Visual Attention Failures towards Vulnerable Road Users at Intersections: Results from On-road Studies

by

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Abstract

Crash data indicate that attention misallocation is a major factor in crashes with vulnerable road users (VRUs) at intersections. However, the extent that drivers fail to scan for VRUs at intersections is unknown. This thesis investigates driver visual attention failures toward VRUs at intersections using an instrumented vehicle and eye-tracking equipment. First, analysis of data collected in an earlier on-road study is presented, which informed the design of the main experiment where 26 drivers (ages 35-54; 13 cyclists) made 18 different turns at downtown Toronto intersections, half of which were identified to be higher risk. Almost half of the turns had a visual attention failure; and most were towards cyclists. The failures were significantly more common at higher risk intersections and among non-cyclist drivers. Overall, prevalence of failures is alarming. Further research is needed to generalize these findings. The thesis also provides an overview of the countermeasures on cyclist safety.

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Chapter 1

1 Introduction

Vulnerable road user (VRU) (e.g., pedestrians, cyclists) safety is a major public health concern. Given the minimal personal protection VRUs have, they are more likely to suffer major injuries and fatalities in a collision compared to vehicle occupants (Elvik, 2010; Institute for Road Safety Research, 2012). Further, although the total number of traffic fatalities has been declining over the past decade, VRU safety appears to be deteriorating. Pedestrian fatalities accounted for 16% (5,987) of the total 37,461 U.S. traffic fatalities recorded in 2016, compared to 11% (4,699) of the total 41,259 fatalities in 2007 (National Center for Statistics and Analysis, 2018b). A similar statistic was observed for cyclist fatalities in the U.S. between 2007 and 2016, where an increase from 1.7% (701) to 2.2% (840) was recorded (National Center for Statistics and Analysis, 2018a). A further look at VRU fatalities reveals that the majority of them take place in urban areas. In 2016, 76% of pedestrian (National Center for Statistics and Analysis, 2018b) and 71% of cyclist (National Center for Statistics and Analysis, 2018a) fatalities in the U.S. occurred in an urban setting. In metropolitan areas, most of the VRU fatalities and injuries appear to occur in the inner-city compared to suburban areas, such as for Toronto (Bassil, Rilkoff, Belmont, Banaszewska, & Campbell, 2015). This overrepresentation of city cores in VRU crashes can in part be explained by the shift towards alternative transportation modes in downtown areas, with a higher number of road users becoming increasingly willing to walk or cycle in these areas (City of Toronto, 2018; Toronto Public Health, 2012).

Intersections are of particular concern for VRU safety since VRUs are brought within close proximity of other road users at intersections (e.g. motor vehicles; Robertson, 2013). Fatalities at intersections constitute approximately 35% of U.S. VRU fatalities (National Center for Statistics and Analysis, 2018b, 2018a), and Toronto Public Health reported that between 2008 and 2012, 69% of motor vehicle collisions involving VRUs occurred at intersections (Bassil et al., 2015). An important contributor to VRU - motor vehicle collisions at intersections is turning. Between 2008 and 2012, 72% of pedestrian fatalities and injuries associated with motor vehicle collisions at Toronto intersections occurred when a motor vehicle turned as opposed to proceeding straight through an intersection (Bassil et al., 2015).

Although VRU behaviour can play a role in intersection collisions between VRUs and motor vehicles, driver error appears to play a larger role. Between 2008 and 2012, 90% of pedestrians in Toronto were identified as having the right of way when they were struck by a turning motor vehicle while crossing an intersection (Bassil et al., 2015). Canadian police-reports from 1999 to 2008 list "failing to yield the right-of-way" and "distraction and inattention" as the two most common driver errors leading to pedestrian crashes (Canadian Council of Motor Transport Administrators (CCMTA), 2013). An in-depth analysis from Finland found that cyclist-car collisions occurred most frequently when the driver was turning right; only 11% of these drivers noticed the cyclist before impact -- the drivers were identified to be misallocating their attention because they were mostly looking towards the left for vehicle traffic before making a turn (Räsänen & Summala, 1998). In comparison, 68% of the cyclists noticed the driver, and most of them believed that the driver would give way as required by law. Therefore, it appears that driver attentional failures toward VRUs play a significant role in motor vehicle crashes with VRUs.

The human brain can only process a limited amount of information at any given time (Broadbent, 1958). To accommodate this limited capacity, attention is needed to be allocated effectively so that information can be sorted, prioritized, and processed among a vast amount of incoming distracting stimuli (Carrasco, 2011). Humans primarily attend to objects in their environment by looking at them, and vision is one of the primary means of acquiring information for driving (Sivak, 1996). Although glancing at an area does not necessarily equate to visual attention and then to perception, there is a strong association between eye movements and visual attention and then perception (Corbetta et al., 1998; Itti & Koch, 2000; Theeuwes, Kramer, Hahn, & Irwin, 1998). While seeing requires looking directly at an area of interest so that the image falls directly on the fovea centralis (Nelson & Loftus, 1980), some peripheral processing is also possible. Research has shown that the useful field of view (UFOV) (i.e., area that information can be captured without eye movements) may go up to 30°. However, this is mostly for young-aged individuals (Ball, Beard, Roenker, Miller, & Griggs, 1988) and it does not guarantee detection of an object within this range. In this thesis, gaze direction captured by eye tracking is used as a proxy for visual attention; although it is noted that although a driver may be looking at an object, they may not be perceiving it, and they may perceive an object through peripheral vision even if their gaze does not fall directly on the object.

When maneuvering at intersections, drivers often experience increased visual and mental demands (Cantin, Lavallière, Simoneau, & Teasdale, 2009; Harbluk, Noy, Trbovich, & Eizenman, 2007; Teasdale, Cantin, Desroches, Blouin, & Simoneau, 2004) as they are required to divide their attention in several directions and toward a variety of road users (e.g., other vehicles, pedestrians, cyclists) and control devices (e.g., road signs, traffic signals). As a result, intersections, particularly those that handle large volumes of traffic, represent high-risk locations (Anne Harris et al., 2013; Bassil et al., 2015; Leden, 2002; Osama & Sayed, 2016) and require particular attention from the research community. Through naturalistic and on-road driving research, drivers' visual scanning behaviours have been examined while turning right at signalized-intersections (Wu & Xu, 2017) as well as maneuvering at T- (Angell, Aich, Antin, & Wotring, 2015) and rural cross-intersections (Bao & Boyle, 2009). It has been found that when oncoming vehicle traffic on the left increases, drivers glance more often and for longer towards the left to detect a gap that they can merge in; this results in drivers often failing to scan their right properly while making a turn (Angell et al., 2015; Bao & Boyle, 2009; Wu & Xu, 2017).

In particular to vehicle-VRU interactions, driver gaze patterns were investigated in Wu and Xu (2017)'s study on signalized right-turns, which considered the number of pedestrians on crosswalks and sidewalks near intersections, and Summala et al.'s (1996) study, which examined drivers' gaze behaviour when approaching two T-intersections with a cycle track. Camera data from outside (Summala et al., 1996) and inside (Wu & Xu, 2017) the vehicle showed that drivers' glances were often directed to areas with higher threat to their own safety (e.g., other vehicles), and it was argued that this strategy of allocating attention based on expectations might result in drivers ignoring minor threats (e.g., VRUs) to a certain degree. However, these studies have not specifically quantified the extent of attentional failures towards VRUs.

Infrastructure design can play a particularly significant role on the attentional demands placed on drivers while maneuvering an intersection. Two urban on-road studies investigated intersection-related driver errors (e.g., turning too fast) and their relation to driving experience and age; Young, Salmon, and Lenné (2013) recruited 9 novices and 16 experienced drivers, while Gstalter and Fastenmeier (2010) recruited 22 novices (ages 18 to 24), 20 experienced (ages 25 to 55) drivers, and 20 older experienced (older than 63) drivers. In the first study (Young, Salmon and Lenné, 2013), two in-vehicle observers manually recorded the errors made during the drive. As the primary purpose of this study was to identify whether driver errors occurred at intersections or on stretches of road between intersections, the pre-identified list of errors were based on items related to vehicle control (e.g., lane keeping) and overall driver performance (e.g., accelerating too fast) as opposed to attentional failures relevant to VRUs; these particular failures were not considered given the minimal interaction between drivers and VRUs during these road stretches. The observed errors drivers made were then further classified into five categories (i.e., action errors, cognitive/decision making errors, observation errors, information retrieval errors, and violations) as indicated by Stanton and Salmon's (2009) driver error taxonomy; this was accomplished by using additional sources of information, such as eye tracking data. It was found that intersections are a potential source of driver errors related to driver misjudgement, over-action, and mistimed behavioural responses. Young et al. (2013) also examined intersection complexity and how it relates to driver errors at intersections. They found that drivers were 96% less likely to exhibit intersection-related errors (e.g., blocking intersection) at intersections with dedicated signal phases for right turns when compared to partially signalized intersections. It was argued that increased visual demands at partially signalized intersections lead to drivers having conflicts with other road users (e.g., failing to observe a pedestrian on the right). However, this study has not distinguished overall errors from attentional failures pertinent to VRUs.

In a similar vein, Gstalter & Fastenmeier (2010) examined driver errors at intersections with three objectives: (1) defining correct behaviours for each manuevering task by following a previous framework (Fastenmeier & Gstalter, 2007), (2) translating the visual requirements of each maneuver into an error list, and (3) running an observational study to register the errors associated with these maneuvers and to develop a driver reliability index. Potential errors were identified as (1) various aberrant driver actions (e.g., speeding too fast), which were in part related to attentional failures, but were not clearly identified as observational failures, (2) low frequencies of checking particular areas of interest (i.e., close ahead, right, left, lateral (AOIs)), which were related to but were not quantified as attentional failures towards VRUs in the study (e.g., proportion of driver glances were translated into an error term), and (3) three specific errors related to VRU-driver interactions (i.e., too far into pedestrian/cycle crossing, impedes pedestrians, fails to give the right of way). The limitation with the three specific errors was that they were more related to violations and were also limited to the level of VRU traffic on the road. Although Gstalter and Fastenmeier (2010) considered driver gaze failures towards particular AOIs (e.g., low frequency of lateral checking), participant observation was limited to data obtained by means of vehicle-mounted video cameras and a human investigator in the car; no eye tracking software was used. Gstalter & Fastenmeier (2010) found that the overall number of driver errors were highest when performing left turns at stop-controlled T-intersections and while navigating a roundabout, as opposed to turning right, left or proceeding straight at a signalized cross-intersection. Further, the most prevalent error was found to be low frequency of checking rear, while low frequency of lateral checks (blind-spot check) was the second most prevalent; this was particularly evident when making a right turn at a signalized intersection. This finding is important as blind-spot checks are essential for acquiring relevant information on the position of VRUs. Due to the limited assessment techniques used in Gstalter & Fastenmeier (2010) (i.e., no eye tracker was used to determine the gaze position accurately), more specific areas of interest could not be determined and failures towards VRUs could not be distinguished from the ones towards other driving-related objects (e.g., other vehicles, road signs). Thus, this study can only surmise that low frequency of checking is prevalent and that this may pose a risk to VRU safety but cannot identify the extent of attentional failures towards VRUs. Therefore, there is a need for studies to examine driver visual attention failures particularly towards VRUs, by studying more specific areas of interest through eye tracking technology.

Prior experience and knowledge shape what people expect to see, and thus, what they look for (Neisser, 1976). A major individual factor impacting expectancy in driving is driving experience. There have been numerous studies examining how driving experience affects attention allocation

(Bjørnskau & Sagberg, 2005; He & Donmez, 2018; Mackenzie & Harris, 2017; Mayhew, Simpson, & Pak, 2003; Underwood, 2007); results indicate that with accumulated driving experience, individuals become increasingly accurate and quicker at identifying potential hazards (Crundall et al., 2012). Further, drivers familiar with the road environment may have stronger expectations about the area, which can lead to shorter glances to objects that contain information they already know (e.g., road signs) (Kircher & Ahlstrom, 2017; Martens & Fox, 2007). In line with this idea, experience with actively using other modes of transportation, such as riding a bicycle, might impact drivers' behavior and attention toward individuals who use these modes. Research to date has explored the differences between cyclists and non-cyclists through a self-reported online survey (Johnson, Oxley, Newstead, & Charlton, 2014), reviews of video clips (Beanland & Hansen, 2017; Lehtonen, Havia, Kovanen, Leminen, & Saure, 2016), and a simulator study (Robbins & Chapman, 2018). Cyclist-drivers were found to be more likely to report safe driving behaviours related to cycling-safety (e.g., over-the-shoulder check) as well as report positive attitudes towards cyclists than non-cyclist drivers (Johnson et al., 2014). Further, drivers that were frequent cyclists were significantly better at detecting potential hazards (Lehtonen et al., 2016) and faster at identifying changes in driving-related objects on the road (i.e., road sign, car, pedestrian, cyclist) compared to drivers that were novice cyclists (Beanland & Hansen, 2017). In relation to visual attention allocation, Robbins and Chapman (2018) compared cyclist (i.e., a driver who rides a bicycle frequently) and non-cyclist drivers (i.e., a driver who does not cycle frequently) in a simulator in terms of their gaze proportions towards oncoming targets from different distances (e.g., a cyclist on the road) - as a measure of how much visual attention was biased toward the target - while making several turns at road sign-controlled (i.e., either stop or yield) T-intersections. While participants' proportion of gaze toward the target cyclist was higher when the cyclist was approaching from nearby than from far, no significant difference between the two driver groups was found. Although simulators are useful tools to study driver behavior in general, they are arguably not the best way to study urban intersection maneuvers given issues in resolution and realism of the behavior of traffic agents. In general, there is a need for on-road studies to validate these survey, video review, and simulator findings on cycling experience in particular related to driver attention at intersections.

Another individual factor that may have an impact on whether drivers properly allocate their attention to VRUs at intersections is their general attentional abilities. Literature indicates that visual attention can be deployed in at least two forms, object-based (Scholl, 2001) and spatial-covert attention (Carrasco, 2011). Object-based visual attention refers to paying attention to specific objects based on their features (Scholl, 2001), whereas spatial-covert attention refers to attending to an area in the periphery without directly gazing toward it (Carrasco, 2011). These two forms of visual attentional ability are often examined through two types of computerized tasks: visual search tasks investigating object-based attention in the presence of distractor objects, and spatial cueing paradigms investigating spatial-covert attention to a certain location primed by a stimulus (McMains & Kastner, 2009). Employing such computerized attention tasks can be informative on scanning behaviour at intersections since drivers often orient their attention to a new location where salient or relevant information is located (Trick, Enns, Mills, & Vavrik, 2004). Given that tracking multiple driving-related targets in the presence of non-driving-related objects is an essential cognitive operation for drivers (Trick et al., 2004), studies have examined the link between measures of object-based visual attention and driving performance using a simulator (Mackenzie & Harris, 2017) and on-road driving test (Bowers et al., 2011). The Multiple Object Tracking (MOT) paradigm, a task assessing object-based attention, was found to be a significant predictor of driving performance (Bowers et al., 2011) compared to another computerized test UFOV (Ball et al., 1988) and appeared to have a stronger relation to more demanding settings such as urban environments compared to less demanding settings such as highways and rural environments (Mackenzie & Harris, 2017). Participants with poor attention performance in the MOT task received higher penalty ratings for their driving (Bowers et al., 2011; Mackenzie & Harris, 2017), and exhibited narrower lateral scanning (Mackenzie & Harris, 2017). However, relation between intersection-negotiation skills and general visual attention abilities hasn’t been studied.

Although crash data indicates that misallocation of attention is a major source of VRU crashes at intersections (Räsänen & Summala, 1998), to the best of our knowledge, no study to date has used an instrumented vehicle along with eye-tracking equipment to accurately assess where drivers are looking while turning at urban intersections. Video recordings from outside

(Summala et al., 1996) and inside (Angell et al., 2015) the vehicle indicate that drivers allocate their attention based on their expectations but the extent that drivers fail to properly scan for VRUs at intersections is not known. In addition, on-road studies (Gstalter & Fastenmeier, 2010; Young et al., 2013) have explored infrastructure-related components and their effect on overall driver errors . Although these studies address some driver scanning errors at urban intersections, they do not clearly examine driver attention failures towards VRUs. Further, individual factors such as cycling experience and general attentional skills have not been explored to understand driver attention allocation at intersections despite their relation to other aspects of driving behaviour (Beanland & Hansen, 2017; Bowers et al., 2011; Mackenzie & Harris, 2017).

1.1 Study Objectives

The main objective of this research was to assess the prevalence of drivers' visual attention failures toward VRUs at busy intersections. Another objective was to assess how these attentional failures are modulated by individual differences (e.g., cyclist status of driver, general attentional ability, and road design). Finally, a last objective was to review the literature to identify countermeasures that could help mitigate this issue.

First, an analysis was conducted on an existing on-road driving dataset (reported in **Chapter 2**). This dataset came from an instrumented vehicle study conducted in downtown Toronto to study the effects of parking search on the behavior, attention, and physiology of experienced drivers. The participants wore an eye-tracker as they drove through a pre-set route. This thesis utilized the gaze position data collected from 19 drivers as a proxy for visual attention and investigated how drivers allocated their visual attention while making turns at two intersections. A visual attention failure was defined to occur when a participant failed to gaze at a certain area of importance (e.g., bike lane on the right) with "enough" frequency; "enough" was subjectively determined based on traffic conditions and turn duration by independent coders. It was found that eleven of the 19 participants had a failure in at least one of the two intersections they turned; and all failures related to checking for cyclists. Further, at a marginally statistically significant level, it was found that participants who drove in downtown Toronto more frequently (i.e., a few times a week of more) were less cautious of VRUs than those who drove in downtown less frequently. This dataset also provided the opportunity to conduct analysis, and validation, on three intersection-related items of the Driver Behaviour Questionnaire (DBQ) (Parker, West, Stradling, & Manstead, 1995), a widely used tool to assess aberrant driving behaviors. Again, at a marginally significant level, it was found that those who had worse self-ratings were more likely to exhibit attentional failures towards VRUs at intersections. Although interesting insights were gained from this analysis, this on-road experiment was not originally designed to assess visual attention failures towards VRUs.

As discussed earlier, there might be other factors contributing to these failures such as cycling experience of the driver, type of intersection, and general attentional skills which had to be studied in a more controlled manner. A better understanding of the relations between visual attention failures, individual differences, and road design can inform the development of interventions to enhance VRU safety. With this motivation, another instrumented vehicle study was designed and conducted in downtown Toronto, ON with a focus to again examine the prevalence of visual attention failures towards VRUs at urban intersections (reported in **Chapter 3**), but also how individual differences and road design moderated it. Eye tracking data allowed for accurate assessment of the gaze position, again used as a proxy for visual attention. Three coders watched the recorded videos independently and evaluated if the drivers performed necessary checks for VRUs when they were performing 18 different turns total at 13 different intersections. The gaze requirements (e.g., frequency, gazing area) for “necessary checks” were subject to turn duration and traffic conditions, where absence of a necessary check towards a pre-determined area of importance during the entire turn was labelled as a failure with high criticality; if checks were performed with low frequency or were deemed late, the failure was categorized as low criticality.

Half of the intersections, at which the investigated turns were performed, were selected to have a *higher intersection risk* by following the pedestrian intersection safety index (Carter, Hunter, Zegeer, Stewart, & Huang, 2007), which uses number of lanes, control types, average speed, and traffic volume, but also by reviewing fatal crash records and on-street parking lane presence for each intersection. The analysis of the existing dataset (Chapter 2) revealed that the presence of an on-street parking lane separating cycle tracks from traffic up until an intersection created higher attentional demands on drivers at intersections. Parked cars blocked drivers' ability to see cyclists as they approached an intersection, necessitating an over-the-shoulder check before a right turn. Therefore, the presence of such parking lanes was considered in labeling intersection risk.

Half of the participants were selected to use a bike themselves (i.e., at least a *few days a month*) as a transportation tool, whereas the other half did not cycle (i.e., responded *never* for transportation purposes and at most *a few times or less over the year* for recreational purposes). To further understand why certain individuals may be more likely to exhibit failures towards VRUs, we collected data on drivers' general attention abilities through two computerized laboratory tasks, Multiple Object Tracking (Pylyshyn & Storm, 1988) and the Posner's cue-target (Posner, 1980) paradigms. Participants also self-reported their overall awareness on their aberrant driving behaviours, everyday absent-mindedness, attention-related driving failures, and sensation seeking through four questionnaires; DBQ - Driver Behaviour Questionnaire (Parker et al., 1995) (Appendix A), CFQ - Cognitive Failures Questionnaire (Broadbent, Cooper, FitzGerald, & Parkes, 1982) (Appendix B), AFDQ - Attentional Failures during Driving Questionnaire (Choi & Feng, 2014) (Appendix C), and Arnett Inventory of Sensation Seeking Scale (Arnett, 1994) (Appendix D).

The results showed again that attentional failures towards VRUs was high; almost half of the turns (42%, n=186) were labeled as a failure where 63% (n=117) of these failures were with high criticality, meaning the participant failed to gaze at a certain area of importance (e.g., bike lane on the right) during the entire turn. Further, the failures were significantly more common at higher risk intersections and among non-cyclist drivers. Relation to general attentional abilities (lab task scores) and self-reported driving behaviour (i.e., DBQ and AFDQ) was found to be significant at a marginal level. Again, the failures identified in this study, similar to the analysis on the existing dataset, were predominantly related to checking for cyclists. Thus, a literature review was conducted on implemented and/or proposed interventions to support detection of cyclists by drivers but also in for general cyclist safety (reported in **Chapter 4**).

Chapter 2

2 Preliminary Analysis on Existing On-road Data

To explore driver visual attention failures toward VRUs at intersections, a preliminary analysis was conducted on an existing on-road dataset. This dataset came from another instrumented vehicle study focusing on urban driving demands (i.e., search for on-street parking) where participants were instructed to drive a pre-set route in downtown Toronto, ON, while wearing a head-mounted eye-tracker. More details on this particular experiment can be found in Ponnambalam, Cheng, & Donmez (2018) and Ponnambalam (2018).

Eye-tracking data was analyzed from 19 drivers between the ages of 35 and 54 who participated in this on-road instrumented vehicle study. Each participant made two right turns from a major arterial road. In addition to attention allocation failures, we assessed whether the objective data was correlated with experience driving in the area as well as with drivers' subjective responses about their intersection-related errors collected through the Driver Behaviour Questionnaire (DBQ) (Parker et al., 1995), a widely used questionnaire for assessing self-reported aberrant drivers behaviours. The methods and results are presented in this chapter. It was found that 11 of the 19 participants had a failure in at least one of the intersections; all failures related to checking for cyclists. At a marginally statistically significant level, attentional failures were more likely for those who drove more frequently in downtown Toronto and for those who had larger error scores on intersection-related questions of DBQ.

The findings of this analysis have been reported in a conference proceeding article (Kaya, Ayas, Ponnambalam, & Donmez, 2018):

> **Kaya, N. E.**, Ayas, S., Ponnambalam C. T., & Donmez, B. (2018). Visual attention failures during turns at intersections: An on-road study. *In Proceedings of the 28th Canadian Association of Road Safety Professionals Conference,* Victoria, BC.

Although this instrumented vehicle study was not designed for assessing visual attention failures, this exploratory work formed the basis for a more comprehensive investigation which is discussed in detail in Chapter 3.

2.1 Methodology

In this instrumented vehicle study, each participant drove through the same pre-determined routes in downtown Toronto following turn-by-turn directions provided by the experimenter. This exploratory analysis focuses only on two right turning events performed by each participant without any additional experimental tasks (e.g., searching for parking). The experiment was approved by the University of Toronto Research Ethics Board (Protocol ID 32795).

2.1.1 Participants

Participants were recruited mainly through notices posted on online public forums. Due to insurance constraints, they were required to be between 35-54 years old and to have held a full driver's license for over 3 years. Thus, they represent a fairly low crash-risk age group (Cooper, 1990; McGwin, Jr & Brown, 1999). In addition, participants were required to drive without glasses to improve eye tracking accuracy; contact lenses were allowed. In this analysis, we report data from 19 participants (9 males, 10 females), who had a complete dataset (several participants' eye-tracking data were lost due to equipment failures). Participants' mean age was 42 (SD = 5.9, Min = 36, Max = 54) and they self-reported to be safe drivers with an average response of 8.7 (SD=1.06) on a scale of 1 (very unsafe) to 10 (very safe). While all participants self-reported to be a frequent driver (i.e., drive at least a few times a week), nine out of the 19 participants also self-reported to drive at least a few times a week in downtown Toronto. The experiment took approximately 3 hours and participants were reimbursed at a rate of C$15/hr.

