planning ability by assessing participants' ability to plan a route around a zoo. In the first trial participants were given a map of a zoo and instructed to plan a route around a zoo, starting at the entrance and finishing with a picnic. Along the route participants had to visit specified locations in any order while following set rules, such as only using specific paths twice and not visiting unspecified locations. Participants' planning time and time to complete the task was recorded. In the second trial participants had to plan a route around the same zoo, following the same rules, and visiting the same locations but in a specified order. Again, the participants' planning time and time to complete the task was recorded. Participants were scored based on visiting the correct locations and points were deducted when participants broke the rules and exceed time limits for planning on the second trial. There was only one correct route on both trials, therefore, if participants do the task correctly their route for trial one will mostly match the route for trial two. The only exception being the order in which they go around a loop section of the map."

How many interactions were included in the models?

There were 2 interactions: age group * pedestrian presence, age group * traffic density. I have clarified this in the text by altering the paragraph starting "The crossing decisions were analysed using linear mixed models..." in the statistical analysis subsection of the Methods section of Chapter 3 to the following:

"The crossing decisions were analysed with linear mixed models with fixed effects of age group (above or below 60y/o), traffic density, distractors, and zoo map score. The model included two interactions one between age group and traffic density, and one between age group and distractors."

What is the logic of removing all random effect slopes rather than following a pruning procedure such as that described in the parsimonious mixed model paper (Bates et al. 2015)

I started with a maximal model as suggested by Barr et al. (2013), as this model did not converge I pruned the model by reducing the complexity of the random effects structure. I did not have a hypothesis of which fixed factor random slope was more important to take into account in the random effects structure, therefore I removed the slopes for all the factors.

Performing the pruning again using the pruning procedure suggested by (Bates et al., 2015) for the iMap model and the duration of button presses model, the most maximal model that converges is the model with all random slopes removed. For the model on the time to impact data and the number of crossing decisions was pruned to a model with only random slopes for the BADS zoo map test, as well as random intercepts for subject and item (video clip). The results remain the same but I have updated the text in the statistical analysis subsection of the methods for Chapter 3, the numbers in the Results section and Tables A.1, and A.4 in Appendix B.

I wonder again if older adults looking at distractors is impacted by their potential vulnerability. It may not be the case that other pedestrians are irrelevant to safe crossing decisions

Assessing the location of the other pedestrians is only important for when older adults are walking on the sidewalk, they do not provide any indication of whether it is safe to cross the road. Indeed, by attending to the pedestrians older adults would be unable to take in information about where the vehicles are on the road, preventing them from being able to make a safe crossing decision as they do not have the information required to do so.

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