2.1.2 Apparatus

The instrumented vehicle was a 2014 Toyota RAV4. A vehicle-mounted camera recorded the front view of the vehicle, and a Dikablis Eye Tracker by Ergoneers was used to collect gaze location data at 50 Hz (Figure 1). With this eye tracking system, the gaze position is calculated automatically using two cameras pointed at the pupils, then overlaid on video captured by the front-facing camera of the eye tracker. Although electrocardiogram and galvanic skin response sensors were also utilized, only data collected by the eye-tracking system was considered in the current analysis. The D-Lab software by Ergoneers was used to collect and sync data from all devices. A computer and display in the back seat allowed for real-time monitoring of data collected. The apparatus used for this study was the same as the one used for the follow-up experiment presented in Chapter 3. However, electrocardiogram and galvanic skin response sensors were not utilized in the follow up experiment and a more advanced version of the eye tracker was used (that is lighter, less intrusive, and collects data at 60 Hz).

Figure 1 Driver outfitted with the previous model eye tracker

2.1.3 Procedure

Experiments began only on weekends at either 10:30 AM or 1:30 PM, in order to maintain experimental control for density of traffic and parked cars, and to avoid interruptions by roadwork or delivery/garbage trucks. The study ran from July to October 2017, mostly on dry days but with one participant experiencing light rain during the experiment. Before driving the vehicle, participants completed a set of questionnaires including one on demographics, general driving history, and experience driving in downtown Toronto. They also completed the U.S. version of the Driver Behaviour Questionnaire (DBQ) (Reimer et al., 2005), which consists of 24 questions asking participants how often they exhibit certain driving behaviours. The responses are collected on a six-point scale ranging from “never” (coded as 0 for analysis) to “nearly all the time” (coded as 5).

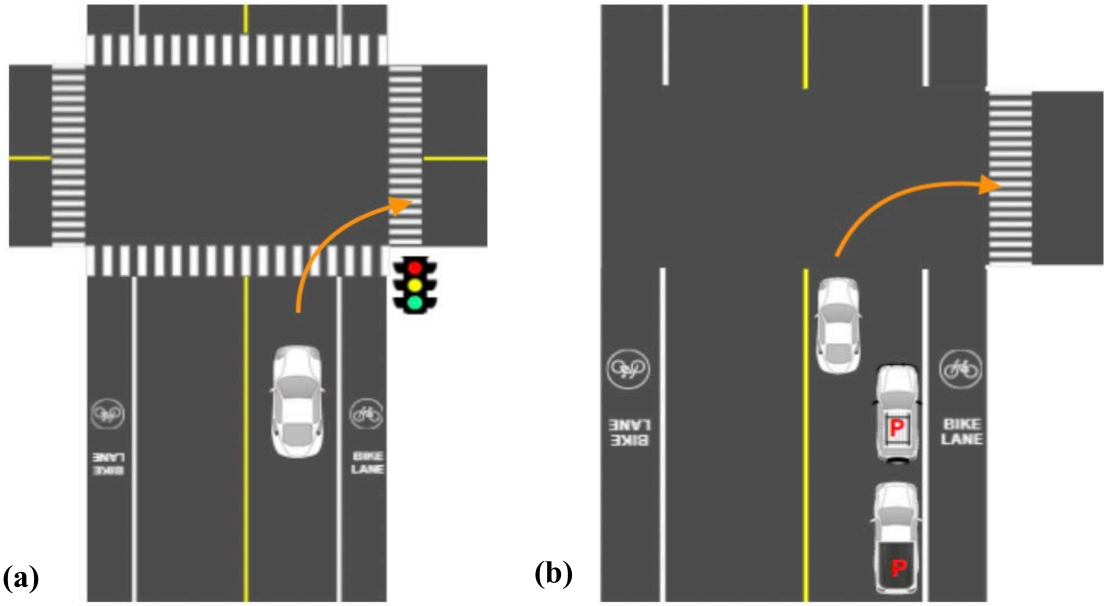
Parker et al. (1995) introduced three categories of behaviours within the context of the Driver Behaviour Questionnaire (DBQ) (J. Reason, Manstead, Stradling, Baxter, & Campbell, 1990): lapses, errors, and violations. Lapses are attention and memory failures that are unlikely to have an impact on safety (e.g., missing an exit). Errors are failures of planned actions that can result in safety consequences (e.g., failure to notice pedestrian when turning). Violations are deliberate deviations from practices that are believed necessary for safety (e.g., speeding). Based on the literature, it appears that driver actions most relevant to VRU crashes fall under the error category within this taxonomy. Canadian police-reports from 1999 to 2008 list “failing to yield the right-of-way” and “distraction and inattention” as the top two most common driver errors leading to pedestrian crashes (Canadian Council of Motor Transport Administrators (CCMTA), 2013), and Räsänen & Summala (1998) found “misallocation of attention such that others are not detected” to be a common mechanism underlying motor vehicle and cyclist crashes.

In fact, the two VRU related items of the DBQ are also grouped under the error category (Reimer et al., 2005): (1) fail to notice pedestrians crossing when turning onto a side street, and (2) when making a right turn, you almost hit a cyclist or pedestrian who has come up on your right side. Both items are also related to making turns at an intersection. The DBQ has one more error item that is related to making turns at an intersection: (3) when preparing to turn from a side road onto a main road, you pay too much attention to the traffic on the main road so that you nearly hit the car in front of you. Thus, these three questions were used in the analysis as intersection-related items.

After filling out this questionnaire, participants were asked to drive in a mixed retail/residential area of downtown Toronto (see Figure 2) with the head investigator seated in the passenger seat and another researcher in the back operating the computer and monitoring data collection, and they were instructed to “keep talking to a minimum unless necessary”. Participants first completed a 5 to 10-minute familiarity drive to get accustomed to the instrumented vehicle and its controls. After, participants were equipped with the head-mounted eye tracking device, as well as the ECG and GSR sensors. Following the initial set-up, participants drove through the designated routes, where, among other tasks, they were asked to make a right turn at two intersections (details provided in the following section). Their total driving time after the practice drive was approximately 35 minutes.

2.1.4 Analyzed Intersections

The same major arterial road (Bloor St.) was used for both turns: the first turn was toward a collector road (Palmerston Ave.) on a signalized 4-way cross intersection, and the second was toward a local road (Major St.) on a non-signalized T-intersection (Figure 2). Bloor St., the major arterial road, has a single lane in each direction separated by a yellow line, with a semi-protected bike lane. It also contains a street parking lane on the right side, when approaching the second turn, separating the bike lane from vehicle traffic; 10 m before the intersection the bike lane and vehicle traffic are separated by a traversable median and a bollard. There are no dedicated bike lanes on the collector and local roads.

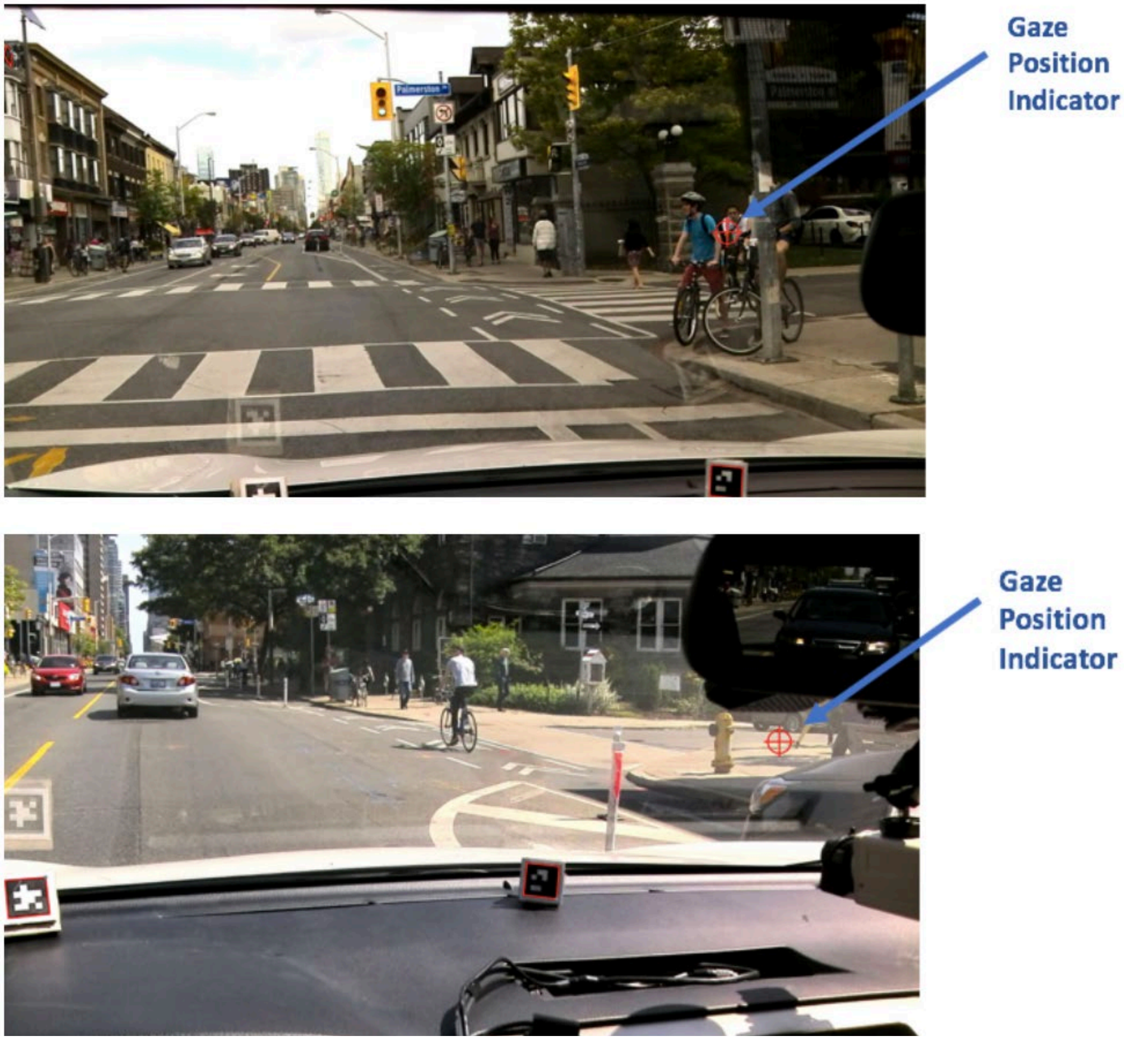


(a) (b)

Figure 2 Analyzed intersections: (a) Turn 1: a right turn at a signalized 4-way cross intersection. (b) Turn 2: a right turn at an uncontrolled T-intersection. Both turns have a semi-protected bike lane on the right. Turn 2 also has on-street parking lane ending 10 meters before the intersection, parked cars denoted with red "P".

2.1.5 Visual Attention Failure Coding

As mentioned previously, the gaze position data calculated by the eye-tracking system was overlaid automatically on video captured by the front-facing camera of the eye tracker. Figure 3 provides example snapshots of the video data recorded by the eye tracking system. The red crosshairs indicate gaze position. Eye-tracking videos along with the videos captured through the stationary dashboard-mounted camera (Figure 4) were used in determining whether the participants had visual attention allocation failures during a turn.



(a)

(b)

Figure 3 The two intersections where the drivers made right turns. The snapshots were taken from the video data of the eye tracker, where the red crosshair indicates gaze position. (a) Turn 1: toward a collector road (right turn from Bloor St. to Palmerston Ave.). (b) Turn 2: toward a local road (right turn from Bloor St. to Major St.).

A turn was defined to start when the stop line of the intersection was at the bottom of the windshield in the dashboard-mounted camera view; the turn ended when the stop line of the target road disappeared from the same camera view (Figure 4). Given that drivers start preparing for a turn before they arrive at an intersection, we coded whether our participants had attentional failures starting from 15 seconds prior to the beginning of the turn. We ended the coding at the end of the turn. Three coders watched the videos independently and identified if the drivers performed necessary checks for VRUs. A visual attention failure was defined to occur when a participant failed to gaze at a certain area of importance (e.g., bike lane on the right) with enough frequency ("enough" subjectively determined based on traffic conditions and duration of a turn). To assess drivers' attention to cyclists, the coders looked for failures to check the bike lane on the right through over-the-shoulder and/or mirror checks, and for failures to check for potential bikes coming from the left (on the collector road with no dedicated bike lane). Participants were not expected to perform an over-the-shoulder check for cyclists in all circumstances. For example, when the street parking lane was empty on the second turn, participants could properly see the dedicated bike lane through their right mirror. However, when there were parked cars, an over-the-shoulder check had to be performed for this turn. To assess attention to pedestrians, the coders looked for failures to check the sidewalks and crosswalks. The overall agreement between the three coders was 85%. Given that coders had to make a decision for each turn, the fixed-marginal kappa was calculated to assess interrater reliability (Chen, Zaebst, & Seel, 2005). Kappa was calculated to be 0.67, considered to represent a substantial level of agreement (Landis & Koch, 1977). After independently coding the videos, the coders discussed their ratings in person and came to a consensus on whether there was a failure or not for each turn.

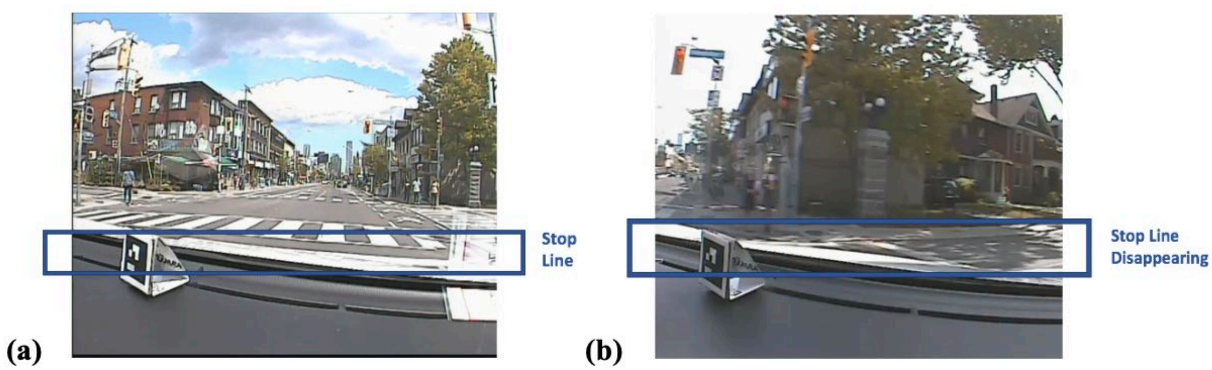


Figure 4 Example snapshot of the video data recorded by the dashboard-mounted camera for Turn 1. (a) Start of a turn: Stop line approaching the intersection is visible at the bottom of the windshield. (b) End of a turn: Stop line of the target road about to disappear from camera vision.

2.2 Results

2.2.1 Driver Behaviour Questionnaire (DBQ): 3-Intersection Related Error Items

As mentioned earlier, participants completed the DBQ (Reimer et al., 2005) before they started driving; and their responses were collected on a six-point scale ranging from “never” (coded as 0 for analysis) to “nearly all the time” (coded as 5). Overall, participants had an average lapse score of 0.92 (SD=0.42), error score of 0.88 (SD=0.42), and violation score of 1.07 (SD=0.46). These statistics were in line with the findings of (Reimer et al., 2005) that were obtained on a sample with an age range comparable to our sample. The three error items related to attentional failures during turns at intersections are presented in Table 1. For rest of the DBQ questions, the reader is referred to (Reimer et al., 2005). Overall, participants reported exhibiting these intersection-related failures either "never" (coded as 0), "hardly ever" (coded as 1), or "occasionally" (coded as 2). As shown in Table 1, the average scores fell between “never” and “hardly ever”, again in line with the findings of (Reimer et al., 2005).

Table 1 DBQ scores on intersection-related error items

DBQ items on intersection-related errors	Average	SD
Question: How often do you do each of the following?		
(1) fail to notice pedestrians crossing when turning onto a side street	0.89	0.57
(2) when making a right turn, you almost hit a cyclist or pedestrian who has come up on your right side.	0.74	0.65
(3) when preparing to turn from a side road onto a main road, you pay too much attention to the traffic on the main road so that you nearly hit the car in front of you.	0.74	0.65

2.2.2 Visual Attention Failures toward VRUs

Out of the 19 participants, six were found to exhibit an attentional failure during Turn 1 (signalized 4-way cross intersection), whereas this number increased to 10 participants for the second turn (uncontrolled T-intersection). Overall, five of the participants failed in both turns, 6 failed in one of the turns (5 failed in Turn 2), and 8 did not fail in either turn. All failures were related to checking for cyclists. In Turn 1, four out of the six failures were due to participants entirely failing to check the dedicated bike lane on the right side. Two had made a check but not frequent enough for the duration of their turn and the level of traffic. As mentioned earlier, in Turn 2, the on-street parking lane was separating the bike lane from vehicle traffic. When the parking lane was occupied, participants had to do an over-the-shoulder check to be able to see the cyclists behind as they could not see the cyclists as they approached the intersection with parked cars blocking their view For 7 of the 10 failures recorded for this turn, participants checked their right mirror but failed to perform an over-the-shoulder check once they cleared the parked cars. Two participants failed entirely to check the dedicated bike lane and one participant was too late in the turn when they made a check.

The likelihood of exhibiting an attentional failure was investigated through an ordered logit model. The outcome variable was the number of turns where a failure was observed for a participant (*no failure* (0), *failure at one turn* (1) and *failure at both turns* (2)). The predictor variables were DBQ score on intersection-related errors (lower versus higher; Table 2) and frequency of driving in downtown Toronto (frequent versus non-frequent; Table 3). We did not have enough statistical power to assess interaction effects. Both DBQ score and frequency of driving in downtown Toronto were grouped into two categories based on the distribution of the data. Drivers who had an average score of 1 or more (in the three DBQ items related to intersection errors) were categorized into the higher error score group (n=10), the rest were categorized into the lower error score group (n=9). As for frequency of driving in downtown Toronto, drivers who reported to driving a few times a week or more in downtown Toronto were categorized to be frequent downtown Toronto drivers (n=9), the rest (i.e., “a few days a month” and “a few days a year”) were categorized to be non-frequent downtown Toronto drivers (n=10). No multicollinearity was found between these two predictor variables (Table 4) based on a Fisher’s exact test, $\chi^2(1) = 1.35$, $p = .37$.

Table 2 Number of participants by level of visual attention failures (outcome) and DBQ intersection-related error score groups (predictor 1)

	DBQ intersection-related error score		*Total # of participants*
Visual attention failures	Higher Error	Lower Error	
No failure	2	6	8
Failure at one turn	4	2	6
Failure at both turns	4	1	5
Total # of participants	10	9	19

Table 3 Number of participants by levels of visual attention failures (outcome) and the frequency of driving in downtown Toronto (predictor 2)

	Downtown Toronto driving		*Total # of participants*
Visual attention failures	Frequent	Non-Frequent	
No failure	1	7	8
Failure at one turn	5	1	6
Failure at both turns	3	2	5
Total # of participants	9	10	19

Table 4 Number of participants by levels of downtown Toronto driving (predictor 1) and DBQ intersection-related error score groups (predictor 2)

	DBQ intersection-related error score		*Total # of participants*
Downtown Toronto driving	Higher Error	Lower Error	
Frequent	6	3	9
Non-Frequent	4	6	10
Total # of participants	10	9	19

The statistical model was built in SAS University Edition using the GENMOD procedure with the cumulative logit link function and the multinomial distribution specifications. Both DBQ error scores and downtown Toronto driving frequency were found to be significant at a marginal level. Higher intersection-related DBQ error scores were associated with an increase in the likelihood of attentional failures, Odds Ratio (OR) = 6.04, 95% Confidence Interval (95% CI) = 0.84, 43.73, p=.07. Further, the likelihood of attentional failures was higher for those who drive at least a few times a week in downtown Toronto compared to those who drive a few times a month or less, OR = 6.04, 95% CI = 0.84, 43.73, p=.07.

2.3 Discussion

In an instrumented vehicle study conducted in downtown Toronto, ON, we examined drivers' attention allocation failures regarding checks for vulnerable road users while they made right turns at intersections. The focus was on high traffic areas. The two right turns that were investigated were on a busy major arterial, i.e., Bloor Street, which carries approximately 24,000 motor vehicles and 3,300 cyclists per day (City of Toronto, 2018). This analysis is the first to utilize eye-tracking to investigate the extent that drivers fail to properly scan for VRUs at urban intersections. Glance data collected via an eye tracker from 19 drivers, aged 35 and 54, were analysed. Eleven participants (58%) had an attentional failure in at least one of the turns (5 in both turns; 6 in one turn). The prevalence of failures observed in our study is concerning especially given that our participants represented a fairly low crash-risk age group (Cooper, 1990; McGwin, Jr & Brown, 1999). Our results also provided evidence for attention misallocation and expectation misplacement at intersections such that areas for VRU traffic are not always properly scanned (Angell et al., 2015; Räsänen & Summala, 1998; Summala, Pasanen, et al., 1996; Wu & Xu, 2017). In addition to attention allocation failures, we assessed whether the objective data we collected was correlated with self-reported driving experience in downtown as well as with drivers' subjective responses about their intersection-related errors collected through the DBQ (Reimer et al., 2005). At a marginally significant level, attentional failures were more likely for those who drove more frequently in downtown Toronto and for those who had larger error scores on intersection-related questions of the DBQ.

All failures we identified were related to checking for cyclists. It appeared that participants were better at attending to areas of importance for pedestrians (i.e., crosswalks and sidewalks) than they were to areas of importance for cyclists (i.e., bike lane). One potential reason is the difference in effort: It is more effortful for drivers to check for cyclists given that over-the-shoulder-checks require head movements (Lavallière, Laurendeau, Simoneau, & Teasdale, 2011). Another reason is the difference in how long a VRU stays within the drivers' field of view: In mixed traffic intersections, where there are pedestrians and cyclists, pedestrians are in the drivers' view for longer durations of time and hence drivers' attention may be captured by pedestrians more than cyclists. We have observed this phenomenon in our data; when a pedestrian was detected, participants tended to follow the pedestrian's movement, allocating most of their attention to the areas of importance for pedestrians. Further, although we did not observe any failures of attention toward pedestrians, it should be noted that we defined a failure of attention as not looking toward an area of importance. Directing gaze toward a location is a pre-requisite for perception but it does not guarantee perception (Dewar & Olson, 2015). Thus, even when the drivers were scanning areas of importance for pedestrian traffic, there is a chance that they may not have been noticing pedestrians.

As for the two intersections used in data collection, we found more failures on the turn toward the local road (Turn 2) than the one toward the collector road (Turn 1). There were many infrastructure differences between the two intersections (e.g., signalized 4-way cross vs. non-signalized T); however, it appeared that the major driving factor for the difference in failures observed was the on-street parking lane that separated the bike lane from vehicle traffic leading up to the intersection (the parking lane ended 10 m before the intersection). In Turn 2, when the parking lane was occupied, the parked vehicles blocked drivers' view of the cyclists as the drivers approached the intersection, necessitating an over-the-shoulder check after the parking lane ended to properly scan for cyclist traffic. The effects of different structural elements should be examined further in future research. For example, there are differences in the prevalence of crashes at intersections with different traffic control devices: Among the intersection or intersection-related crashes recorded in the U.S. in 2015, 26% had no traffic control device, 54% had a traffic signal, and 14% had a stop sign (National Highway Traffic Safety, 2015). An on-road study with a higher level of experimental control can tease apart the effects of these different control devices on drivers' attention allocation at intersections.

Both intersections utilized in data collection were on the same major arterial road (Bloor Street), which had a dedicated bike lane surrounding these intersections. The dedicated bike lane was introduced in May 2016, thus some of the participants may not have been as familiar with the new design as others. However, we found that, at a statistically marginally significant level, those who drove in downtown Toronto more frequently (i.e., a few times a week of more) had more attentional failures than those who drove in downtown less frequently. Thus, drivers who drove in the area less often appeared to be more cautious of vulnerable road users. Less familiarity seems to have created a positive effect here. It should be noted that the question utilized for assessing familiarity asked about driving in downtown Toronto, but not specifically about the area that the experiment took place. This limitation was addressed in the follow-up experiment.

Another point of interest for the study was to assess the relation between attentional failures observed on the road and participants' subjective responses on intersection-related error items of the DBQ (Reimer et al., 2005). The DBQ is widely used in driving research to assess aberrant driving behaviours and has been validated using self-reported crash data (De Winter & Dodou, 2010; Donmez, Mehler, Lee, Mehler, & Reimer, 2017) as well as on-road studies (Amado, Arikan, Kaça, Koyuncu, & Turkan, 2014; Zhao et al., 2012). However, to the best of our knowledge, no study to date focused on the validity of the intersection-related error items of the DBQ. In their validation, Zhao et al. (2012) collected on-road data on a highway and Amado et al. (2014) excluded DBQ items related to VRUs. Our statistical model showed that, at a marginally significant level, drivers who self-reported making more intersection-related errors did have more attentional failures. Thus, our data provides support to the validity of the intersection-related error items of the DBQ in an urban setting. However, we only had marginal statistical significance likely due to our relatively small sample size.

In general, sample size is a limitation of our study. Collecting on-road data is costly and time intensive, and on-road studies lack the level of experimental control that can be introduced in a simulator thus requiring even larger sample sizes. There were variations in signal status and traffic flow that likely introduced variability to drivers' behaviours. However, compared to a simulator study, our study has a higher level of ecological validity. Still, it was an experiment with two researchers present in the vehicle, which may have also influenced the drivers' behaviours. Although the participants were instructed to keep talking to a minimum, the mere fact that they were being observed could have affected their behaviour (Hansson & Wigblad, 2006). Further, our participants were between the ages of 35 and 54 and were not novice drivers.

Most importantly, this particular on-road study was not specifically designed for visual attention failures toward VRUs at urban intersections. A follow-up study was designed and conducted for this particular objective with a larger sample size and a focus on different intersection types.

Chapter 3

3 Instrumented Vehicle Study

To further investigate driver visual attention failures toward VRUs at intersections, a new instrumented vehicle study was designed in which half of the participants were recruited from those drivers who cycle. Twenty-six experienced drivers (aged 35 to 54; 13 cyclists and 13 non-cyclists) drove a pre-determined route in downtown Toronto, ON. A cyclist-driver was defined as riding a bike for transportation purposes at least a *few days a month*. Participants drove through a pre-set route and completed 18 different turns of interest (in addition to others) at thirteen particular intersections. Five out of 18 turns were made at some of the same intersections with different travel directions. This made a total of eighteen turns; these 18 turns of interest were then categorized into two intersection-risk groups (higher and lower). As a guideline for this categorization, we followed a pedestrian intersection safety index that is based on multiple infrastructural factors (Carter et al., 2007) and reviewed on-street parking and previous fatal crash presence. After the drive, all participants were asked to perform two computerized attention tasks examining general visual attention abilities as well as complete four questionnaires investigating driver behaviour, everyday absent-mindedness, driving-related attentional failures and sensation seeking.

In this chapter, the methodology of the on-road experiment will be introduced and then findings will be discussed. It was found that 42% (186) of the turning events (442) were identified to have a visual attention failure towards VRUs, meaning the participant failed to gaze at a pre-identified area of importance with enough frequency (refer to Section 3.2 for details). Visual attention failures were found to be significantly more common at higher risk intersections for both groups of drivers, while non-cyclist-drivers had significantly more failures than cyclist-drivers. No other statistically significant results were found for other included measures (i.e. attentional abilities and self-reported driving behaviour). It was found that most of the attention failures were related to checking for cyclists.

3.1 Methodology

Twenty-six participants (13 male, 13 female) were recruited in which half were self-reported to use a bicycle as a transportation tool at least *few days a month* (7 male, 6 female). This manipulation of cycling exposure allowed for comparison of visual scanning behaviour between cyclist-drivers and non-cyclist drivers. The scope of our study was narrowed to busy urban intersections in downtown Toronto that contained a high occupancy of VRUs. The purpose of this was to understand the effect of control elements and intersection layout on drivers' visual attention failures towards VRUs. The Bloor-Bathurst neighbourhood was chosen as the experiment area since it met the following criteria: (1) accommodating heavy motor vehicle traffic, (2) offering a dedicated bike lane for cyclists and (3) having retail buildings for potential high pedestrian traffic. Various pilot drives were conducted in the area to finalize route design. By reviewing previous fatal crash records, on-street parking lane presence and abiding by a pedestrian intersection safety index that was based on control type, road layout, average speed, and traffic volume (Carter et al., 2007), 18 different turns were grouped into high and low intersection risk. As part of this study design, participants repeated some of the intersections with different turn directions (see Appendix M for detailed intersection sketches).

Experiments were only conducted under good weather conditions (e.g. no heavy precipitation) on roads that had no on-going construction. Experimental equipment was tested numerous times to ensure that data loss would not occur during sessions. Drivers were not allowed to use their cellphones or any other equipment during the drive and talking was kept to a minimum. No crashes occurred. After participants drove, they filled out four validated questionnaires that focused on driving behaviour, everyday absent-mindedness, driving-related attentional failures and sensation seeking. Participants were also asked to perform two computerized laboratory tasks to separately assess their object-based and spatial-covert attention. The University of Toronto Research Ethics Board (REB) approved the study (Protocol ID 34660). Each participant provided written consent prior to participating in the experiment.

3.1.1 Participants

Participants included 26 drivers (13 male, 13 female) aged 35-54 (Mean (M) = 42, Standard Deviation (SD) = 4.5), since we wanted to examine low-crash risk drivers and this age group has been found to have the lowest relative probability of crash responsibility (i.e., % of at-fault drivers divided by % of crash-non-responsible drivers) (Cooper, 1990; McGwin, Jr & Brown, 1999). A further reason for selecting this age group was so that we could validate findings from the pilot study (Chapter 2) with a similar sample characteristic. Finally, this age range is excluded from most insurance restrictions for on-road driving studies and is free from most REB restraints.

Participants had to have a full G driving license (or equivalent) for at least three years. On average, participants were licenced for 21 years (Min = 5, Max = 32). 65% (n = 17) of participants indicated that they drove their car "every day or almost every day", with only one participant indicating that they drove their car "a few days a month". 35% (n=9) of participants indicated that they were somewhat familiar with driving in visually demanding areas "every day or almost every day", whereas 31% (n=8) indicated "a few days a week" and 4% (n=1) "a few days a month". Participants indicated on paper that they had normal or corrected-to-normal vision in line with regulations set by the government of Ontario (Ministry of Transportation of Ontario, 2019); glasses and eye makeup were not allowed as they interfere with the eye tracker accuracy. They also self-reported being reasonably good in hearing and memory, as well as without any neck restriction. A final restriction for participants was that they could not have participated in in a previous on-road study, as this could potential bias the results. For the screening questionnaire, the reader is referred to Appendix E.

Recruitment was done through papers posted near the university campus (see Appendix F), university mailing lists (e.g., MIE, AMIGAS) and public online platforms (e.g., Kijiji, Craigslist). Individuals who met the study requirements were contacted via email (see the detailed script in Appendix G). Prior to the start of the experiment, participants were required to complete and sign the consent form (Appendix I). Each participant was informed that they could choose to withdraw at any point during the experiment. In the end, each participant was compensated on a pro-rated basis at $15 per hour.

3.1.2 Apparatus

3.1.2.1 Part 1: Driving Task

This study used a 2014 Toyota RAV4 car with an automatic transmission as the instrumented vehicle. For safety reasons, a secondary brake was installed so that the principal investigator could initiate an emergency braking response if necessary; in our data collection, there was no emergency incident requiring the use of this secondary brake. Real-time data monitoring was executed through a monitor linked to the Vehicle Testing Kit (VTK) computer (Figure 5); VTK is secured with two ISOFIX straps on the back seat behind the driver. The data was collected through the D-Lab software 3.50.8786.0.

Figure 5 Computer setup in the instrumented vehicle

Two dashboard-mounted cameras were used. One of the cameras was front-facing and recorded the road scene, while the other camera faced the driver seat from a right angle (this camera captured participants' facial expression and head movement; see Figure 6). The axis decoder underneath the rear seat transformed the analog signal of these cameras (PAL-Signal) into a digital signal (h.264 signal) for D-Lab software. A Logitech USB camera was also mounted for voice recording.

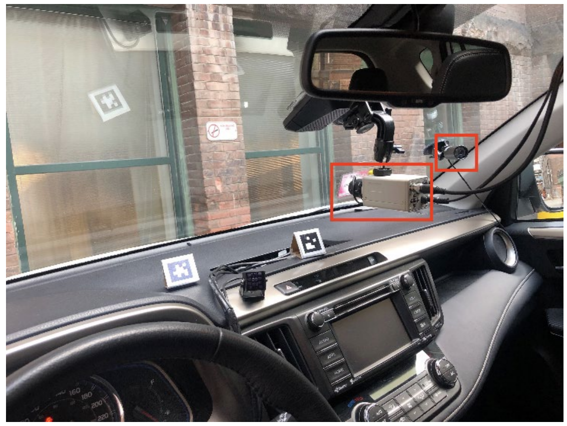


Figure 6 Camera facing the front scene (left) and facing the driver seat (right)

Eye movements were recorded by use of the head mounted Dikablis eye tracking glasses 3 (Figure 7), a device by Ergoneers. Following calibration for each individual, the eye tracker detects the pupil accurately by utilizing its two cameras pointed toward the eyes (tracking frequency of 60 Hz and a resolution of 648 x 488 pixels). The device overlays this gaze position on video data captured by its front-facing field (scene) camera (resolution of 1920 x 1080 at 30 fps). The manufacturer reported pupil tracking accuracy to be 0.05^{o} visual angle, and glance direction accuracy to vary between 0.1 to 0.3 ^{o} of visual angle. The scene camera's field of view is 92^{o} horizontal and 67^{o} vertical. Its synthetic material and relatively low weight of 52 g provides wearing comfort and freedom of head movement for drivers. In addition, QR codes were attached on the vehicle dashboard and A-pillar (i.e., roof support structure on either side of a vehicle's windshield), close to the areas that were examined in the study. Eye tracking video data can detect these markers by using image processing algorithms, which allows for automatic calculation of areas of interest (AOIs) in the analysis stage.

Figure 7 Driver outfitted with the new eye tracker

3.1.2.2 Part 2: Computerized Attention Tasks

The second part of the study was conducted in a quiet laboratory room with normal interior lighting. A desktop computer with an Intel Core i7-4770 processor and a monitor that had a 16:9 aspect ratio (1920x1080 pixels spatial resolution and a 60 Hz refresh rate) were utilized for the two computerized attention tasks. Participants responded by using a mouse and a Qwerty keypad. Real time gaze position information in relation to the monitor screen was recorded by the head mounted Dikablis eye tracker 3 and Dlab software. An adjustable head-chin rest (Figure 8) was placed to stabilize the head position in order to standardize binocular viewing distance at 50 cm from the screen as well as to maintain gaze fixation at the center of the monitor during the task.

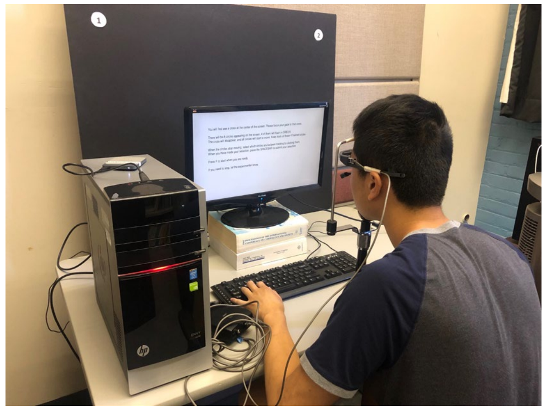


Figure 8 Experiment setup for computerized attention tasks

3.1.3 Experimental Design

Previous research has argued that road users (e.g., motor vehicle drivers, cyclists) differ in underlying attention allocation mechanisms. Motor vehicle drivers typically scan relevant areas for other motor vehicles and signals, whereas cyclists try to proceed safely at intersections (Salmon, Lenne, Walker, Stanton, & Filtness, 2014). This disparity in scanning behaviours motivates the inspection of whether these attention allocation mechanisms among road users persist even when they alter their mode of transportation. Studies with various methods (survey-, videoclip- and simulator-studies) have been conducted to investigate whether driving behaviour differs based on cycling experience (Beanland & Hansen, 2017; Johnson et al., 2014; Lehtonen et al., 2016; Magazzù, Comelli, & Marinoni, 2006; Robbins & Chapman, 2018). Cyclist-drivers appear to significantly differ from others in terms of traffic knowledge and attitude towards cyclists (Johnson et al., 2014), detecting hazards (Lehtonen et al., 2016), and identifying changes in driving-related objects (e.g., a cyclist on the road) (Beanland & Hansen, 2017). Building upon this aspect, the current experiment was designed as a between subject design to explore the effect of cycling experience on drivers' attention allocation towards VRUs at intersections. All participants were recruited as experienced drivers where half of the participants were identified to be frequent cyclists (i.e., riding a bike for transportation purposes; ranging from a *few days a month* to *every day*). The only factor differentiating the two groups was their reported cycling exposure (refer to section 3.3.1 for further comparison).

As part of this between-subjects study (cyclist-drivers vs. non-cyclist drivers), we also aimed to determine how roadway design influences visual attention failures towards VRUs. 18 different turning tasks were chosen from various types of urban intersections (some intersections were repeated). These18 turns of interest were grouped into two categories; higher (n=9) and lower (n=9) intersection risk based on various infrastructural factors as per a pedestrian safety index (Carter et al., 2007), previous fatal crash statistics and on-street parking lane presence. For categorization details, the reader is referred to the following section. In summary, the experiment was a 2x2 mixed design with intersection risk as a within subject factor and cycling exposure as a between subject factor (Table 5).

Table 5 Experimental design

	Experienced drivers (n = 26)	
Intersection Risk	Cyclist drivers (n=13)	Non-cyclist drivers (n=13)
Higher (n=9)	X	X
Lower (n=9)	X	X

3.1.4 Experiment Tasks

3.1.4.1 Part 1: Driving

In order to give participants a break in the middle, two routes (Route A and B) (Appendix K) were designed in the city block surrounded by Harbord Street, Bathurst Street, Bloor Street, and Spadina Avenue, which is a mixed retail and residential area with high road user traffic and a dedicated bike lane on both Harbord and Bloor Streets. Each route consisted of various intersections and midblock stretches ranging from residential to arterial ones; the two routes did not differ in terms of length and the number of turns; and each route had 9 turns of interest. Although some intersections (5) were repeated, the 18 investigated turns were unique. Table 6 provides details of the investigated turning actions from Route A and B (see to Appendix M for detailed intersection sketches).

Table 6 Details of the investigated turns from route A and B

Route A

Turn Code	From	To	Turn direction	Intersection geometry	Control type
1	Local Road	Major Arterial	right	Cross junction	Signalized
2	Major Arterial	Local Road	left	Cross junction	Signalized[1]
3	Local Road	Major Arterial	right	Cross junction	Signalized
4	Major Arterial	Major Arterial	right	Cross junction	Signalized
5	Major Arterial	Local Road	left	T-intersection	Uncontrolled
6	Local Road	Major Arterial	left	Cross junction	Signalized[1]
7	Major Arterial	Local Road	left	Cross junction	Uncontrolled
8	Local Road	Major Arterial	right	Cross junction	Stop sign
9	Major Arterial	Local Road	right	T-intersection	Uncontrolled

[1]: with a dedicated left-turn lane

Route B

Turn Code	From	To	Turn direction	Intersection geometry	Control type
10	Local Road	Major Arterial	right	Cross junction	Signalized
11	Major Arterial	Major Arterial	right	Cross junction	Signalized
12	Major Arterial	Local Road	left	T-intersection	Uncontrolled
13	Local Road	Major Arterial	right	Cross junction	Signalized
14	Major Arterial	Local Road	right	Cross junction	Uncontrolled
15	Local Road	Major Arterial	right	Cross junction	Signalized
16	Major Arterial	Local Road	left	Cross junction	Uncontrolled
17	Local Road	Major Arterial	left	Cross junction	Signalized
18	Major Arterial	Minor Arterial	left	Cross junction	Signalized

Although these intersections share some similarities in intersection geometry and control type (Table 6), these characteristics do not uniquely determine how demanding these intersections are. In order to identify risk levels associated with each turn, the Toronto version of the Pedestrian Intersection Safety Index (Ped ISI) (Carter et al., 2007) was adopted, where a score from 1 (the safest) to 6 (the least safe) was assigned per intersection. Researchers from the University of Toronto, Civil Engineering Department, implemented this index to downtown Toronto by following the Ped ISI guideline provided by the U.S. Department of Transportation in 2007 (Carter et al., 2007), which can be accessed online for free ("Intelligent transportation system of systems (ITSoS) service," 2018). As opposed to its original approach calculating a score per intersection leg, the Toronto-version provided the average score across the intersection legs.

Based on this Ped ISI score, the eighteen turning tasks investigated were categorized as *lower* or *higher* intersection risk. The intersections with the safety score of 3 or higher were grouped as *higher* intersection risk, where the rest, whose Ped ISI values lower than 3, were labeled as *lower* intersection risk (Table 3).

The original index indicates "hazardous" intersections separately for pedestrian and cyclist safety (i.e., Ped ISI and Bike ISI) by evaluating road characteristics and road user behaviour, where the Toronto version is adopted only for pedestrian intersection safety. Both indices, Ped and Bike ISI, consider various factors including control type (signalized or stop sign), road geometry (4-way or T-intersection), average daily traffic volume, 85^{th}-percentile speed allowed on the main road, number of lanes and predominant land use purpose (residential or retail). Further, each equation factor has a distinct contribution to the overall safety score. For example, increase in the number of lanes (coefficient of 0.335) and average speed (coefficient of 0.018) both increase the Ped ISI value, but with different ratios (Carter et al., 2007). To determine these unique variable coefficients, a video dataset from 68 types of intersections across the U.S. was obtained. Then, these safety index models were developed based on two methods. Traffic safety experts rated perceived VRU safety and comfort level in addition to observing particular road user interactions such as lane changes in response to other road users' behaviours to construct the index calculations (Carter et al., 2007).

However, there were certain limitations associated with this implemented tool and the assigned categorization was revisited for the following reasons. First, Carter and colleagues' (2007) safety index calculations lack review of previous crash data. Using previous crash statistics along with annual traffic flow is not an unusual method to divide intersections into risk groups. Taking this approach, Bao and Boyle's (2009) on-road study found significant differences in visual scanning patterns at "lower-" and "higher-risk" intersections (Bao & Boyle, 2009). Thus, fatal crash reports (for all types of crashes – not limited to ones with VRUs) from City of Toronto (City of Toronto, 2018) and Toronto police service ("Killed or Seriously Injured (KSI) Dataset from 2007 – 2017," 2019) were reviewed for the chosen intersections. Notably, what the index indicated matched the fatality presence; the turn #18 was the only exception. Despite its Ped ISI index 2.5

out of 6, this turn was moved to the higher risk category since the presence of a fatal crash already informs about a “risk” (Table 7, the asterisk (*)). Second, the adopted Toronto-version was restricted to Ped ISI calculation and did not consider cyclist road characteristics as opposed to the separate index in the original approach (Bike ISI) (Carter et al., 2007). In addition to the components of the Ped ISI, the original Bike ISI also introduces new factors such as bike lane, on-street parking lane on the approach, turning vehicle presence and calculates three separate scores for each travel direction of a cyclist (straight, right and left). Although these data were not avialable to us, our results from the existing on-road dataset showed that parked vehicles were blocking the drivers’ view of cyclists when they were placed between the motor vehicle and cycle lanes (Kaya et al., 2018). Thus, the presence of on-street parking lane between motor vehicle traffic and cycle lanes approaching intersections might affect demands associated with the turn. With these considerations, 18 turns were revisited before finalizing the intersection risk categorization in Table 7; information about the parking did not change the categorization of turns.

Table 7 The investigated turns categorized into two groups, *higher* or *lower* intersection risk, by a median split of their Ped ISI score after reviewing previous fatal crash and on-street parking lane presence.

Turn Code	Ped ISI Score [1(safest) - 6]	Previous Crash Presence	On-street Parking Presence	Intersection Risk
8	4	fatal	affects the turn	higher
4	3	fatal	-	higher
7	4.6667	nonfatal	affects the turn	higher
5	5	none	affects the turn	higher
9	5	none	affects the turn	higher
16	4	fatal	affects the turn	higher
11	3	fatal	-	higher
12	4.6667	none	-	higher
18*	**2.5**	**fatal**	-	**higher**
14	2.6667	nonfatal	-	lower
15	2.6667	none	-	lower
10	2.6667	nonfatal	-	lower
17	2.6667	nonfatal	-	lower
1	2.6667	none	-	lower
2	2.6667	none	-	lower
3	2.6667	none	-	lower
6	2.6667	none	-	lower
13	2.6667	none	-	lower

"-" signifies that turn is not affected by any on-street parking lane

3.1.4.2 Part 2: Computerized Attention Tasks

3.1.4.2.1 Object-based Visual Attention: Multiple Object Tracking (MOT) Task

To measure object-based visual attention skills, our study adopted the Multiple Object Tracking (MOT) task (Pylyshyn & Storm, 1988). The task was coded on Python (Appendix M) and consisted of 4 practice trials followed by 50 experimental trials. Written instructions (Appendix N) were provided before the practice and repeated for the experimental trial. Since tracking performance depends on object spacing (Drew, Horowitz, & Vogel, 2013), speed (Drew et al., 2013) and features (e.g., being identical or having unique features) (Makovski & Jiang, 2009), all these factors were considered in the task design. The moving objects were chosen to be homogenous white-filled circles with a radius of 35 pixels (px); and each circle subtended a visual angle of 2 degrees at 50 cm viewing distance. Pylyshyn and Storm (1988) found that tracking performance significantly degrades after the number of targets increases to five. Given that tracking performance remains fairly good (85.6% response accuracy) up to five targets out of ten objects (Pylyshyn & Storm, 1988), four targets over four distractors were chosen. On a light grey background (Bowers et al., 2011; Makovski & Jiang, 2009), these eight white circles were presented at random locations with a fixation cross at the center of the display.

During each trial, four circles were randomly assigned as "targets" and these were indicated by green flashing for 1s (one second) (Figure 9). After the green flash, the targets' colour changed successively back to white and all eight homogenous circles started moving arbitrarily with a constant speed of 2 px/frame. During the circles' motion, they could occlude each other as in a previous study (Lochner & Trick, 2014). After moving around arbitrarily for 6s, participants were asked to indicate the four target circles by clicking on them with the mouse (participants had 60 s to do so). Once selection was completed, the response was submitted by pressing the space button on the keyboard. After each trial, the response accuracy (i.e., how many targets out of 4 had been successfully tracked) was presented as feedback for the span of 1s; and this score was recorded for analysis purposes. Response time - defined as the time interval from the stop of motion to the input on the keyboard - was also measured in seconds as a mental chronometry variant.

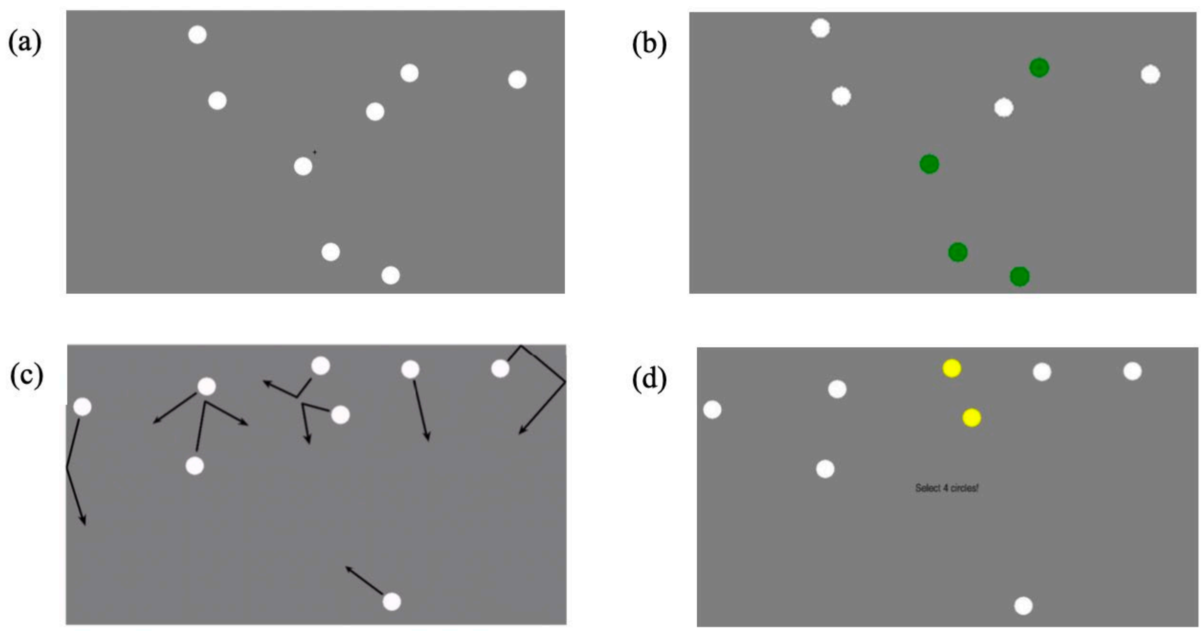
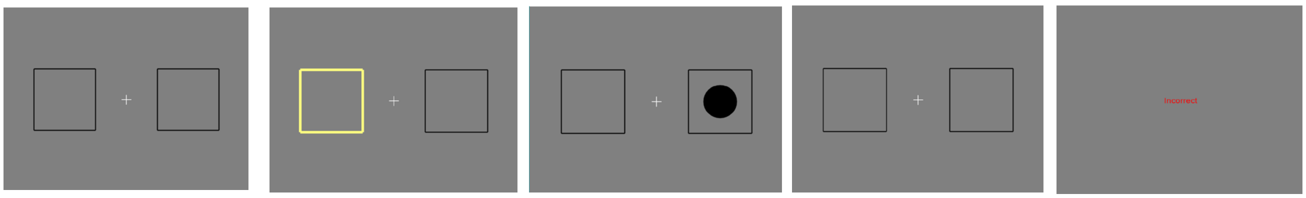


Figure 9 Procedure of the MOT task: (a) Initial screen, t = 0 - 1.5 s. (b) 4 targets flash with green colour over 4 other distractors, t = 1.5 – 2.5 s. (c) All items move randomly for 6 s. (d) at t = 8.5 s, participants were asked to indicate the four targets.

3.1.4.2.2 Spatial-covert Visual Attention: Posner's Cue-Target Paradigm

Our study employed Posner's cue-target paradigm for spatial-covert visual attention assessment. Its coding (Appendix P) was completed on Python for 10 practice and 100 real trials. Before the practice and real trials, participants were informed on the experiment procedure (Appendix Q) via written text on the computer monitor. Dark grey was chosen as a background colour. Each trial started with an initial screen consisting of a white fixation cross (+) at the center and two black unfilled squares (size of 200×200 px with an outline width of 3 px) on both left and right sides. These area-of-interest (AOI) squares were aligned symmetrically according to the fixation cross and the display's edge. After 1500 milliseconds (ms) of the initial screen (Figure 10a), the exogenous cue was presented to the participant for 50 ms; the cue had one of the AOI squares briefly change colour to yellow with an 8 px outline (Figure 10b). Once the cued AOI square was returned to its original colour, the "target" (i.e., a black filled circle with a radius of 50 px) appeared in the center of one of the squares for 50 ms (Figure 10c). From that point on, the target location (i.e., right or left) had to be detected and indicated as quickly as possible within a time frame of 60 ms by using the keyboard arrows (Figure 10d).



(a) (b) (c) (d) (e)

Figure 10 Procedure of the Posner task: (a) Fixation screen, t = 0 – 1500 ms. (b) Cueing; one of the boxes (left box in the figure) flashes yellow briefly (for 50ms). (c) A black circle appears in one of the boxes as a target, t = 1550 – 1600 ms. (d) Responding to the target location in a second. (e) Feedback prompt.

As part of the task, the location of the exogenous cue (yellow flash) and target (black circle) altered each trial. The target appeared on both sides with an even chance (i.e., 50% of the trials on the right side, 50% on the left). To be consistent with the Posner's experimental design (Posner, 1980), trials where the cue correctly indicates the location of the subsequent target were labeled as valid trials (80% of the real trials), other 20% were "invalid" trials. For example, if the target appears at the opposite side of the cued location as in Figure 10, then it is named as a "trial with invalid cue".

The target location (i.e., right or left) was indicated by using the keyboard arrows (right/left). Successively, a feedback prompt popped up reminding participants to give a response or indicating if the given response was *correct* or *incorrect* (Figure 10e). If the given response matched with the shown target location (i.e., correct spatial position), then it was coded as a correct response; otherwise, an incorrect response. If no response was made within the 1000 ms time frame, it was recorded as a *lack of response*. For each response, its accuracy (i.e., if it matches with the target location) and response time (s) were recorded. Response time was calculated as the elapsed time between the target disappearance and input on the keyboard.

Results have generally shown that attending to the correct location with the help of a correct cue (i.e., valid-conditions) increases response accuracy and decreases response time; stimulus detection is faster when the trial has a valid cue (Ede, Lange, & Maris, 2012; Posner, 1980). Each trial lasted no more than 3600 ms depending on the corresponding response time.

3.1.5 Experiment Procedure

3.1.5.1 Part 1: Driving

The experiment was completed between April and May 2019 in downtown Toronto, where drivers drive on the right-hand side of the road. In order to have higher experimental control, the study was started at three different time slots 10:00 AM, 1:00 PM or 4:00 PM on either Saturdays or Sundays. This time schedule provided some control over pedestrian, cyclist, and other motor vehicle traffic. Other decision factors for this experiment schedule were the availability of the participants, and the lack of on-site work for construction and garbage trucks on weekends. All individual trials were under relatively good weather conditions, however, one participant experienced light rain during the experiment. From the screening questionnaire (Appendix E), the eligible individuals were informed of the experimental task and setup through email. Each participant was scheduled for a timeslot and instructed to arrive at the Rosebrugh Building (RS) Room 313 at the University of Toronto St. George Campus at the start of their time slot. The experiment (including both off-road and on-road components) took an average of 2.5 hours in total.

The driving part of this study had the following procedures:

1) **Training and Pre-drive Survey:** Researchers met with the study subjects in RS 313 to go over the experiment agenda. To participate in the study, subjects were required to complete and sign the consent form (Appendix I). Upon this recruitment, a photocopy of the participant's driver's license was made for license verification and insurance purposes. Participants were also asked to fill out a pre-drive survey (Appendix J) that collected information on their driving history as well as some demographic information.

The participants were also informed that they should exhibit natural driving behaviour and follow the rules of the road, including giving right of way to the emergency vehicles (Appendix S).

2) **Familiarization Drive and Initial Setup of Sensors:** Participants were then taken to the instrumented vehicle parked on Discovery Lane (adjacent to the RS Building) with their driving license and valuable belongings. From this stage on, there were always three people in the vehicle: (1) the participant, who drove the car; (2) the graduate research assistant in the passenger seat, who was in charge of providing verbal route directions and operating the dual-brake; and (3) another research assistant in the rear seat, who monitored the VTK computer. Participants were asked to adjust the features of the vehicle (e.g. driver seat, mirrors) for their convenience, and put their phone on silent mode to avoid any interruptions to the driving task. For the 10-minutes long familiarization drive, participants received turn-by-turn directions guided by the graduate research assistant and they were allowed to ask any questions about the procedure and the vehicle. Upon arrival to the experiment start point, participants were asked to pull over. They were then outfitted with the eye tracker and went through the calibration process. For calibration, the participant was asked to gaze directly at four defined points outside the vehicle without moving their head facing the front; these four points were pointed by the researcher's fingertip standing outside the vehicle. After calibration, the eye-tracking software showed a crosshair on the field camera view so that researchers could detect where the participant was looking at in real time. To ensure that calibration was successful, participants were asked to fixate their eyes towards various locations in the environment; the experimenter checked on the display that the participant gaze position indeed fell on these locations.

3) **Driving - Route A and B:** Participants were instructed to try to keep talking to a minimum during the experimental route. Participants completed two pre-set routes, A and B, which were counterbalanced in order across participants. Both routes A and B had participants make nine turns at intersections. Similar to the familiarization drive, turn-by-

turn directions were provided by the graduate research assistant (Appendix L). Upon the end of each drive (approximately 15 minutes), on an iPad, participants indicated the effects of the task demand through a commonly-used self-report workload questionnaire, the NASA Task Load Index (TLX) (Hart & Staveland, 1988) (Appendix T). Initially, subjects completed a pairwise comparison of six types of workload (i.e., mental demand (MD), physical demand (PD), temporal demand (TD), performance (PE), effort (EF) and frustration level (FR)) based on which they felt contributed more to their workload. This calibration was done only once per participant after the first route. Then, as part of the questionnaire, they also indicated the level that each subscale of the NASA TLX (i.e., MD, PD, TD, PE, EF and FR) contributed to their workload after each route.

4) **Post-drive Items:** After the completion of the drives, the eye tracker was removed and the principal investigator switched seats with the participant. Upon arrival at the university, participants were brought to the laboratory room located in RS313 that had normal interior lighting (e.g., 100-150 lumen/m^2) and a quiet setting. Participants were then asked to fill out several questions on a desktop computer; we had participants fill out these questionnaires after the experimental drives to avoid response bias (Zwane et al., 2011) since these questionnaires included items on VRUs. Participants first rated themselves on how natural and cautious they were while driving using a five-question post-drive survey (Appendix U). To further investigate driver characteristics and understand their self-awareness on exhibiting aberrant driving behaviour including attentional failures, day-to-day driving failures and sensation seeking activities were assessed with several adopted questionnaires delivered in an online platform with the following order:

(1) the 24-item Driver Behaviour Questionnaire (DBQ) (Parker et al., 1995) measured on a 6-point Likert scale ranging from *never* to *nearly all the time* (Appendix A)
(2) the 25-item Cognitive Failures Questionnaire (CFQ) (Broadbent et al., 1982) measured on a 5-point Likert scale ranging from *never* to *very often* (Appendix B)

(3) the 19-item Attentional Failures during Driving Questionnaire (AFDQ) (Choi & Feng, 2014) measured on a 6-point Likert scale ranging from *never* to *nearly all the time* (Appendix C)
(4) the 40-item Arnett Inventory of Sensation Seeking Scale (Arnett, 1994) measured on a 4-point Likert scale ranging from *very well* to *not at all* (Appendix D)

The Driver Behaviour Questionnaire (DBQ) (Appendix A) is a widely used self-report measure used to assess aberrant driving behaviours (De Winter & Dodou, 2010; Lawton, Parker, Manstead, & Stradling, 1997; Reimer et al., 2005; Zhao et al., 2012; Zhao, Reimer, Mehler, D'Ambrosio, & Coughlin, 2013). DBQ was first established by Reason et al. (1990) and further developed into three subscales –errors, violations, and lapses – by Parker et al. (1995). This version of DBQ consists of 24 questions, eight items per subscale, with following six anchors: "never", "hardly ever", "occasionally", "quite often", "frequently" and "nearly all the time" (Parker et al., 1995). This widely used tool has been validated in driving research through self-reported crash data (De Winter & Dodou, 2010; Donmez et al., 2017), and has been shown to be indicative of on-road driving behaviour. Instrumented vehicle studies using DBQ have been conducted on the highway (Zhao et al., 2012) as well as in an urban setting (Amado et al., 2014); however, the study conducted for urban settings (Amado et al., 2014) did not include the VRU items (e.g. fail to notice pedestrians crossing when turning), mentioned before.

The Cognitive Failures Questionnaire (CFQ) (Appendix B) is a self-reported measure examining everyday attentional failures (e.g., tasks related to household). Broadbent et al. (1982) introduced 25 items on a 5-point scale, ranging from "never" to "very often". The literature for CFQ indicates strong correlations between CFQ scores and aspects of cognitive limitations and attentional capacity (Wallace, Kass, & Stanny, 2002). In addition, it has been noted that an increased number of self-reported cognitive failures is associated with responding to a target slower under the presence of distracting stimuli (Tipper & Baylis, 1987) and having longer glances toward driving-irrelevant stimuli (Hoekstra-Atwood, Winnie Chen, & Donmez, 2017).

The Attentional Failures during Driving Questionnaire (AFDQ) was recently introduced by Choi & Feng (2014) to assess attention-related driving abilities. Although DBQ is an informative predictor for general driving behaviour, its assessment is not specific to attentional abilities in driving (Choi & Feng, 2014). For example, while DBQ makes a generic statement like “When making a turn, you almost hit a cyclist or pedestrian who has come up on your right side.”, AFDQ examines attentional failures by stating some details such as intersection type (e.g., signalized), area of interest (e.g., checking rear-view mirror) and context a (e.g., roadside advertisements). Similar to DBQ (Reimer et al., 2005), a 6-point Likert scale has been used to self-report perceived frequencies of attentional failures during driving situations; ranging from “never” to “nearly all the time”. AFDQ initially had 33 items (Choi & Feng, 2014), but high internal consistency between questions indicated that some items resemble each other. Thus, overlapping items were removed. The revisited 19-itemized version of AFDQ has been validated by showing high correlations with other established questionnaires (e.g., DBQ) as well as a simulator study on elderly drivers (Choi, Grühn, & Feng, 2015). Although AFDQ was found to be a beneficial tool to self-monitor attentional failures in driving, there is still a need to validate this questionnaire for various driver groups (Choi & Feng, 2014) and in a more complex driving settings with higher ecological validity such as on-road studies (Choi et al., 2015).

The Arnett Inventory of Sensation Seeking Scale (Appendix D) consists of 40 questions, where respondents select the statement that describes them (e.g., “When I listen to music, I like to be loud”) (Arnett, 1994). Reverse-scored items were recorded on a 4-point scale as “very well”, “somewhat”, “not very well” or “not at all”. The Arnett scale has been shown to be predictive of self-reported aggressive and risky driving behaviours when incorporated with several other questionnaires (Dahlen, Martin, Ragan, & Kuhlman, 2005). Relation to driving and off-road glance behaviours have also been validated by an on-road study (J. Lee, Mehler, Reimer, & Coughlin, 2016).

3.1.5.2 Part 2: Computerized Attention Tasks

After the completion of the questionnaires, participants were asked to perform the two visual attention tasks on a standard desktop computer with the eye tracker on. To being with, the Dlab software was turned on, and the eye tracker was calibrated once again for the participant. Each task started when a written instruction appeared on the monitor screen (Appendix N for Multiple Object Tracking (MOT) task and Appendix Q for Posner task) and were followed by a few practice trials. During this phase, the graduate research assistant was present in the room to explain any questions the participant had. Once the practice trials were completed, the instructions were repeated; and the participant was left alone in the room to prevent distractions form the researcher. First, the Multiple Object Tracking (MOT) task (Pylyshyn & Storm, 1988) was completed approximately in 12 minutes and successively, the Posner task (Posner, Nissen, & Ogden, 1978) was performed for 7 minutes.

3.2 Video Data Coding for Visual Attention Failures

A visual attention failure was defined as failing to gaze at a certain area of importance with "sufficient" frequency, as in the analysis reported in Chapter 2. To expand on this explanation and develop a more promising reference point, the approach of Minimum Required Attention (MiRA) Theory, a framework defining driver inattention, has been adopted (Kircher & Ahlstrom, 2017). The first step of MiRA is defining the situation; which in the context of the current experiment would be coding the turn start- and end-points captured through the dashboard-mounted camera view which was stationary throughout the whole study. To set an example, in the presence of a stop line, a turn was defined to start when the stop line of the intersection was at the bottom of the windshield in the camera view as in Turn 3; the turn ended when the stop line on the target road touched the bottom of the camera view (Figure 11). Table 8 provides a detailed list of turn start and end definitions for each turn. While the 18 investigated turns from 13 unique intersections differed in terms of intersection geometry and control type, they were consistent across participants.

Table 8 Turn start and end definitions through the dashboard-mounted camera view

Turn	Route	Turn starts when	Turn ends when
1	A	stop line appears at the bottom of the camera view	stop line on the target road disappears from the camera view
2	A	stop line appears at the bottom of the camera view	stop line on the target road disappears from the camera view

3	A	stop line appears at the bottom of the camera view	stop line on the target road touches the bottom of the camera view
4	A	stop line appears at the bottom of the camera view	stop line on the target road touches the bottom of the camera view
5	A	yellow solid line is about to disappear from the camera view	crosswalk on the target road disappears from the camera view
6	A	stop line appears at the bottom of the camera view	stop line on the target road touches the bottom of the camera view
7	A	yellow solid line is about to disappear from the camera view	crosswalk on the target road disappears from the camera view
8	A	stop line appears at the bottom of the camera view	pavement on the target road touches the bottom of the camera view
9	A	end of the parking lane is adjacent to the vehicle in the camera view	crosswalk on the target road disappears from the camera view
10	B	stop line appears at the bottom of the camera view	stop line on the target road touches the bottom of the camera view
11	B	stop line appears at the bottom of the camera view	stop line on the target road disappears from the camera view
12	B	yellow solid line is about to disappear from the camera view	crosswalk on the target road disappears from the camera view
13	B	stop line appears at the bottom of the camera view	stop line on the target road disappears from the camera view
14	B	yellow solid line is about to disappear from the camera view	crosswalk on the target road disappears from the camera view
15	B	stop line appears at the bottom of the camera view	stop line on the target road disappears from the camera view
16	B	yellow solid line is about to disappear from the camera view	crosswalk on the target road disappears from the camera view
17	B	stop line appears at the bottom of the camera view	crosswalk on the target road disappears from the camera view
18	B	stop line appears at the bottom of the camera view	crosswalk on the target road disappears from the camera view

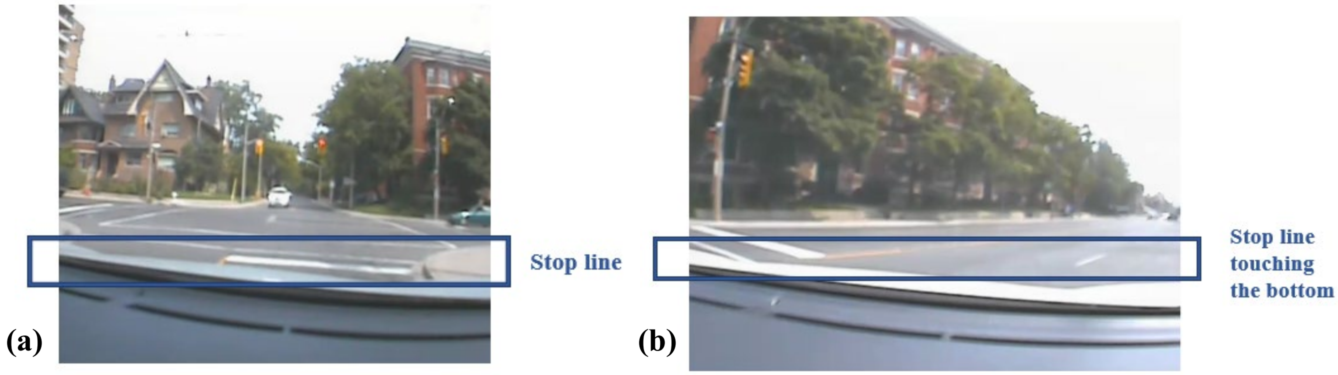


Figure 11 Example snapshot of the video data recorded by the dashboard-mounted camera. (a) Start of the Turn #3: Stop line approaching the intersection is visible at the bottom of the camera view. (b) End of the Turn #3: Stop line on the target road touches the bottom of the camera view.

The second step of MiRA is identifying agents which convey situation-specific information. In the context of our driving experiment, these agents can be control devices as well as the areas of importance (AOIs) for other road user traffic. Depending on the investigated intersection, control elements carry situation-relevant information. Since the focus is on VRUs, the most relevant areas are the ones where VRUs are more likely to appear when approaching an intersection, such as crosswalks, sidewalks, and dedicated bike lanes. These AOIs can be viewed through the windshield, right (passenger-side) and left (driver-side) window, right and left mirror, and rear-view mirror. Stage 3 of MiRA is identifying the minimum information sampling frequency which is highly affected by the volume of road traffic (Angell et al., 2015; Kircher & Ahlstrom, 2017, 2018). Thus, as a next step, traffic density per turn was examined to better understand the demands associated with that particular turn. Three trained evaluators, who are transportation researchers with a valid driving license, independently coded three levels (high, medium, low) of relevant motor vehicle, pedestrian, and cyclist traffic density as captured through the eye-tracking videos. Although trained evaluators are drivers themselves, two of them do not ride a bicycle for transportation or recreational purposes, and one of them rides a bicycle in the summer months for transportation purposes. Inter-rater reliability was calculated for this categorical coding with fixed-marginal kappa calculations (B. Chen, Zaebst, & Seel, 2005). The overall agreement was found as 84% (kappa = 0.66), 90% (kappa = 0.68) and 97% (kappa = 0.29) for vehicle, pedestrian and cyclist traffic, respectively. After coming to a consensus on the disagreed cases through discussion, it was decided that higher level of traffic density requires a higher rate of scanning of the pre-set AOIs. However, regardless of the traffic density, drivers were still expected to scan all AOIs and also check the stationary control elements at least once during the time interval from 10 seconds prior to the turn to the end of the turn. Mcgee et al.'s (1978) work on decision and response initiation for highways informed our choice to start coding the videos 10 seconds prior to the turn start. They recommended decision sight distance of 10 to 14 seconds which includes time to detect a hazard or a sign in a visually cluttered environment, time to decide for an appropriate speed and path as well as time to perform the required action safely. Also, in our preliminary analysis, 15 seconds was chosen to start coding the videos. However, it appeared that this time interval was unnecessarily long given the relatively short stretches between intersections in downtown Toronto.

Driver scanning patterns were captured as accurate as possible through the eye-tracking equipment. The stationary camera recordings facing the driver seat were incorporated with this eye tracking data to observe head movements, particularly over-the-shoulder checks. Even though it is not possible to differentiate the drivers who looked and those who looked-but-failed-to-see, gaze position was used as a proxy for visual attention. The same three independent evaluators, who were also blind to driver characteristics (i.e., being a cyclist or not), watched the video footage frame by frame and coded if drivers met the scanning requirements for each turn, identified through Stage 2 and 3 of the MiRA approach. Failure coding was primarily based on a failure/non-failure dichotomy, similar to the approach used by previous research evaluating driver performance (Bédard, Weaver, Darzinš, & Porter, 2008; Bowers et al., 2011).

Given that drivers start preparing for a turn before they arrive at an intersection, this failure evaluation considered two pre-determined epochs: 1) approaching the intersection starting from 10 seconds before the start of the turn, 2) waiting and initial execution of the turn, which was coded as the interval from the start point to the end point of the turn (i.e., Table 8). The “waiting and initial execution” epoch sets the fundamentals for our failure evaluation since active and effective scanning is not only required but critical during this period. On the other hand, the "approach" epoch allowed the evaluators to code visual attention failures during the "waiting and initial execution" epoch in a more conservative way, since scanning of the environment can be still achieved while actively steering. For example, if a driver scanned the environment clearly while approaching the intersection and did not have to wait at the intersection for maneuvering, gazing at mirrors during "waiting and initial execution" phase was not required. This case was coded as "non-failure" despite the absence of a lateral check, although the Ontario driver manual asks drivers to check their mirrors every five seconds (Ministry of Transportation, 2017). On the other hand, certain stationary objects in the vicinity of the intersection such as parked vehicles could block drivers' view of important areas. For example, when an on-street parking lane that separated bike and motor vehicle lanes was occupied with cars, drivers were required to perform not just a narrow lateral check but also an over-the-shoulder check (gazing at the passenger-side back seat window) since the bike lane was not visible from the passenger-side mirror. With such obstructed vision, Kircher and Ahlstrom (2016) suggested that drivers should practically stop fully to acquire enough information to navigate the turn safely. Taking a conservative approach, we did not require drivers to stop as long as a clear gaze towards these areas was exhibited.

In addition, the three evaluators assigned a low or high criticality label to each failure incident. For the criticality assessment, the frequency of the checks was one of the main criteria. Some turns required more frequent scanning of the environment due to traffic conditions, but "more frequent" scanning is a subjective evaluation based on traffic conditions. On the other hand, we did not require more frequent checks towards certain areas of importance based on the different travel speeds of the vulnerable road users (e.g., we did not require the bike lane to be checked more frequently than crosswalks given that bikes move faster than pedestrians). Following this, each rater categorized the failures as high or low criticality independently; and any disagreements were resolved through discussion. The absence of any essential check was coded as a failure with high criticality (e.g., never checking the bike lane). If a low frequency of checks was observed, it was considered a failure with low criticality. On the other hand, some of the participants gazed towards AOIs with sufficient frequency but with a late - subject to discussion – manner. This incident was observed usually at the intersections with an on-street parking lane.

Participants' eye and/or head movements fell on the bike lane once they already cleared the parked car and were about to complete the turn. Similarly, these late checks fell under the low criticality failure category. Following this detailed benchmark, overall agreement of three raters was found as 82%, and the fixed marginal kappa was calculated to be 0.63 (Chen et al., 2005) which is considered to represent a substantial level of agreement (Landis & Koch, 1977).

3.3 Results

The driving component of the study produced eye-tracking data for 26 participants who each drove two 15-minute-long routes, each containing 9 different turns in the Bloor and Bathurst area; this made a total of eighteen turns. After each experimental route, participants completed the NASA Task Load Index for workload measurement. Participants' general driving behaviour, day-to-day cognitive failures, sensation seeking, and attention abilities were collected through four post-drive questionnaires and two computerized attention tasks, respectively. Due to equipment malfunction, some participants were missing certain data measures. This chapter illustrates the results of the existing dataset.

3.3.1 Participants

Study participants were recruited so that they represented a fairly low-crash risk group with their age range of 35-54 (McGwin, Jr & Brown, 1999). They also had at least five years of driving experience and had an overall driving frequency of "at least few days a week". Overall, participants self-reported to be safe drivers with an average response of 9.1 on a scale of 1 (very unsafe) to 10 (very safe). All participants were reported as having safe driving records. In the past five years, as a driver, only three participants reported receiving one warning, with one participant receiving two warnings. In terms of citation or a ticket, there were slightly more responses, five participants reporting one citation/ticket, and three participants reporting two. Further, none of the participants had been involved in a crash (vehicle, pedestrian or cyclist related) within the past five years. Participants also indicated that they had no medical conditions (e.g., any neck injury causing rotation restriction), which could contribute to decrements in scanning performance (Angell et al., 2015; Lochner & Trick, 2014).

Participants were sorted into two groups (cyclist drivers and non-cyclist drivers) based on their response to the question in the screening survey: "Over the year (excluding winter) how often do you ride a bicycle as a transportation tool?". Respondents who self-reported their cycling frequency as "every day or almost every day", "a few days a week", and "a few days a month" were grouped under *cyclist-drivers* category, whereas the other drivers were recruited as *non-cyclist drivers*. The accuracy of the cycling exposure information obtained through the screening questionnaire was reconfirmed by providing the same question again in the pre-drive survey (Appendix J). Table 9 summarizes the relevant information; no significant differences between the two driver groups were observed for a number of demographic variables including age and mean year of licensure. The only significant difference between groups occurred for participants' cycling frequency in the experiment area (i.e., Bloor Street), where the non-cyclist driver group responded "never", which was expected. Applicants with motorcycle licenses were excluded from the study as not to introduce a confounding factor with cycling exposure.

Table 9 Pre-drive survey responses for cyclist (n=13) and non-cyclist (n=13) driver groups. If the normality assumption has been met, independent t-test was performed, otherwise, the Wilcoxon rank-sum test. The effect size was reported as Cohen's d.

Variable	Cyclist drivers (n=13)	Non-cyclist drivers (n=13)	Group comparison
Gender	7 male, 6 female	6 male, 7 female	-
Mean age (SD)	41.8 (3.3)	43.1 (5.42)	t(19.9) = -0.69, p = .49, d = -0.27
Mean year of licensure (SD)	22.3 (5.2)	19.4 (7.5)	t(21.2) = 1.15, p = .26, d = 0.45
Mean self-reported safe driving (SD)	8.8 (1.1)	9.4 (0.96)	W = 55.5, p = .12, d = -0.60
Self-reported driving frequency			
in general			
Everyday or almost every day	62% (n=8)	69% (n=9)	W = 88.5, p = .83, d = 0
A few days a week	38% (n=5)	23% (n=3)	(negligible)
A few days a month	-	8% (n=1)	
A few times a year or less	-	-	
Never	-	-	
in any downtown			

Everyday or almost every day	46% (n=6)	23% (n=3)	W = 61, p = .21, d = -0.52
A few days a week	31% (n=4)	38% (n=5)	
A few days a month	23% (n=3)	31% (n=4)	
A few times a year or less	-	8% (n=1)	
Never	-	-	
in downtown Toronto			
Everyday or almost every day	38% (n=5)	-	W = 50, p = .06, d = -0.85
A few days a week	31% (n=4)	54% (n=7)	
A few days a month	31% (n=4)	31% (n=4)	
A few times a year or less	-	15% (n=2)	
Never	-	-	
in experiment area			
Everyday or almost every day	15% (n=2)	-	W = 63.5, p = .27, d = -0.49
A few days a week	31% (n=4)	38% (n=5)	
A few days a month	38% (n=5)	23% (n=3)	
A few times a year or less	15% (n=2)	38% (n=5)	
Never	-	-	
Other modes of transport use			
Motorcycle use	100% never	100% never	-
Bicycle use in experiment area			
Everyday or almost every day	8% (n=1)	100% never	W = 26, p < .005**, d = -1.55
A few days a week	15% (n=2)		
A few days a month	23% (n=3)		
A few times a year or less	23% (n=3)		
Never	31% (n=4)		
Walking in experiment area			
Everyday or almost every day	-	-	-
A few days a week	23% (n=3)	23% (n=3)	
A few days a month	15% (n=2)	15% (n=2)	
A few times a year or less	46% (n=6)	46% (n=6)	
Never	15% (n=2)	15% (n=2)	
Having close member riding a bike	38% (n=5)	8% (n=1)	-
Being right-handed	100% (n=13)	92% (n=12)	-

3.3.2 Post-Drive Questionnaires

For analysis purposes, the four questionnaires were coded as follows:

(1) the 24-item DBQ (Parker et al., 1995): from *never* (coded as 0) to *nearly all the time* (coded as 5)

(2) the 25-item CFQ (Broadbent et al., 1982): from *never* (coded as 1) to *very often* (coded as 5)

(3) the 19-item AFDQ (Choi & Feng, 2014): from *never* (coded as 0) to *nearly all the time* (coded as 5)

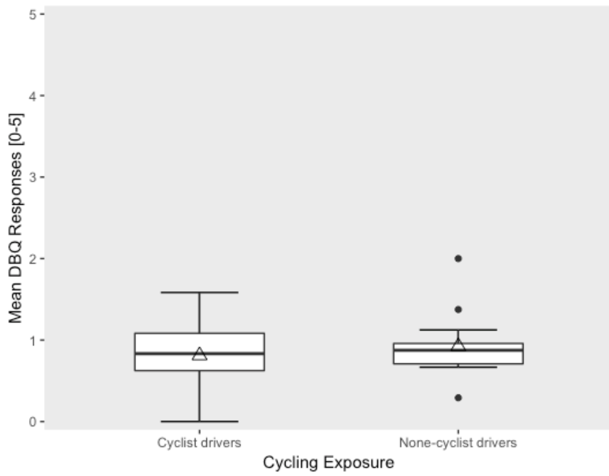
(4) the 40-item Arnett Inventory (Arnett, 1994): from *very well* (coded as 1) to *not at all* (coded as 4)

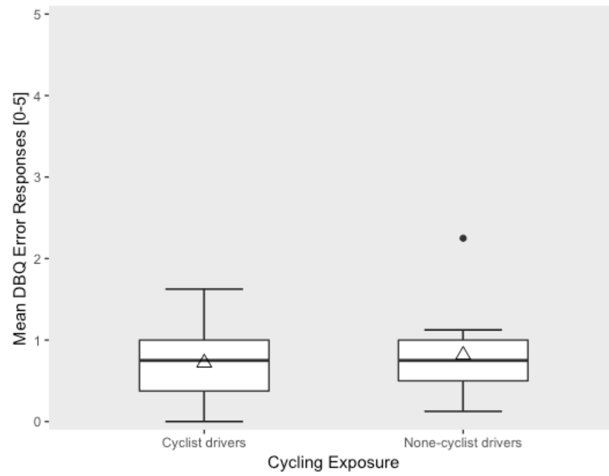
Participants' average score on DBQ, CFQ, AFDQ and Arnett across two groups were normally distributed unless otherwise noted in Table 10. The difference in means between cyclist-drivers and non-cyclist-drivers (independent t-test) were all nonsignificant (Table 10). The boxplots (Figure 12) depict participants' responses for the four questionnaires, including a breakdown of the three DBQ subscales (errors, lapses, and violations) and the intersection-related error items of DBQ as mentioned in Chapter 2. Boxplots are a standardized way of showing the data distribution, where the central rectangle displays the interquartile range with whiskers below and above representing the minimum and maximum data point. The triangle indicates the mean, whereas the horizontal line showed the median.

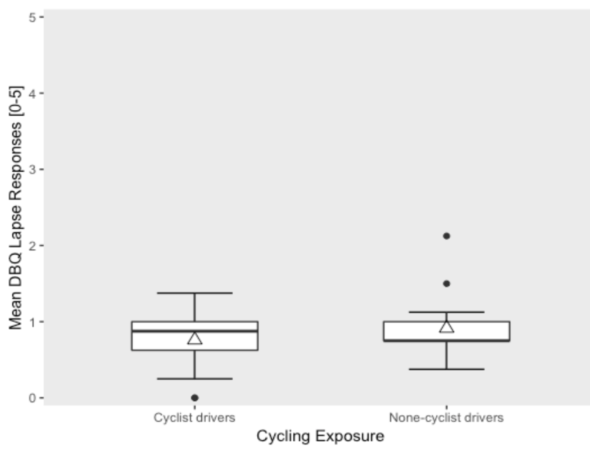
Table 10 Post-drive questionnaires' average responses for cyclist and non-cyclist drivers

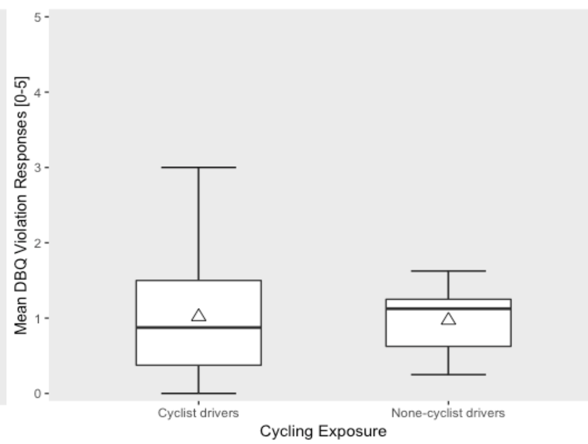
Questionnaires Mean (SD)	**Cyclist drivers (n = 13)**	**Non-cyclist drivers (n = 13)**	**Comparison**
DBQ	0.81 (0.47)	0.92 (0.41)[1]	W = 83, p = .95, d = -0.26
Errors	0.72 (0.49)	0.82 (0.53)	t(23.8) = -0.47, p = .64, d = -0.19
Lapses	0.76 (0.45)	0.91 (0.46)[2]	W = 79, p = .79, d = -.34
Violations	1.02 (0.86)	0.97 (0.44)	t(17.8) = 0.18, p = .86, d = 0.07
Intersection-related items	0.66 (0.51)	0.85 (0.48)	t(23.9) =, -0.92, p = .36, d = -0.36
CFQ	0.78 (0.48)	0.67 (0.34)	t(21.8) = 0.67, p = .51, d = 0.26
AFDQ	0.78 (0.47)	0.67 (0.34)	t(21.8) = 0.67, p = .51, d = 0.26
Arnett	2.34 (0.42)	2.4 (0.37)	t(23.7) = -0.37, p = .71, d = -0.15

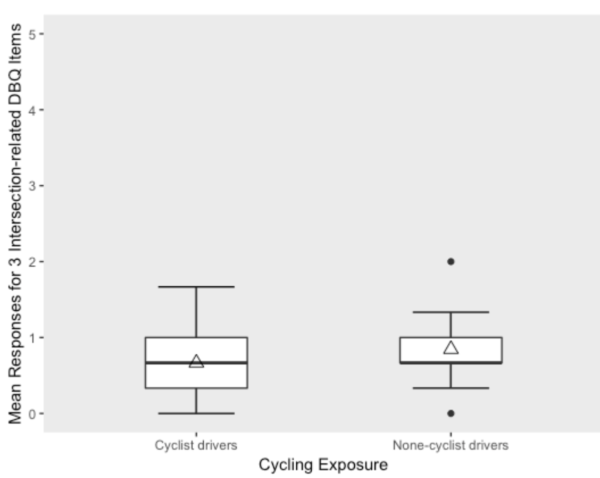
[1] non-normal: W = 0.86, p < .05
[2] non-normal: W = 0.82, p < .05

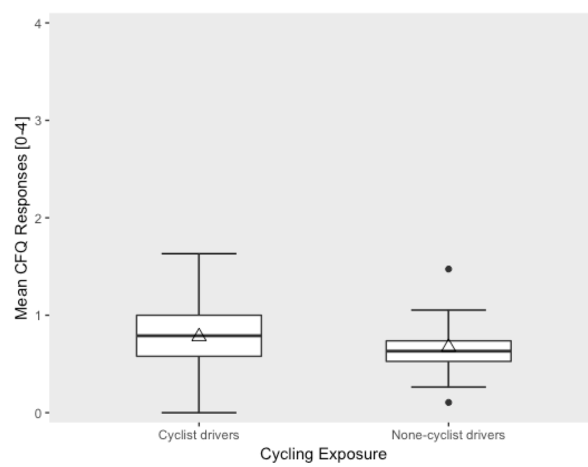

Mean DBQ Responses [0-5]
0
1
2
3
4
5
Cyclist drivers
None-cyclist drivers
Cycling Exposure


Mean DBQ Error Responses [0-5]
0
1
2
3
4
5
Cyclist drivers
None-cyclist drivers
Cycling Exposure


Mean DBQ Lapse Responses [0-5]
0
1
2
3
4
5
Cyclist drivers
None-cyclist drivers
Cycling Exposure


Mean DBQ Violation Responses [0-5]
0
1
2
3
4
5
Cyclist drivers
None-cyclist drivers
Cycling Exposure


Mean Responses for 3 Intersection-related DBQ Items
0
1
2
3
4
5
Cyclist drivers
None-cyclist drivers
Cycling Exposure


Mean CFQ Responses [0-4]
0
1
2
3
4
Cyclist drivers
None-cyclist drivers
Cycling Exposure

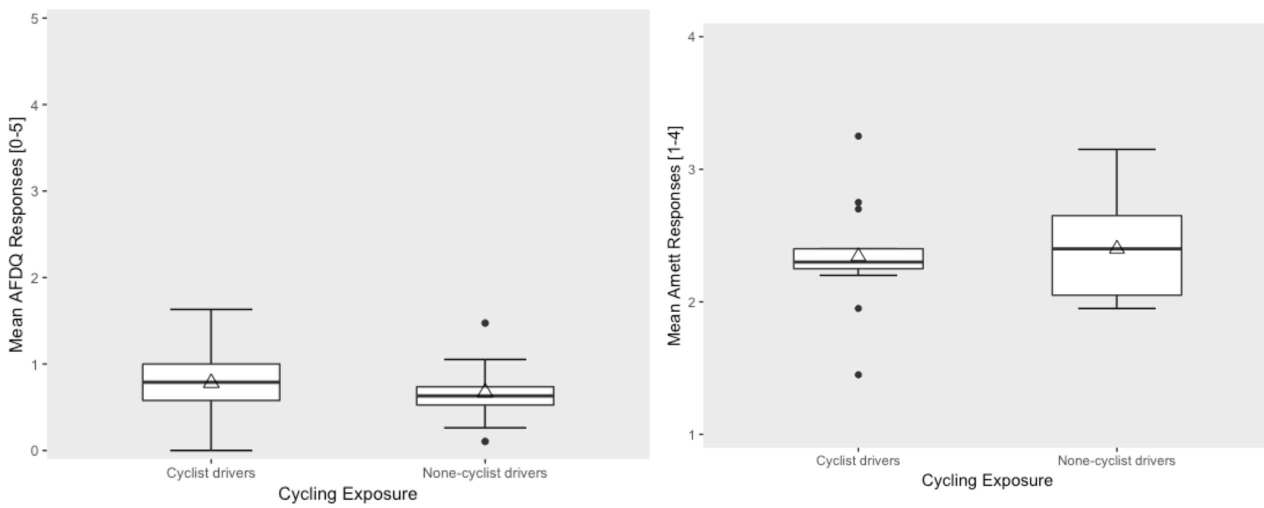


Figure 12 Boxplots for all questionnaire responses by driver group (cyclist vs. non-cyclists)

3.3.3 Computerized Attention Tasks

In terms of general attention abilities, independent t-tests were used to examine whether cyclist and non-cyclist driver groups differred in their responses to the MOT task. Normality requirements for both computerized attention task datasets were met. Due to equipment error, one of the non-cyclist participants data was not saved for the MOT task. Overall, for the MOT task, the cyclist group (n=13) has a mean of 3.17 (SD = 0.4) and non-cyclist group (n=12) mean was 3.26 (SD = 0.46); there was no with no significant difference between the mean scores, $t(22) = -0.51$, $p = .62$, $d = -0.20$ (Figure 13). For the Posner paradigm, A 2x2 ANOVA was built where the average response time for invalid trials was found to be significantly longer than the valid trials as expected; $F(1,17.6) = 96.16$, $p < .0001$. On the other hand, two driver groups did not significantly differ in their average response time; $F(1,22.9) = 0.32$, $p = 0.59$. The interaction term was found to be significant; $F(1,17.6) = 9.08$, $p = .007$.

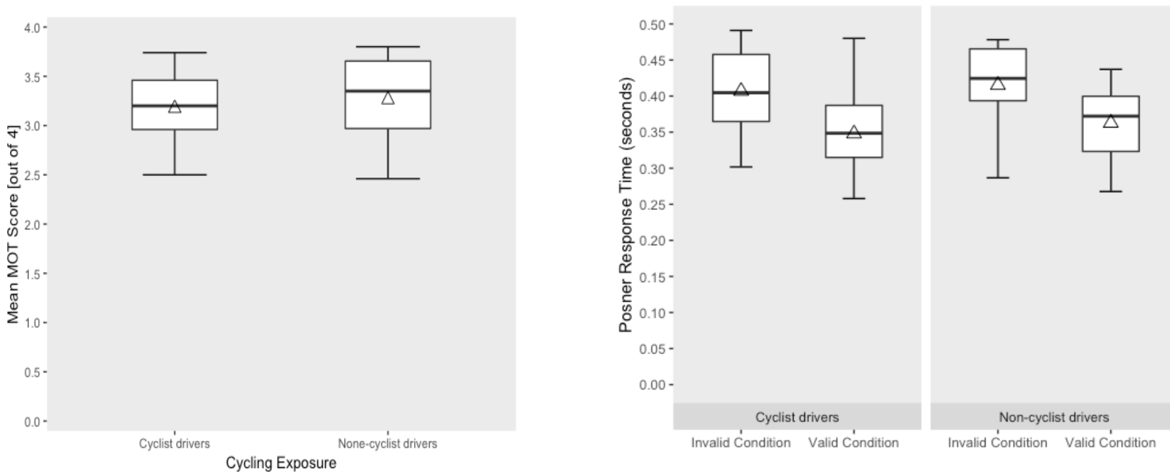


Figure 13 Boxplots showing mean MOT score (out of 4 targets) and mean Posner response time in seconds (s) by cycling exposure

3.3.4 Self-reported Workload NASA-TLX for Routes A and B

Although the routes A and B contained a variety of different roads and intersections, both had similar length with Route A having a mean completion time of 14 minutes (mins) (SD = 2.1) and Route B having a similar completion time (M = 14, SD = 1.9). In addition, self-reported workload as assessed by the NASA TLX were not statistically different (Route A: M = 37.93, Route B: M = 40.16; $t(24) = -1.16$, $p = .26$). After the first drive, each driver completed a pairwise comparison of six types of workload based on what they felt contributed more to their workload during the entire drive. From that initial comparison, NASA-TLX weighting was obtained for each participant, ranging from 0 (the least contributive) to 5 (the most contributive). Since one participant's (#2002) data was lost during data collection, Figure 14 displays each workload types' weight averaged for the cyclist (n = 13) and non-cyclist groups (n =12), excluding this one participant.

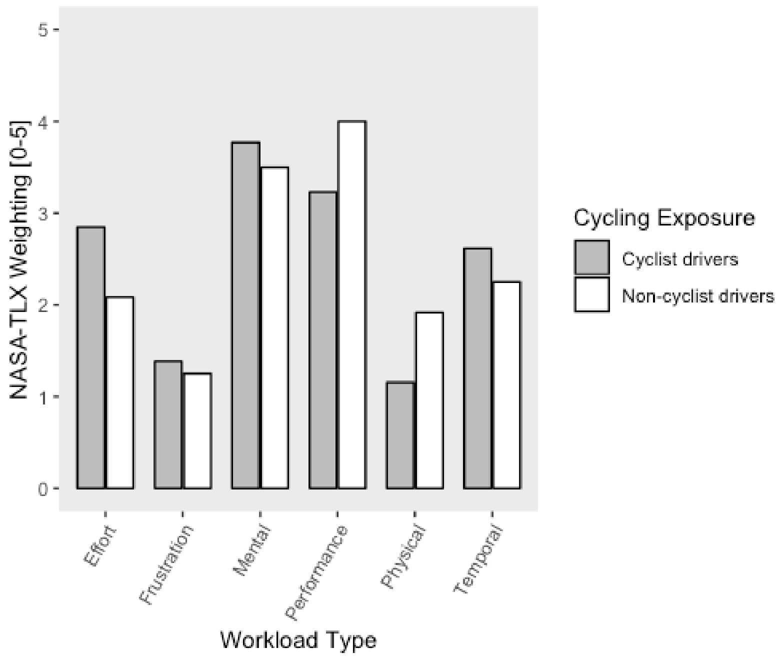


Figure 14 Average NASA-TLX weightings for each workload type by cycling exposure

After NASA-TLX weighting, drivers self-reported the extent of each type of workload on a scale of 0 – 20 for both experiment routes A and B separately. For each type of workload, their responses were multiplied by the initially reported weights. Successively, for each experimental drive, a total weighted average of workload was calculated out of 100 based on (Hart & Staveland, 1988). Normality assumptions were met for each subgroup. No significant difference was found between driver groups and routes for the TLX weighted ratings as well as for each workload type (Table 11). Overall, participants rated their experience for each type of workload in the following decreasing order of means: mental (57.4), effort (46.8), temporal (37.7), physical (28.5), frustration (25.4) and performance (15.3) out of 100. The same descending order was obtained for the breakdown of Route A and B. The relevant data distributions are presented in Figures 15 and 16.

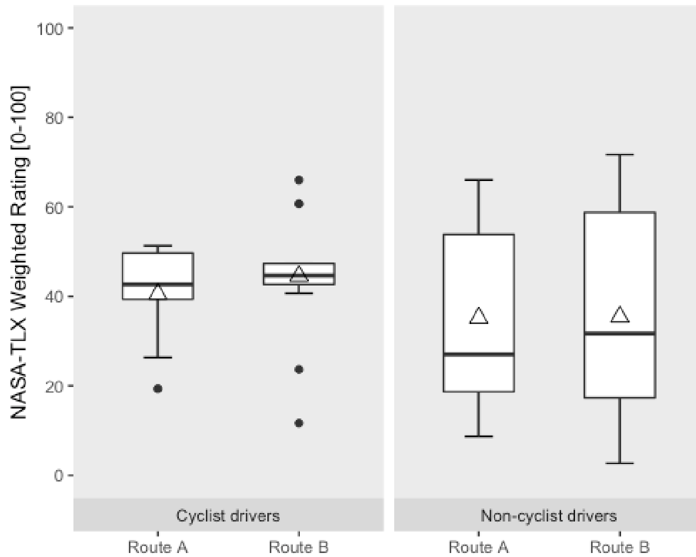
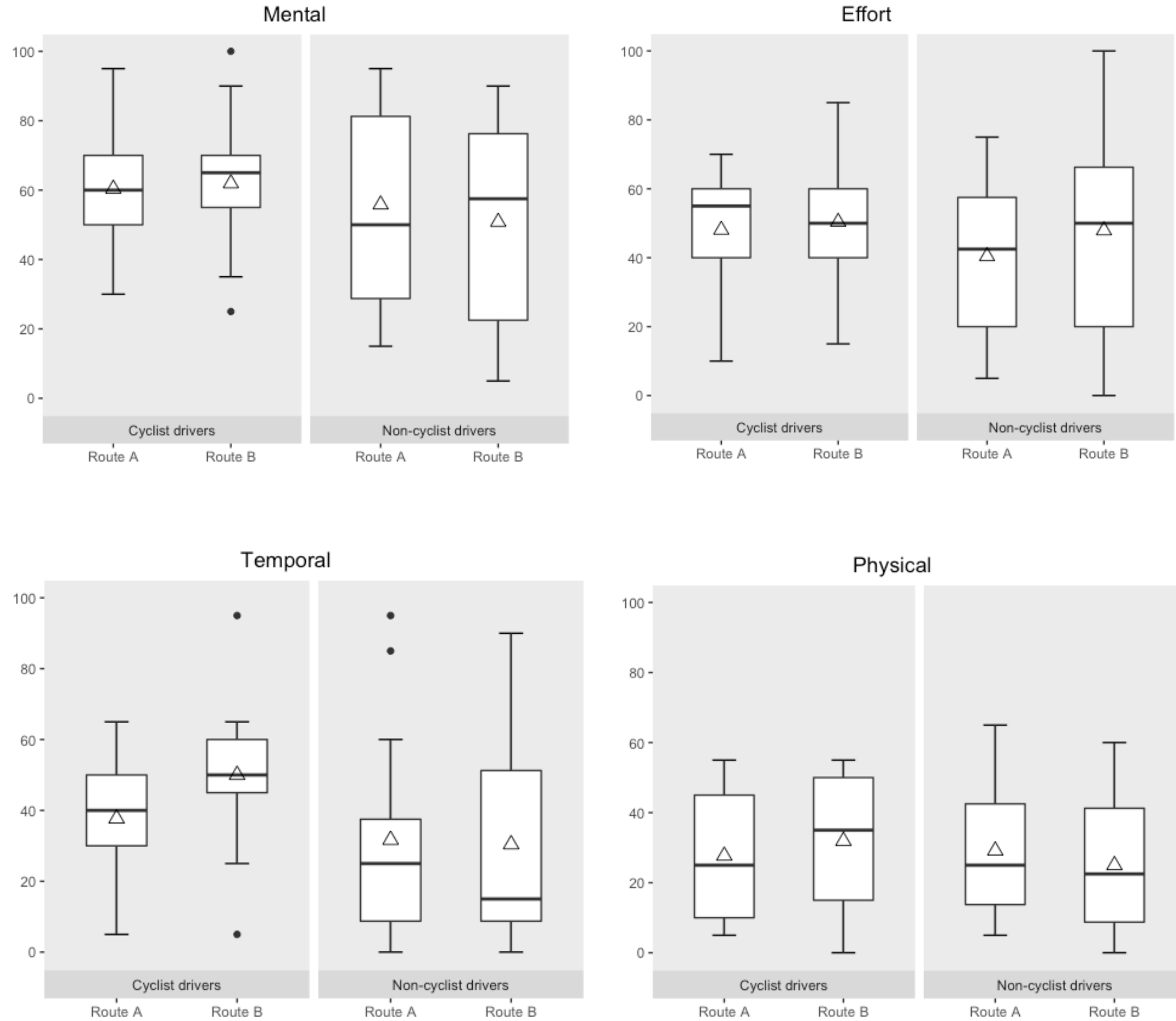


Figure 15 NASA TLX weighted ratings by routes (2 levels: A and B) and cycling exposure (2 levels: cyclist- and non-cyclist-drivers)

Table 11 NASA TLX weighted rating and its workload type comparisons.

NASA TLX and its workload type		**F-value**	**p-value**
Weighted Rating	Cycling exposure	F(1,16.4) = 1.07	.31
	Route	F(1,22.6) = 1.27	.27
	Cycling exposure x Route	F(1,22.6) = 1.01	.33
Mental	Cycling exposure	F(1,18) = 0.66	.43
	Route	F(1,22.6) = 0.26	.62
	Cycling exposure x Route	F(1,22.6) = 0.94	.34
Effort	Cycling exposure	F(1,18.8) = 0.41	.53
	Route	F(1,16.5) = 1.03	.32
	Cycling exposure x Route	F(1,16.5) = 0.30	.60
Temporal	Cycling exposure	F(1,15.3) = 1.68	.21
	Route	F(1,15.4) = 2.06	.17
	Cycling exposure x Route	F(1,15.4) = 3.09	.10
Physical	Cycling exposure	F(1,23) = 0.14	.71
	Route	F(1,18.9) = 0.05	.89
	Cycling exposure x Route	F(1,18.9) = 1.44	.23
Frustration	Cycling exposure	F(1,20.9) = 1.48	.23
	Route	F(1,19) = 0.08	.78
	Cycling exposure x Route	F(1,19) = 0.08	.78
Performance	Cycling exposure	F(1,16.5) = 0.02	.89

Route	F(1,13.5) = 0.11	.74
Cycling exposure x Route	F(1,13.5) = 1.41	.25



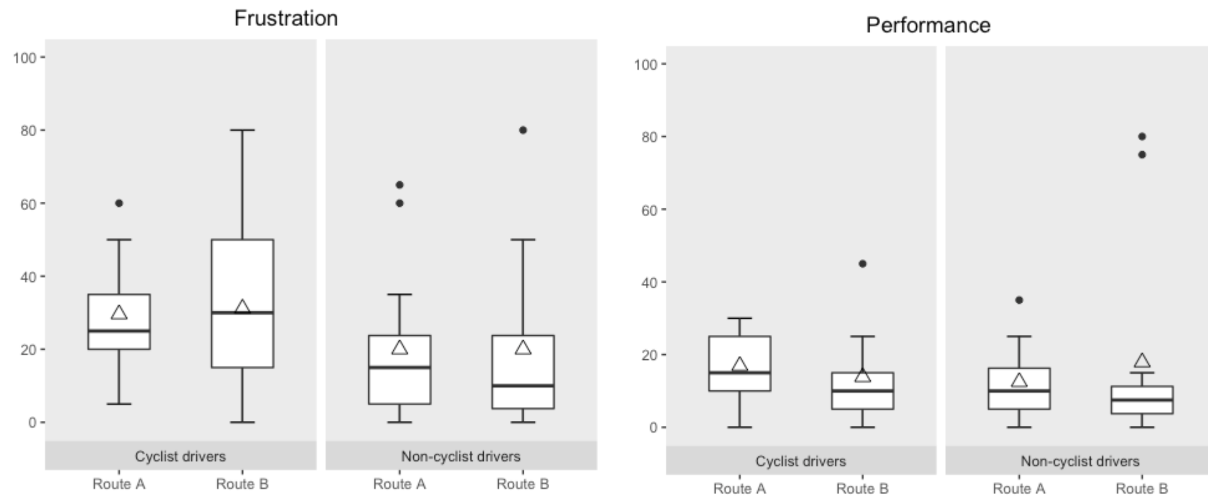


Figure 16 NASA TLX workload type boxplots by cycling exposure and routes

3.3.5 Visual Attention Failures towards VRUs

To investigate visual attention failures, glance data was recorded via eye tracker for 26 experienced drivers where they performed 18 different turns at various urban intersections. After independently coding the videos, the evaluators discussed their ratings in person and came to a consensus on whether a visual attention failure has occurred or not for each turn. In case of a failure, its criticality was expected to be agreed on among three coders. For the two driver groups (cyclist and non-cyclist), the number of participants who had no failure, a failure with low and a failure with high criticality is presented for each turning task in Table 12. Although 26 participants were recruited for this study, due to device malfunction, there was some data missing. As can be noticed in the last column in Table 12, some intersections have less than 26 participants. Overall, there were 442 unique turning events which were labeled as a failure or not. 42% (n=186) of them were coded as a failure of which 117 were of high criticality. No crashes occurred in the experiment. There were three conflicts: on three turns, participants had to apply the brake rapidly to avoid a collision with a VRU; once with a pedestrian and twice with a cyclist.

Table 12 Number of participants who had no failure, failure with low and high criticality at 18 turns by cyclist and non-cyclist driver groups

		No failures		Failures with low criticality		Failures with high criticality		
Code	Intersection risk	Cyclist driver (Cyc)	Non-cyclist drivers (Non-cyc)	Cyc	Non-cyc	Cyc	Non-cyc	Total # of participants
I4	higher	10	4	1	1	2	8	**26**
I5	higher	4	3	2	3	7	7	**26**
I7	higher	4	4	6	4	3	5	**26**
I8	higher	6	1	1	2	6	9	**25**
I9	higher	8	7	2	0	3	5	**25**
I11	higher	7	4	3	4	3	3	**24**
I12	higher	9	10	3	1	1	0	**24**
I16	higher	9	3	2	1	2	6	**23**
I18	higher	11	9	1	1	1	0	**23**
I1	lower	7	5	2	3	4	5	**26**
I2	lower	13	12	0	0	0	1	**26**
I3	lower	9	3	3	4	1	6	**26**
I6	lower	13	11	0	1	0	1	**26**
I10	lower	6	4	4	3	3	4	**24**
I13	lower	10	2	1	3	2	6	**24**
I14	lower	12	6	0	2	1	1	**22**
I15	lower	6	2	2	2	5	6	**23**
I17	lower	13	9	0	1	0	0	**23**
	Total	157	99	33	36	44	73	**442**

To illustrate the percentage of participants with low and high critical failure, two separate graphs were created for cyclist- (Figure 17) and non-cyclist (Figure 18) drivers. Overall, the majority of the observed failures were related to checking for cyclists and involved a lack of gaze towards the right-side mirror or an over-the-shoulder visual check if required. A further look at the 13 cyclist-driver participants showed that more than half had a failure with high criticality, meaning the participant failed to gaze at a pre-identified area of importance, at Turn I5 and I8 (Figure 17). Both turns had an on-street parking lane approaching the intersection, the former (I5) being a left turn from a major arterial at an uncontrolled T-intersection and the latter (I8) being a right turn onto a major arterial with a stop-sign. When on-street parking lane was occupied, participants had to do an over-the-shoulder check to have a better understanding of oncoming cyclist traffic.

Notably, looking at easy intersection risk category, cyclist participants seem to exhibit failures the most at I15, which is a right turn onto a major arterial at a signalized cross intersection.

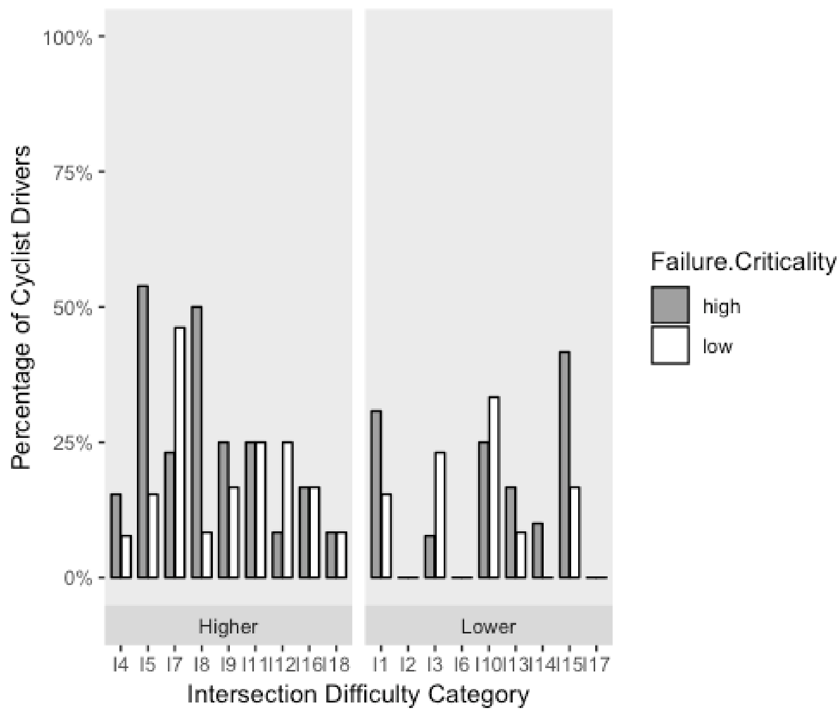


Figure 17 Percentage of cyclist drivers who had a visual attention failure with high and low criticality by 18 turns.

On the other hand, there were more visual attention failures attributed to non-cyclist drivers, as shown in Figure 21. While I5, I7, I8, and I15 revealed a higher percentage of failures for this group compared to the cyclist drivers, failures were also prevalent at other turns. Thus, intersection risk categorization seems to be less important for the non-cyclist group given that a high proportion of drivers were found to exhibit failures at low risk intersections as well. Notably, the second most prevalent failure occurred at I4, a right turn at a signalized cross intersection from a major arterial (Spadina Ave.) onto another major arterial (Bloor St.).

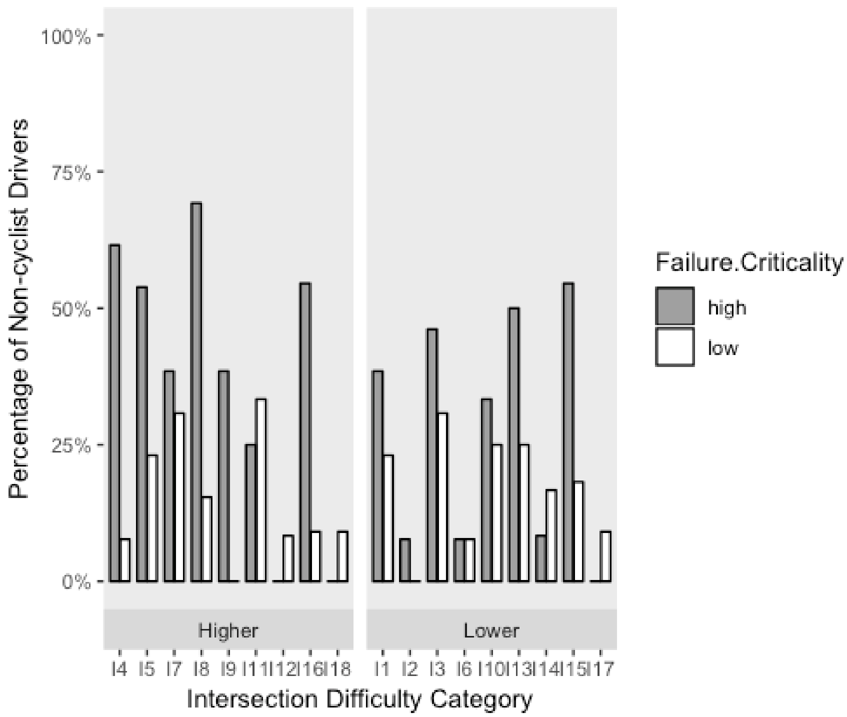


Figure 18 Percentage of non-cyclist drivers who had a visual attention failure with high and low criticality by 18 turns.

3.3.5.1 Statistical Models for Visual Attention Failures

In an attempt to provide a more conservative estimate of visual attention failures, only failures with high criticality were included as outcome variable for statistical model building. A series of regression models were constructed to explore the association between these failures, road design, cycling exposure, two computerized attention tasks, and questionnaires (DBQ, CFQ, AFDQ and Arnett). To investigate the impact of road design, the intersection risk categorization was used, where half of the turns were grouped under higher intersection risk, and the other half under lower. When evaluating the turn events, all raters were blind to individual differences, whereas one of these three coders (i.e., the author) was not blind to intersection risk categorization.

3.3.5.1.1 Model 1

Visual attention failures with high criticality were examined as an outcome through repeated measures ANOVA, with cycling exposure as a 2-level between-subject factor (cyclist and non-cyclist drivers) and intersection risk categorization as a 2-level within-subject factor (higher and lower). Participants were nested under cycling exposure. A mixed model was built using SAS MIXED procedure for these two independent variables and their interaction (Table 13). Effect sizes were calculated through the general linear model framework, SAS GLM procedure. Model contrast results comparing cyclist (M = 2.44, SD = 2.03) and non-cyclist (M = 4.06, SD = 2.92) drivers showed that cyclist-drivers had fewer high-critical failures towards VRUs; $t(24) = -2.14$, $p<.05$*. Also, compared to lower intersection risk group (M = 2.56, SD = 2.31), turns from higher intersection risk category (M = 3.94, SD = 2.77) accommodate more visual attention failures; $t(24) = 3.18$, $p<.05$*. Interaction effect was found to be nonsignificant.

Table 13 Model 1: Predicting the number of failures with high criticality for between-subject variable cycling exposure and within-subject variable intersection risk

Number of failures with high criticality	F-value	p-value	η_p^2
Cycling exposure	$F(1,24) = 4.56$	**.043***	0.36
Intersection risk	$F(1,24) = 10.14$	**.004***	0.29
Cycling exposure x Intersection risk	$F(1,24) = 0.02$	.89	0.0007

*significant

3.3.5.1.2 Model 2

The correlations between the adopted questionnaires was investigated; as shown in Table 14, the average scores on DBQ, CFQ, AFDQ, and Arnett, as well as the three subscales of DBQ and the three intersection-related error items (the three items that were most relevant to VRU intersection safety) were analyzed. Multiple hierarchical clustering analysis in SAS using Ward's minimum-variance method was employed on significantly correlated variables to identify a meaningful grouping. After several attempts, two clusters were identified for two interrelated factors, the average score of DBQ and ADFQ (Figure 19).

Table 14 Correlation matrix (n=26) for the average score of each questionnaire, including DBQ with three subscales (error, lapse, and violation) as well as its intersection-related error items. Significant p-values were indicated in bold.

	DBQ							
	DBQ	**error**	**lapse**	**violation**	**intersection**	**CFQ**	**AFDQ**	**Arnett**
DBQ	1.00000							
Error	0.83864 **<.0001**	1.00000						
lapse	0.75652 **<.0001**	0.68943 **<.0001**	1.00000					
violation	0.77490 **<.0001**	0.46856 **0.0158**	0.28125 0.1640	1.00000				
intersection	0.81021 **<.0001**	0.78124 **<.0001**	0.71132 **<.0001**	0.47726 **0.0137**	1.00000			
CFQ	0.43287 **0.0272**	0.42440 **0.0307**	0.61444 **0.0008**	0.16601 0.4177	0.33885 0.0904	1.00000		
AFDQ	0.50039 **0.0092**	0.54973 **0.0036**	0.65568 **0.0003**	0.14577 0.4774	0.61962 **0.0007**	0.52250 **0.0062**	1.00000	
Arnett	-0.06963 0.7354	0.10628 0.6054	-0.05576 0.7867	-0.03201 0.8767	-0.15867 0.4388	-0.02286 0.9117	-0.31481 0.1173	1.00000

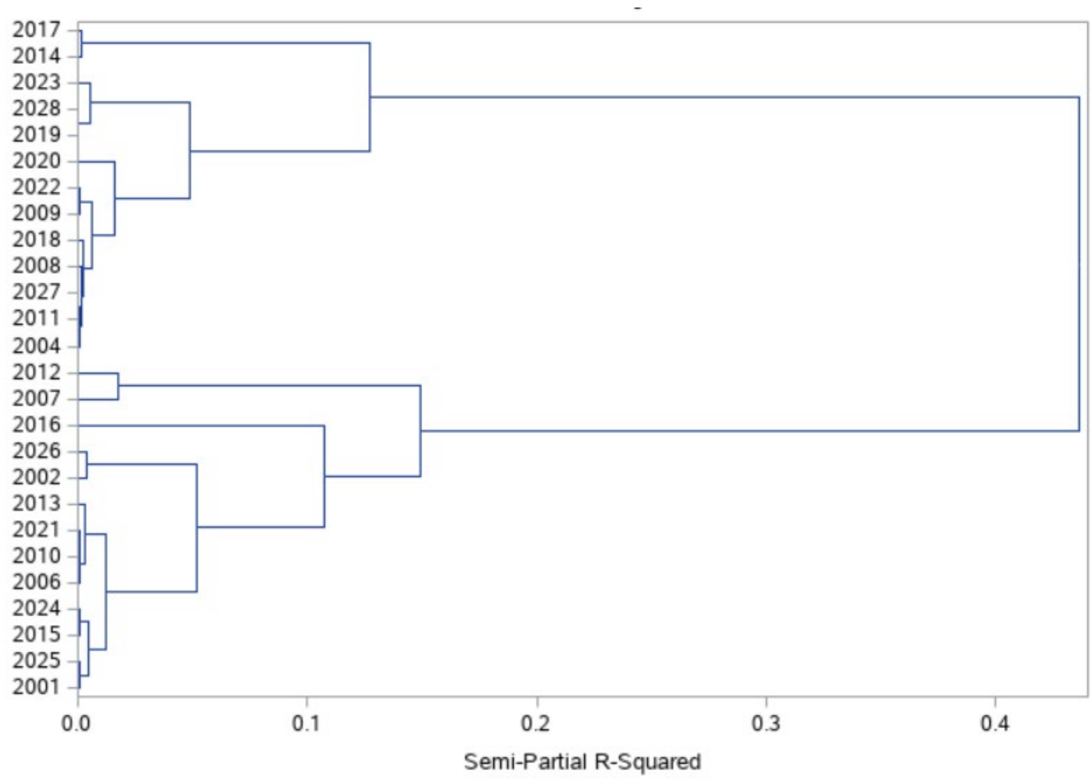


Figure 19 Dendrogram illustrating the arrangement of the clusters for the variables average score of DBQ and ADFQ

Clustered average scores of DBQ and AFDQ were labeled as higher and lower self-reported driving behaviour, where the higher self-reported scores indicate higher awareness of failures that might potentially occur or have occurred during everyday driving. With three 2-level predictors (cycling exposure, intersection risk, and self-reported behaviour), another statistical model was built in SAS using the MIXED procedure for n=26 (Table 15). Similar to the previous model, cycling exposure and intersection risk were significant predictors; lower number of failures were observed for the cyclist-driver group ($t(23) = -2.36$, $p<.05$*) and also under lower intersection risk group ($t(23) = -3.14$, $p<.05$*). Unlike the marginally significant result for the 3 intersection-related error items of DBQ in the pilot study (Chapter 2), the findings were not significant. Participants who self-reported making more failures in DBQ and AFDQ, so-called higher self-reported behaviour group, did have more visual attention failures at intersections at a marginally significant level, $t(23) = 1.79$, $p = .08$.

Table 15 Mixed model for the outcome number of failures with high criticality for three predictors; cycling exposure, intersection risk, and self-reported driving behaviour identified through DBQ and AFDQ responses.

Number of failures with high criticality	F-value	p-value
Cycling exposure	F(1,23) = 5.59	**.027***
Intersection risk	F(1,23) = 9.89	**.004***
Self-reported behaviour	F(1,23) = 3.22	.086
Cycling exposure x Intersection risk	F(1,23) = 0.03	.863
Intersection risk x Self-reported behaviour	F(1,23) = 0.41	.528

*significant

3.3.5.1.3 Model 3

For this model, one observation (subject # 2002) was removed since the MOT score of this participant was missing. After excluding this datapoint, a significant relationship between average Posner response time (RT) in seconds (s) and average Multiple Object Tracking (MOT) task target detection score (out of 4) was found, $r = -.43$, $p < .005$* (Figure 20). To further explore the underlying dimensions and standardize the two variables, a hierarchical cluster analysis was performed in SAS where Ward's minimum-variance method was used. For this dataset, two clusters were identified (Figure 21). These two clusters were labeled as good- (n=12) and poor-attention (n=13) performance groups and compared to each other by independent t-test (Table 16).

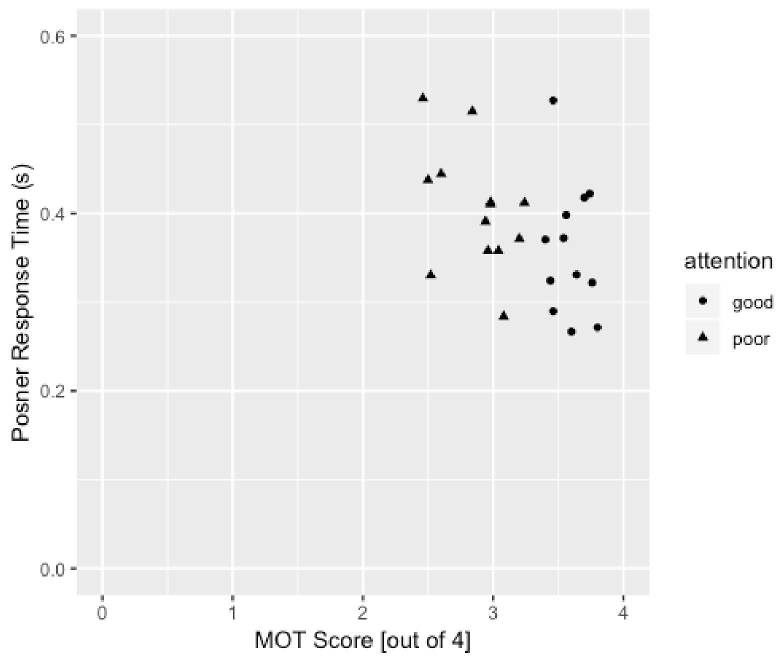


Figure 20 Scatter plot for MOT score and Posner response time; circles representing good attention performance group and triangles illustrating the poor.

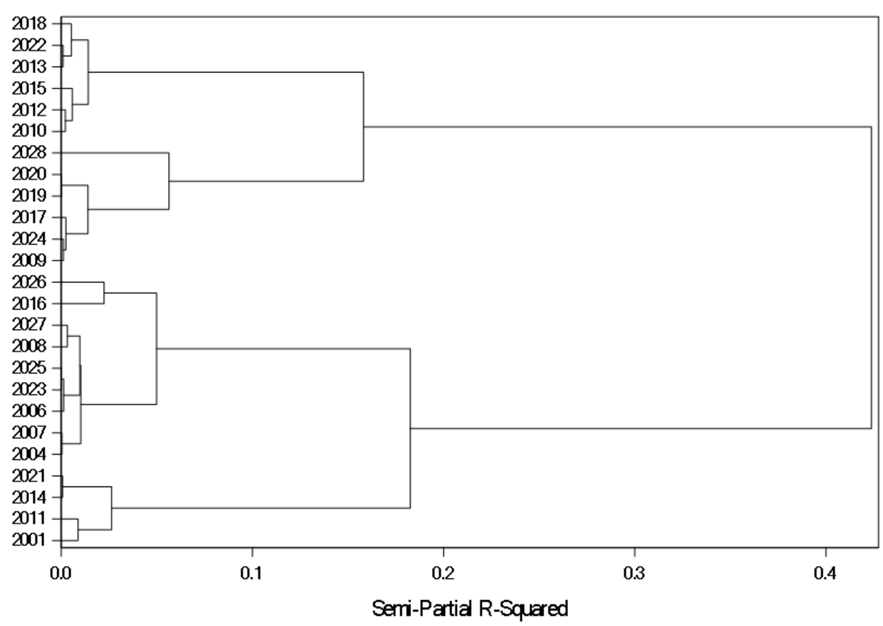


Figure 21 Dendrogram illustrating the arrangement of the clusters for variables average Posner response time (RT) and average MOT score.

Table 16 Mean and standard deviation of average Posner response time (RT) in seconds (s) and average MOT score (out of 4) for two clusters; good- (n=12) and poor-attention (n=13) performance groups.

Computerized attention tasks	Good attention performance (n=12)		Poor attention performance (n=13)		
	Mean	SD	Mean	SD	Comparison
Average Posner RT (s)	0.36	0.075	0.40	0.068	t(23)= -1.55, p=.13
Average MOT score [out of 4]	3.59	0.14	2.87	0.27	t(23)= 8.35, p <.05*

*significant

To investigate high-critical visual attentional failures, another statistical model was built in SAS using the MIXED procedure with three 2-level predictors introduced as a fixed factor; cycling exposure, intersection risk, and attention performance (Table 17). While cycling exposure and intersection risk significantly predicted failures, attention performance and all interaction effects were found to be nonsignificant. Once again, compared to non-cyclist drivers (M = 5.67, SD = 3.05), being a cyclist-driver (M = 3.38, SD = 2.36) resulted in a significantly lower number of failures; t(22) = -2.25, p<.05*. Similarly, more failures were observed under the higher intersection risk category; t(22) = 2.97, p<.05*. Although participants who had better attention performance at two computerized tasks exhibited less visual attention failures, the difference was only marginally significant; t(22) = -1.74, p = .09.

Table 17 Mixed model for the outcome number of failures with high criticality for three predictors; cycling exposure, intersection risk, and attention performance.

Number of failures with high criticality	F-value	p-value
Cycling exposure	F(1,22) = 5.08	**.034***
Intersection risk	F(1,22) = 8.83	**.007***
Attention performance	F(1,22) = 3.03	.095
Cycling exposure x Intersection risk	F(1,22) = 0.04	.847
Intersection risk x Attention performance	F(1,21) = 1.42	.246

*significant

3.4 Discussion

An instrumented vehicle study in downtown Toronto, ON was conducted to investigate visual attention failures towards VRUs while making a turn at urban intersections. The focus of the study was urban intersections on major arterials that contained high traffic volume. This is due to the fact that these locations often pose higher mental and visual demands on drivers, which can lead to unsafe driving behaviour such as lack of adequate scanning. Eye tracking and in-vehicle camera data from 26 experienced drivers (aged between 35 and 54; 13 cyclists and 13 non-cyclists) were analyzed for 18 different turns at intersections. Among the 442 unique turning events, 42% (n=186) of them were identified as a visual attention failure towards VRUs. 63% (117) of the overall failures were labeled as "failures with high criticality", meaning the participant failed to gaze at a pre-identified area of importance. Given that our participants represented a fairly low crash-risk group (McGwin, Jr & Brown, 1999), the prevalence of failures observed in this study is concerning. Further, our statistical models demonstrated that these failures were significantly more common while turning at higher risk intersections and for non-cyclist drivers; no significant relation to general attention abilities and self-reported driving behaviour was found.

Overall, our results support the findings from crash data analysis (Räsänen & Summala, 1998) and an on-road driver behaviour study (Gstalter & Fastenmeier, 2010; Summala, Pasanen, et al., 1996), indicating that misallocation of attention is a major source of conflicts with VRUs at urban intersections. Further, several intersection-studies have indicated that driver glances are often directed to areas with higher potential threat and safety relevance (Angell et al., 2015; Lee, Lee, & Boyle, 2007; Robbins & Chapman, 2018; Summala, Pasanen, et al., 1996; Summala & Räsänen, 2000). This scanning phenomenon has been observed in our dataset as well. Given that other motor vehicles sharing the road pose a higher safety risk due to their larger mass and higher speeds compared to those of VRUs, all of our participants first scanned the center of the road and surrounding lanes for vehicle traffic. This finding also supports the argument that drivers primarily attend motor vehicle traffic since visual information intake should be done more frequently from the ones that their information changes faster (Kircher & Ahlstrom, 2017); higher travel speed results in higher rate of information change.

Notably, majority of the failure incidents were particularly related to checking for cyclists. It was found that upon the arrival to the intersection our participants prioritized the oncoming vehicle traffic, followed by the areas of importance for pedestrian traffic (i.e., crosswalks and sidewalks). The least scanned locations were the areas of importance for cyclist traffic (e.g., bike lane). One potential reason for such scanning strategy might be that drivers are used to expecting potential hazards from the crosswalks and sidewalks more than bike lanes due to overall higher levels of pedestrians compared to the number of cyclists on roads. Also, the dedicated bike lane in the experiment area (Bloor Street) was introduced in 2016; therefore, some of the participants may have been unfamiliar with the bike lane. Another reason drivers may not scan areas of importance for cyclists may be that it is often more effortful for drivers to perform an over-the-should-check requiring a head turn (Lavallière et al., 2011). This is particularly relevant for the situations in which on-street parking lane is present and parking spots are occupied (i.e., during turns at I5, I7, I9, and I16 in this experiment) since cyclist traffic cannot always be detected through a gaze at the windshield or side mirrors in these situations. Consequently, we found that on average, almost half of the participants had a visual check failure during these turns as they did not exhibit an over-the-shoulder. This type of failure was in line with driver errors detected in another intersection-related on-road study (Gstalter & Fastenmeier, 2010), errors due to low frequency of performing an over-the-shoulder check.

A further look at visual attention failures revealed some interesting insights. Among all turns, the ones with the least number of failures observed, namely I2, I6, I12, I17, and I18, appear to be left turns. A possible explanation for this result might be the increased distance between where the vehicle stops and where the relevant bike lane and crosswalk are when the vehicle is making a left turn. During these left turns, drivers often faced the oncoming bike lane and the relevant crosswalk from a perpendicular angle before passing them. It can be argued that gazing at areas located further away takes less effort than engaging in a wider head rotation, which is often required during right turns due to a narrower range of the vision. This outcome supports Madsen and Lahrmann's (2017) video data analysis on bicycle facility layouts at intersections which demonstrated that the risk of being involved in a crash as a cyclist with a left-turning vehicle was lower than with a right-turning vehicle. Further, previous on-road studies have also found that proportion of glances are more evenly distributed (left/right) when drivers are performing left turns compared to right turns (Bao & Boyle, 2009; Summala, Pasanen, et al., 1996). Notably, the remaining three left turns, namely I5, I7, and I16, were at intersections with an on-street parking lane. It is not surprising that more visual attention failures were observed during these maneuvers since parked vehicles near intersections might generate obstructed vision as highlighted by Richter and Sachs (2017).

For the statistical models, we hypothesized that visual attention failures would be more prevalent for the turns grouped under higher intersection risk as per multiple factors based on reviewing the already-existing pedestrian intersection safety index (Ped ISI) (Carter et al., 2007), fatal crash records and on-street parking lane presence. Ped ISI was developed by the U.S. Department of Transportation based on various infrastructural factors such as number of lanes, control element type, average speed and traffic volume. With a statistical significance, environmental complexity and attentional demands associated with the higher intersection risk group were reflected in the higher number of visual attention failures exhibited, which also in part supports the validity of Ped ISI through an on-road driving study. Following this categorization, we can also provide some insights on infrastructure design; uncontrolled (i.e., without any traffic signal or sign) intersections (given that this factor has the highest coefficient determining the index score) as well as intersections with an on-street parking lane nearby and with previous fatal records require further attention. Our results support evidence to similar on-road studies explaining drivers' inadequate visual information sampling in part by intersection demands interfering with their visual search habits (Gstalter & Fastenmeier, 2010; Young et al., 2013).

It was also investigated whether the driving data collected is correlated with the other study design factor, cycling exposure (i.e., being a cyclist-driver vs. non-cyclist-driver). Half of the participants were recruited as cyclist-drivers who self-reported to riding a bicycle at least a few days a month. Research to date had several attempts to identify differences due to cycling exposure in terms of driving attitude and knowledge (Johnson et al., 2014), risk perception (Lehtonen et al., 2016), change detection (Beanland & Hansen, 2017) as well as visual search (Robbins & Chapman, 2018). Our dataset is the first instrumented vehicle study focusing on the impact of cycling exposure at intersections and provides clear evidence that experience in cycling as a driver results in safer scanning behaviour at urban intersections. While only slight differences have been observed between the two driver groups in self-reported driving history, self-reported driving behaviour, general attentional abilities, and subjective workload, significant differences were found in the prevalence of visual attention failures towards VRUs. Compared to cyclist drivers, the number of "high-critical" failures were found to be almost doubled for non-cyclist drivers, from 44 to 73 failure incidents, respectively. In addition, as argued by Robbins and Chapman (2018), awareness of cyclists can also be attained through social exposure, such as having family members or close friends that ride a bicycle frequently. Given that only one of the non-cyclist drivers self-reported to have such an acquaintance compared to eight other cyclist-drivers, this might be an additional factor for such failure prevalence among non-cyclist drivers.

Previous research has argued that high levels of mental workload may impair the endogenous mechanism of visual attention (Lee et al., 2007; Trick et al., 2004). Endogenous control is often referred to as intentionally directing attention toward a relevant stimulus where drivers search for information pertinent to specific goals or intentions (Theeuwes, 1991)**,** which can introduce perceptual advantages (e.g., expectancy) as well. For example, cyclist-drivers might have certain habits such as gazing at locations that cyclists are more likely to appear; but, their performance might degrade with an increased workload (Trick et al., 2004). Thus, we hypothesized that our cyclist participants would have a similar number of critical failures as the non-cyclist group when negotiating the high risk intersections. However, the insignificant interaction effect between cycling exposure and intersection risk might be attributed to the relatively lower environmental and maneuver demands during the experiment. While receiving turn-by-turn directions, our participants were not engaged in any secondary task and were not under time pressure. Although urban intersections, in general, generate mental demands on drivers, driving a pre-set route might not result in higher than normal workload levels. Also, some of cyclist-drivers in our experiment adopted a strategy by least prioritizing sidewalks and crosswalks, but still exhibited a check towards these locations. We may argue that under circumstances where environmental demands go beyond human attention capacity, these cyclist-drivers may fail to scan areas for pedestrians.

Scanning behaviour associated with individual differences might stem from multiple factors. For example, while two drivers come from the same cyclist group, the one with stronger general attentional skills may exhibit more effective scanning. To explore some potential complementary factors, driver awareness through self-reported questionnaires and general attention abilities through computerized attention tasks were introduced to the statistical models. This would also help to determine the most appropriate predictor tool(s) to assess visual attention failures towards VRUs at intersections separately or in combination. The model results showed that although some measures have predicted visual attention failures, we only had marginal statistical significance for these relations. This can be attributed to several reasons. Although data collection by self-reports (post-drive questionnaires) provides valuable information, poor understanding of the questions and survey dynamics might introduce response bias (Rosenman, Tennekoon, & Hill, 2011). Besides, questionnaires often come with certain validation problems. For instance, AFDQ is a relatively recent tool which has not been validated through on-road data. Additionally, while DBQ has been extensively used in driving research and validated through several methods, it lacks the frequency reporting of the errors being made (Salmon, Lenné, Stanton, Jenkins, & Walker, 2010). For instance, one can exhibit a failure only a few times and can select "most of the time" if that condition is very unlikely to occur. Another issue might arise due to social norms; participants might respond in a way that their attitudes and behaviours match with the appreciated norm of society (Rosenman et al., 2011). For example, one can self-report that they never speed even though they do.

In addition, individual differences were analyzed through computerized attention tasks, where participants appeared to perform significantly better at the Posner cue-target paradigm compared to the Multiple Object Tracking (MOT) task. Although the scores of both tasks were initially standardized for clustering analysis, the wider range of the MOT score distribution dominated the results of the general attentional ability categorization. The MOT task adopted in a laboratory environment might not be a significant predictor of scanning performance at intersections as opposed to being a measure of overall driving performance in urban areas (Mackenzie & Harris, 2017) due to certain restrictions in replicating very demanding intersection characteristics. Further, potential targets at intersections are mostly other road users whose trajectory and speed are unknown and often unpredictable; and they also differ in form and appearance as opposed to tracking a fixed number of targets on a desktop computer. Also, by its nature, tracking at intersections requires multitasking (e.g., steering, adjusting speed) whereas MOT is a sole task to be accomplished.

3.4.1 Study Limitations

In general, the sample size is a limitation of our study. In practice, collecting on-road data is costly and time-intensive. These experiments are often limited to 10-20 participants due to the effort involved in data collection (each participant required about 3 hours of data collection). Thus, 26 participants were a reasonable number regarding all the constraints that must be followed when conducting graduate-level research, including the Research Ethics Board approval. Also, since this study is based on voluntary participation, the recruitment process comes with a sampling bias (Tyrer & Heyman, 2016). Given that our subjects participated in such a driving evaluation study, our sample represent those who are in general safer drivers. Although all study applicants were informed about the study confidentiality and anonymity, some individuals who didn't partake in the study might have felt hesitant about participating. Overall, it was proposed that our participants represented a fairly low crash risk group, although we do not have access to confirm the accuracy of participants' demographics and driving history (Rosenman et al., 2011). Thus, we cannot conclude for certain that our sample matches other samples that have been identified as having a low crash risk. Participants were also asked to recall the incidents within the past five years, and memory failures might have occurred when answering such survey questions (McGwin, Owsley, & Ball, 1998).

There are also certain limitations associated with on-road data collection. Uncontrolled environmental factors such as variations in road user traffic and weather conditions might introduce differences in participants' behaviours. Also, to eliminate the effect of weather to a certain degree, the experiments were run only under good weather conditions (e.g., without rain, snow) within a definite period (April-May). It was also argued that the presence of the researchers could impact participants' social and psychological mechanisms where the effects often occur in the form of performance increase (Hansson & Wigblad, 2006). Due to this so-called Hawthorne effect, people often become more cautious when they know that they are being watched. For example, participants in our on-road study might have performed better and taken safer actions as two investigators were present in the instrumented vehicle. Despite being an experimental limitation, this issue instead supports the concerns regarding the prevalence of failures observed.

While peripheral vision can aid drivers for tasks not requiring direct gaze such as lane-keeping (Summala, Nieminen, & Punto, 1996), our experiment focuses on foveal vision captured through the eye tracker. To record this scanning behaviour, participants were asked to wear the Ergoneers Dikablis eye tracking headset so that it does not bother them or distract them during the drives. Although it is not always possible to ensure a perfectly-working system, the cutting-edge eye tracking technology has promising accuracy in detecting eye pupils after calibrating for each individual (Ergoneers, 2018). Further, given the assumption that visual attention and gaze position are intrinsically linked (Corbetta et al., 1998; Itti & Koch, 2000; Theeuwes et al., 1998), the gaze position was used as a proxy for visual attention in failure coding. Even though directing gaze toward a location does not guarantee perception, it is still a pre-requisite for perception (Dewar & Olson, 2015). From this aspect, there is a chance that drivers may not be noticing VRUs even when they are scanning areas of importance for VRU traffic. Thus, we can argue that our findings from gaze data may be a genuine underestimate of visual attention failures, and all these issues mentioned should not detract the rigor of the findings.

Chapter 4

4 Countermeasures to Enhance Cyclist Safety

In this chapter, a review of countermeasures suggested or implemented to improve cycling safety is presented. These countermeasures can be used to address some of the issues that we have observed in our on-road driving studies as well as other potential cycling-safety problems. As a first step, we decided to focus on cycling safety since the number of cyclists who die or are severely injured in crashes has been increasing despite the decline in overall traffic fatalities and injuries (Brand, George, Goodman, Weekes, & Df Statistics Staff, 2015; National Center for Statistics and Analysis, 2018a). The scope was restricted to cyclist-driver interactions since bicycle-bicycle and bicycle-pedestrian collisions tend to be less severe (Haileyesus, Annest, & Dellinger, 2007; Shinar et al., 2018).

It can be argued that the increase in cyclist injuries/fatalities is likely due to the existing vehicle, infrastructure, and policy designs failing to facilitate the increase in cycling volume. From this perspective, we also proposed a taxonomy dividing these countermeasures into three design categories: gear/vehicle, infrastructure, and policy. Based on the somewhat limited evidence reported in the literature, it appears that infrastructure design solutions are the most effective. This review and the taxonomy has been published as a conference proceeding paper (Kaya & Donmez, 2019):

> **Kaya, N. E.** & Donmez, B. (2019). A taxonomy of countermeasures for cyclist-vehicle crashes. In *Proceedings of the 29th Canadian Association of Road Safety Professionals Conference*, Calgary, AB. **(CARSP Student Paper Competition, 4th Place)**.

4.1 Background

The overwhelming majority of people living in large cities with busy downtown areas, such as Toronto, Ontario, do not prefer to drive due to traffic congestion and limited parking resources (City of Toronto, 2018). As downtown areas continue to grow, residents are encouraged to walk, cycle, and take transit (Pucher, Dill, & Handy, 2010). Overall, cycling is experiencing a growth in urban areas (Pucher et al., 2010). For instance, from 2001 to 2006, the percentage of Toronto commuters who chose cycling over other forms of transportation went from 1.3 to 1.7%, an increase of 31% (Toronto Public Health, 2012).

Despite the benefits of cycling, cycling safety within motor vehicle traffic appears to be deteriorating. Given the minimal level of protection cyclists have, they are more likely to suffer major injuries or fatalities in a crash compared to vehicle occupants (Stipdonk & Reurings, 2012). Although the total number of traffic fatalities have been declining in the past decade, an increase in the rate of cyclist fatalities has been observed: Cyclist fatalities accounted for 2.2% (840) of the total 37,461 U.S. traffic fatalities recorded in 2016, compared to 1.7% (701) of the total 41,259 fatalities recorded in 2007 (National Center for Statistics and Analysis, 2018a). Similarly, from 2005 to 2014, the percentage of cyclists killed or seriously injured in the UK among all fatalities and serious injuries has doubled from 7% (2,360) to 14% (3,514) despite the decline in the total number of traffic fatalities and major injuries from 32,155 to 24,582 (Brand et al., 2015).

The annual mileage traveled is significantly less for bicycles than for motor vehicles. For example, the average annual distance traveled per person in the UK in 2014 was found to be 90 km for cycling and 5,272 km for driving (Brand et al., 2015). Controlling for mileage exposure, it was found that in the Netherlands there are about 5.5 times more traffic fatalities per kilometer traveled by bicycle than by car (de Hartog, Boogaard, Nijland, & Hoek, 2010). Controlling for trip exposure (i.e., number of trips taken), U.S. cyclists have been found to be 2.3 times more likely to die in a crash compared to a vehicle occupant (Beck, Dellinger, & O'Neil, 2007).

A further look at severe cyclist crashes reveals that the majority of them take place in urban areas: 71% percent of U.S. cyclist fatalities in 2016 occurred in urban settings (National Center for Statistics and Analysis, 2018a); this rate was 75% for the UK (RoSPA, 2017). Within large cities, such as Toronto, most cyclist fatalities appear to occur in the downtown core, which can in part be explained by the growing demand for cycling in busy city cores: 69% of cyclist fatalities recorded in Toronto in 2010 occurred in downtown areas (Toronto Public Health, 2012).

Although crash data indicate an increase in the rate of cyclist fatalities and serious injuries, the data collected may not fully reflect the extent of the problem. Underreporting of cyclist crashes to police has been shown to be a worldwide problem (Shinar et al., 2018). Even in a bike-friendly country such as the Netherlands, police-report data showed a 26% decrease in cyclist serious injuries from 2000 to 2009, whereas hospital records indicated a 35% increase (OECD/International Transport Forum, 2013). The disparity between reality and police records is likely to be larger for non-severe cyclist crashes (Stipdonk & Reurings, 2012). In a survey of 7,015 active cyclists across 17 countries, 37.6% of the cyclists who self-reported to having been admitted to hospital after a crash said that they reported the crash to the police; the police-reporting rate was only 3.9% for crashes with no medical attention (Shinar et al., 2018).

Overall, it is clear that cycling safety is becoming a greater concern as cities grow around the world. Efforts are underway around the world to eliminate cyclist fatalities and serious injuries through Vision Zero programs. The first Vision Zero act was established in Sweden in 1997 to entirely eliminate serious injuries and fatalities that occur on the roads (Kristianssen, Andersson, Belin, & Nilsen, 2018). Since then, Vision Zero has been implemented in other European countries and more recently in Canada (City of Toronto, 2017) and in the U.S. (Coleman & Mizenko, 2018). These programs take on a comprehensive approach to enhance road safety, targeting policy, infrastructure, and vehicles (Kristianssen et al., 2018). With this perspective, it is important to systematically identify ways to prevent or mitigate cyclist crashes, which may be due to several factors including improper road user behaviours, poor infrastructure design, and lack of policy and enforcement (Useche, Montoro, Alonso, & Oviedo-Trespalacios, 2018).

4.2 Proposed Taxonomy

We proposed a taxonomy (Table 18) to systematically categorize design interventions on vehicle/gear, infrastructure, and policy that target cyclist-driver interactions and related crash outcomes. The scope was restricted to cyclist-driver interactions for this first effort to create a taxonomy since bicycle-bicycle and bicycle-pedestrian collisions tend to be less severe. For example, in the U.S. between 2001 and 2004, cyclists who were injured in a collision with a motor vehicle were 2.6 times more likely to warrant hospitalization or transfer for specialized medical care compared to cyclists who were injured in other collision types (Haileyesus et al., 2007). We also provided an overview of the available evidence regarding countermeasure effectiveness and also highlighted potential interventions that require further evaluation.

Table 18 Taxonomy of countermeasure design for cycling safety; an example was provided for each countermeasure

<table>
<tr><th>ROAD USER</th><th>Vehicle/Gear</th><th>Infrastructure</th><th>Policy Design</th></tr>
<tr><td>DRIVER</td><td>Maintenance
e.g., quality of windshield wipers

Assistive Car Technology
e.g., blind spot detection</td><td rowspan="2">Maintenance
e.g., adequate quality of road surface

Control Elements
e.g., dedicated bicycle signals

Road Layout
e.g., dedicated bicycle lanes</td><td>Education & Training
e.g., right-of-way knowledge

Regulatory Laws
e.g., no right-turn-on-red

Enforcement
e.g., fines for the intrusion to bicycle facilities</td></tr>
<tr><td>CYCLIST</td><td>Maintenance
e.g., tire pressure

Detection Enhancing Gear
e.g., reflective vest, bell

Assistive Bicycle Gear
e.g., rear-view mirror on bicycle

Protective Gear
e.g., helmet</td><td>Education & Training
e.g., avoiding dark clothing

Regulatory Laws
e.g., license plates for bicycles

Enforcement
e.g., detection system for violations</td></tr>
</table>

4.2.1 Vehicle/Gear Design Countermeasures

Crash risk and severity can be reduced through the introduction and adoption of enhanced protective and assistive technologies, as well as the adoption of regular maintenance schedules. Proper ***maintenance of vehicles*** (cars and bicycles) is required to ensure that both cyclist and driver actions are carried out as intended. For example, proper tire type and pressure translate to efficient braking (Rievaj, Vrábel, & Hudák, 2013) and working windshield wipers and signals prevent delays in visual detection (Bernardin et al., 2014).

Assistive car technologies can aid drivers in detecting other road users, particularly cyclists, and reacting to complex scenarios. For example, blind spot detection technology has been implemented within cars with about 78% precision rate for vehicle and motorcycle detection (Ra, Jung, Suhr, & Kim, 2018), but needs further development for detecting cyclists (Silla et al., 2017). More comprehensive detection systems have been proposed with the system presenting peripheral cues on a head-up display informing the driver to switch their attention to areas/objects of importance (Gruenefeld, Löcken, Brueck, Boll, & Heuten, 2018). Results from two of our instrumented vehicle studies conducted in downtown Toronto (Chapter 2 and 3) found that majority of drivers failed to allocate proper attention to cyclists at intersections. Therefore, there is a need to alert drivers about cyclists in their vicinity. The alerting can be through the visual modality as is the case for head-up displays, but also through other modalities such as through auditory or tactile warnings. Auditory and tactile warnings are omnidirectional (Meng & Spence, 2015) and can alert drivers of the presence of a cyclist even when the driver's visual attention is not directed towards the visual display.

Assistive technologies can go one step further from aiding the driver in cyclist detection to also assisting them in vehicle control, for example, by applying the brakes if the driver fails to react in a timely manner. There are such systems implemented in current production vehicles; Tesla Model S provides automatic braking if an imminent crash is anticipated (Endsley, 2017). These types of systems might be particularly useful for cars that have wider A-, B- or C- pillars that can block the view of the driver. In general, the reliability of assistive car technologies need to be improved, and various efforts are underway to develop smarter vehicle and infrastructure systems (e.g., roadside radars and cameras understanding cyclist intentions and communicating this information to vehicles, direct communication between vehicles so that the car is aware of the bicycle trajectory) (Silla et al., 2017). Although there has been a substantial upsurge in intelligent transport system research in the past decade, most of these systems are not yet ready for implementation; it is estimated that, by 2023, only around 50% of vehicles will be equipped with such systems (Silla et al., 2017). Also, a major concern is overreliance of drivers/cyclists on such technologies that are less than perfect as the primary agent to detect and react to roadway conflicts.

A major issue is overreliance of drivers/cyclists on such technologies that are less than perfect as the primary agent to detect and react to roadway conflicts. For example, a blind-spot detection system can aid drivers to detect cyclists when the drivers' visual attention is focused elsewhere. Drivers may get accustomed to having a blind-spot detection system and may lose the habit of performing over-the-shoulder checks for cyclists. Such a maladaptation would be particularly dangerous when drivers switch vehicles and need to drive a car without a blind-spot detection system.

Between 2010 and 2015, 12.1% of U.S. cyclists were fatally struck as they were not visible (Coleman & Mizenko, 2018). Therefore, cyclist visibility plays a large role in their detection and can be enhanced by adopting ***detection enhancing gear***, such as reflective vests, flashing lights, and bells. Wearing fluorescent and reflective vests (Wood, Lacherez, Marszalek, & King, 2009) in addition to light clothing, installing pedal reflectors and flashing or steady lights (OECD/International Transport Forum, 2013) have been recommended to increase visibility. Daytime usage of bicycle lights has been correlated with a 30% reduction in self-reported crashes (J. Madsen & Overgaard, 2006). The importance of reflective clothing in low lighting appears to be recognized more by drivers (95% of surveyed drivers) than by cyclists (72% of surveyed cyclists) (Wood et al., 2009). Therefore, this type of countermeasure may need to be supported through policy and education.

Cycling performance can be improved through ***assistive bicycle gear***, such as the installation of a rear-view mirror on the bicycle to extend the field of view of the cyclist, and through gloves and sunglasses to improve grip and to protect vision from the sun and debris. On the other hand, ***protective gear*** worn by cyclists, such as helmet and knee/elbow pads, can reduce the impact of a crash on the cyclist. About 45% of the U.S. cyclists who were hospitalized due to a collision with a motor vehicle, had a head/neck injury, followed by 27% who had an injury of lower extremities. Among those with a head injury, 85% were diagnosed with a concussion (Haileyesus et al., 2007). Therefore, head is an important body part to protect as a cyclist. Helmet wearers are significantly less likely to experience fatality (odds ratio, OR: 0.27) and head injury (OR: 0.40) (Attewell, Glase, & McFadden, 2001). Wearing a helmet is generally highly recommended by government agencies but is not compulsory in many jurisdictions around the world (Wegman, Zhang, & Dijkstra, 2012).

4.2.2 Infrastructure Design Countermeasures

Proper design and maintenance of infrastructure can also significantly mitigate driver-cyclist crashes. Proper ***maintenance*** *of* road surface, markings, control elements, along with roadside furniture (e.g., trees limiting sight distance) is essential for road safety. Maintenance of bike paths is also critical since the accumulation of any obstacle on the path (e.g., debris, snow) or poor pavement quality is deterrent to cycling (Pucher et al., 2010) and can force cyclists to ride closer to vehicles. The elimination of highway defects from four districts in the UK was forecasted to increase proportion of cycling to work by 1.3 to 12.9% (Parkin, Wardman, & Page, 2008). Further, obstacles on cyclists' path can create distractions for cyclists. For example, a survey of 1064 cyclists from various countries found that about 84% of cyclists consider obstacles on their path as distractions (Useche, Alonso, Montoro, & Esteban, 2018). Adequate road lighting should also be ensured; police reports between 1997 and 2002 from the U.S. revealed that cyclist fatality probability is higher by 111% on dark, unlit roads compared to those with streetlights or under daylight conditions (Kim, Kim, Ulfarsson, & Porrello, 2007).

Motor vehicle and bicycle traffic are informed and directed through ***control elements***. Clear, legible and salient road furniture tailored to particular circumstances (e.g., maneuvering) and driver groups (e.g., unfamiliar drivers) can ease the task of negotiating the road environment (Smiley, Courage, Fitch, & Currie, 2011). Warnings on upcoming events can lead to safer driving actions; implementing signal countdown timers (i.e., showing the remaining red and green phases) (Sharma, Vanajakshi, Girish, & Harshitha, 2011) and a flashing green phase prior to the amber phase (Mussa, Newton, Matthias, Sadalla, & Burns, 1996) have both been found to reduce red-light running incidents. Similarly, a flashing amber beacon mounted at stop-controlled intersections can alert drivers in advance about the presence of an upcoming stop sign (Srinivasan, Carter, Persaud, Eccles, & Lyon, 2008). This intervention appears to be more beneficial for rural sites (Srinivasan et al., 2008), which encompass long stretches between intersections and thus drivers are more likely to miss an intersection (Golembiewski & Chandler, 2011). Advanced-stop lines for cars (a.k.a., green bike box project) can make cyclists more visible and facilitate safer left-turn areas for them. Upon installation of advanced-stop lines in Portland, U.S., drivers were found to exhibit better yielding behaviours to cyclists during right turns, and the overall number of conflicts between cars and bicycles reduced by 30% (Dill, Monsere, & Mcneil, 2011). Further, dedicated bicycle signals at intersections can separate cyclists from vehicle traffic in time. Over a 35-month span after signal modification, no vehicle-cyclist crashes were reported in Davis, California, where there were 12 incidents in the preceding 35-month time period (Korve & Niemeier, 2002).

In terms of the ***road layout***, separating cyclists from motor vehicle traffic to various extents is the most common intervention suggestion, since cycling mixed with vehicle traffic is less preferred (Shafizadeh & Niemeier, 1993). Robbins & Chapman (2018) argue that crashes are more likely to be linked to drivers' attention failures towards cyclists when cyclists and vehicles share the same road. Further, the presence of motor vehicle traffic can be a source of distraction for cyclists, leading to attentional failures on their part. For example, the survey from 1064 cyclists reported earlier also found that about 84% of cyclists considered other road users to be sources of distraction (Useche, Alonso, et al., 2018). The separation between the two modes of transportation can be introduced by pavement coloring (e.g., a solid white line), physical barriers (e.g., bollards, roadside planters), raised median, and cycle tracks (i.e., exclusive two-way bike tracks) (Pucher et al., 2010). On-street parking lanes have also been implemented between motor vehicle and bicycle traffic as they can act as a buffer between the two modes of transport (DiGioia, Watkins, Xu, Rodgers, & Guensler, 2017). However, this approach can introduce unanticipated hazards for cyclists such as dooring from the passenger side (City of Toronto, 2017) or blocking the drivers' view of cyclists until the two traffic modes mix again at intersections (Kaya et al., 2018).

In a meta-analysis study, DiGioia et al. (2017) found that cycle tracks are the most effective road layout strategy for preventing injury among the ones that were investigated (bicycle boulevard, bike box, bike lanes, cycle track, multi-use path, neighborhood traffic circle, raised bicycle crossing, removal of on-street parking, roundabout bike lane, roundabout general, roundabout mixed traffic, roundabout multi lane, roundabout separated bike facility, street lighting). The risk ratio compared to a similar road without any cycle tracks was estimated to be around 0.12. Removal of on-street parking was also found to be effective, with a risk ratio of around 0.61. Cyclists also appear to perceive cycle tracks as the safest and prefer to use them; survey respondents from Toronto and Vancouver, Canada reported that they feel safest when riding on cycle tracks and prefer them highly (Teschke et al., 2012).

Cycle tracks are effective in reducing injury risk, but their effectiveness may degrade when they are designed to merge with motor vehicle traffic at intersections. In general, it is important to provide undisrupted pathways for cyclists not only throughout midblocks, but also through intersections, which can be facilitated through delineated markings, cyclist undercrossing, overcrossing, floating bus stop (i.e., directing cyclist traffic around bus stop zone), or jug-handle left turns for cyclists (Arason, 2018). Although a report on crashes on 148 roundabouts in Belgium (Daniels, Brijs, Nuyts, & Wets, 2010) suggested the removal of roundabouts as they had been found to increase injury risk for cyclists by 27%, a recent before-after study from Denmark argued that single-lane roundabouts with a dedicated bike path are safer than mixed conventional intersections, as they allow cyclists to operate separately from motor vehicle traffic (Jensen, 2017). In addition, a more comprehensive approach, such as a road diet (i.e., a lane reduction or road channelization) can introduce or add bike lanes to an area, eliminate on-street parking lanes that may create hazards to cyclists (e.g., dooring), and even reallocate traffic to create vehicle-free streets (Pucher et al., 2010). A road diet treatment in three U.S. states indicated a 29% reduction in the total number of collisions as well as a reduction in speed. With two through lanes and a center lane for turning, cars were restricted by the speed of the vehicles ahead (Tan, 2010). In addition, removal or separation of streetcar and railroad tracks from traffic is advised (Ministry of Transportation-Ontario, 2017) since these tracks impede riding activity, and significantly increase the cyclist injury risk by threefold (Teschke et al., 2012)

4.2.3 Policy Design Countermeasures

Policy design offers guidance on the development, implementation, and adoption of the vehicle/gear and infrastructure strategies that have been discussed above.

Education and training countermeasures can range from the redesign of driver handbooks to marketing campaigns to driver/cyclist training programs. For example, driver handbooks can be updated to clearly convey right-of-way information related to cyclists; educational marketing campaigns can raise awareness, correct misinformation to reduce unsafe driver/cyclist behaviours, and promote safer ones (e.g., helmet use, vehicle maintenance, bicycle signaling knowledge, minimizing smartphone use while riding/driving, avoiding wearing black clothing); training specific to cycling and interacting with cyclists can be incorporated in graduated driver licensing programs (Dellinger & Sleet, 2010). Safety education can also be provided through mentorship programs. For example, a cycling mentorship program implemented and evaluated in Toronto, Canada increased the adoption of cycling by targeting two barriers that the research team identified: owning a bicycle (a bicycle was provided on loan) and lack of confidence riding on street (through hands-on mentorship, e.g., through rides and route planning) (Savan, Cohlmeyer, & Ledsham, 2017). At the end of the 16-week program, participants reported to preferring a bike in 25% of their trips, whereas this proportion was 5% at the program entry. There was an 84% increase in how much participants were willing to spend on bicycle accessories, a control group that was also surveyed at the start and the end of the 16-week program had 4% decrease.

Regulatory laws and ***enforcement*** are fundamental for road safety and should be informed by research and supported by education campaigns. However, although research may suggest the effectiveness of an intervention, adopting it on large scale may result in different outcomes. For example, helmets are clearly beneficial to cyclist safety, but, few countries made it mandatory for cycling, including Australia where there was a decline in bicycle usage after the helmet law was introduced (Robinson, 2006). Further, enforcement is also important for the law to work. For example, a law requiring a license plate for bikes has been suggested in the UK to discourage aggressive and reckless riding (Halfords, 2017). China has implemented a similar law just for electric bikes; however, due to a lack of punishment and enforcement, 70% of 844 electric bike users surveyed indicated that they did not register a licence plate (Guo, Li, Wu, & Xu, 2018). In general, although there are laws concerning cyclist behaviours, these are few and the enforcement is not sufficient, potentially leading to unsafe behaviours being common among cyclists (e.g., running red light, riding between motor vehicles). Literature suggested stronger police enforcement to penalize aberrant cyclist behaviours (Dewar, 2015).

The following interventions have been suggested in the literature to be implemented into regulation and enforcement: (1) no right-turn-on-red as limited attentional resources of drivers can lead to conflicts with other road users and the introduction of right-turn-on-red has been found to increase crashes with pedestrian and cyclists (Preusser, Leaf, DeBartolo, Blomberg, & Levy, 1982); (2) distraction engagement for cyclists, in particular smartphone use, as it has been found to be a common behaviour among cyclists and its prevalence has been found to be correlated with self-reported crash history of cyclists (Useche, Alonso, et al., 2018); and (3) fines for motor vehicle intrusion to bicycle facilities without exception as this poses a risk to cyclists (OECD/International Transport Forum, 2013).

4.3 Discussion

This section provided a review of countermeasures for improving cyclist-driver interactions and grouped them in a taxonomy in three categories: vehicle/gear, infrastructure, and policy design. It appears that, among the existing interventions, infrastructure-related ones are the most effective, in particular if they separate cyclists from motor vehicle traffic. However, it should be noted that evaluations of specific interventions are very limited. We could identify one meta-analysis paper comparing different road-layout interventions that found cycle-tracks to be one of the most effective. However, the number of studies that were included in this meta-analysis was limited and most had methodological limitations (DiGioia et al., 2017). Therefore, there is a need for further evaluations of different interventions in general, and more rigorous ones in particular.

Further, technological advances now enable vehicle-to-vehicle and vehicle-to-infrastructure communication, along with artificial intelligence that can be leveraged to support driver-cyclist interactions. Although the resulting systems aimed to enhance cyclist safety are not yet mature enough, they are very promising. Infrastructure and policy design can shape the behaviour of drivers and cyclists, but vehicle technology can also help extend drivers' information processing capabilities such as overcoming the limits of visual attention. For example, a blind-spot detection system can aid drivers to detect cyclists when the drivers' visual attention is focused elsewhere, and vehicle-to-vehicle communication can help motor vehicles predict bicycle trajectories. However, with such technology, concerns for maladaptive behaviours also emerge. For example, drivers may get accustomed to having a blind-spot detection system and may lose the habit of performing over-the-shoulder checks for cyclists. Such a maladaptation would be particularly dangerous when drivers switch vehicles and need to drive a car without a blind-spot detection system.

Road transportation is a complex system with many agents. According to the systems approach for human error management, a system should have several defense barriers to prevent errors from occurring or propagating (James Reason, 2000). With this view, cyclist-safety programs should utilize multiple approaches and create defense barriers at the vehicle/gear, infrastructure, and policy levels. The effectiveness of a specific intervention alone may not indicate its ultimate success in a more comprehensive program. Future research should evaluate different interventions in combination.

Chapter 5

5 Conclusion and Future Work

This thesis investigated drivers' visual attention failures towards VRUs when making turns at urban intersections with glance data captured through eye tracking and video camera technology. First, two right turns from an existing on-road driving dataset were analyzed. This was followed by an instrumented vehicle study with higher experimental control designed specifically for assessing driver attention allocation towards VRUs. Both the analysis of the existing data and the follow-up instrumented vehicle study showed that driver visual attention failures towards VRUs were prevalent while turning at urban intersections. It was found that driver visual attention failures were predominantly related to checking for cyclists, rather than checking for pedestrians. These findings indicate an urgent need for road safety interventions for cycling safety. This thesis reviewed literature and created a taxonomy of implemented and/or proposed countermeasures that aimed to enhance overall cyclist safety. The taxonomy identified three different approaches to address driver-cyclist conflicts: the design of (1) vehicle/gear, (2) infrastructure, and (3) policy. It appears that, among the existing interventions, infrastructure-related strategies seem to be the most promising, in particular when they involve the separation of cyclists from motor vehicle traffic.

No study to date had assessed the extent of visual attention failures towards VRUs by examining behaviour of cyclist- and non-cyclist-drivers. In our study, exposure to cycling was found to make drivers significantly more attentive toward VRUs, with cyclist-drivers having fewer attentional failures while making turns at urban intersections. We also examined individual differences in general attentional abilities. While better deployment of attentional resources can aid drivers' navigational skills at intersections, the relation between basic attention tasks performed in the laboratory and attentional failures towards VRUs recorded on the road was only at a marginally significant level. This research also contributed to the literature by examining the effect of intersection risk on drivers' gaze patterns. We found that visual attention failures towards VRUs were more prevalent for the intersections that were categorized as being high risk.

An interpretation of this finding is that uncontrolled intersections (given that this factor has the highest coefficient which is used to determine the Ped IS index score; (Carter et al., 2007)), as well as intersections with a fatal crash record and on-street parking lanes, require further scrutiny. The insights garnered from our instrumented vehicle study may inform municipalities and city planners about the influence of intersection design and complexity on driver attention allocation towards VRUs.

The analysis of the existing dataset revealed that lower levels of familiarity with a driving area might cultivate a safer scanning pattern towards the surroundings, which may make drivers more attentive to VRUs. This familiarity effect informed the recruitment process of our follow up study; our participant groups (cyclist- and non-cyclist drivers) did not significantly differ in their frequency of overall driving or driving in any downtown area (including the experimental area of the Bloor/Bathurst neighborhood). However, the effect of familiarity on attentional failures was not studied further in the follow-up experiment due to sample size limitations. The analysis of the existing dataset also provided support for the validity of the intersection-related error items of the DBQ; participants who self-reported making more errors in DBQ exhibited more visual attention failures, although at a statistically marginally significant level (n=19). In the follow up instrumented vehicle study, we examined a slightly larger sample size (n=26). After carrying out a similar analysis, we found that intersection related attentional failures relate to subjective responses on a combination of the DBQ and AFDQ at a marginally significant level. Taken together, it appears that self-report measures, such as the DBQ, may not strongly predict the number of attentional failures at urban intersections. This finding highlights the importance of actual-driving studies as these types of experiments can capture measures that can be elusive in self-reports.

This thesis work had several limitations. Given the somewhat limited sample size and the selectiveness of the age-range in our experiments, it is harder to generalize our findings across the general driving population. Future research should investigate different driving scenarios across various driver groups. For example, cyclist-drivers with various biking frequencies can be recruited to investigate the effect of level of cycling experience on attentional failures towards

VRUs, in particular to other cyclists, while turning at intersections. Further, driver fitness can be a factor influencing overall intersection navigation performance. Impaired cognitive and motor skills may impact decision-making by necessitating more information (Yanik, 1986) as well as more time (Sammons, 1987) to choose a response. Besides, after a certain age, neck restrictions become more prevalent. Given the loss of about 4 degrees in neck rotation flexibility per decade of age (J. Chen, Solinger, Poncet, & Lantz, 1999), teens were found to exhibit significantly wider head turns compared to other driver groups (Angell et al., 2015). Under most of the turning scenarios, particularly during right turns, over-the-shoulder checks requiring wider head rotation are essential. Therefore, future investigations should also consider elderly drivers since their scanning behaviour and visual information processing abilities may differ from our experienced, middle-aged driver sample.

Further, experienced drivers are known to have lower crash risks compared to novices (Cooper, 1990; Mayhew et al., 2003). In addition, with the accumulation of mileage, drivers gradually become better at exhibiting better anticipation skills (He & Donmez, 2018) and performing extensive scanning (Underwood, 2007); for example, experienced driver visual scanning behaviours were found to better match the complexity of the traffic environment than the unexperienced drivers (Underwood, 2007). With experience, drivers also develop better vehicle control (Bjørnskau & Sagberg, 2005). Since novices tend to spend more mental resources on vehicle control given that they have not yet automatized many driving tasks, they often lack necessary attentional resources to scan certain areas of importance. They are also more likely to require their focal vision for tasks that experienced drivers use their peripheral vision for, such as lane-keeping (Mourant & Rockwell, 1972; Summala, Nieminen, et al., 1996). To enhance the generalizability of our study findings, future research should study novice drivers compared to experienced drivers to examine whether they commit more visual attention failures at intersections.

A further limitation of this research was that participants in both experiments were not engaged in any secondary tasks. For experienced drivers (as used in our study), driving can be a highly automized task, and thus, it is presumable that drivers in a normal day-to-day driving setting might engage more with secondary tasks while driving. As indicated by the largest naturalistic driving study to date (Dingus et al., 2016); drivers are distracted from the primary driving task about 45% of the time by legal activities (e.g., interaction with passenger). Thereby, considering impact of secondary task engagement, visual attention failures might be more prevalent than observed in this study. A more accurate depiction of visual attention failures at intersections could be observed in a naturalistic driving setting without the influence of the experimenter's presence.

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Appendices

Appendix A: Driver Behaviour Questionnaire (DBQ)

1) Please enter your Participant ID number: *

2) Try to pass another car that is signalling a left turn.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

3) Select the wrong turn lane when approaching an intersection.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

4) Fail to 'Stop' or 'Yield' at a sign, almost hitting a car that has the right of way.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

5) Misread signs and miss your exit.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

6) Fail to notice pedestrians crossing when turning onto a side street. *

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

7) Drive very close to a car in front of you as a signal that they should go faster or get out of the way.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

8) Forget where you parked your car in a parking lot.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

9) When preparing to turn from a side road onto a main road, you pay too much attention to the traffic on the main road so that you nearly hit the car in front of you.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

10) When you back up, you hit something that you did not observe before but was there.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

11) Pass through an intersection even though you know that the traffic light has turned yellow and may go red.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

12) When making a turn, you almost hit a cyclist or pedestrian who has come up on your right side.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

13) Ignore speed limits late at night or very early in the morning.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

14) Forget that your lights are on high beam until another driver flashes his headlights at you.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

15) Fail to check your rear-view mirror before pulling out and changing lanes. *

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

16) Have a strong dislike of a particular type of driver, and indicate your dislike by any means that you can. *

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

17) Become impatient with a slow driver in the left lane and pass on the right.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

18) Underestimate the speed of an oncoming vehicle when passing. *

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

19) Switch on one thing, for example, the headlights, when you meant to switch on something else, for example, the windshield wipers.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

20) Brake too quickly on a slippery road, or turn your steering wheel in the wrong direction while skidding.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

21) You intend to drive to destination A, but you 'wake up' to find yourself on the road to destination B, perhaps because B is your more usual destination.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

22) Drive even though you realize that your blood alcohol may be over the legal limit.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

23) Get involved in spontaneous, or spur-of-the-moment, races with other drivers. *

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

24) Realize you cannot clearly remember the road you were just driving on.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

25) You get angry at the behaviour of another driver and chase that driver so that you can give him/her a piece of your mind.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

Appendix B: Cognitive Failures Questionnaire (CFQ)

1) Please enter your Participant ID number: *

2) Do you read something and find you haven't been thinking about it and must read it again?*

Never Very Rarely Occasionally Quite Often Very Often

3) Do you find you forget why you went from one part of the house to the other?*

Never Very Rarely Occasionally Quite Often Very Often

4) Do you fail to notice signposts on the road?*

Never Very Rarely Occasionally Quite Often Very Often

5) Do you find you confuse right and left when giving directions?*

Never Very Rarely Occasionally Quite Often Very Often

6) Do you bump into people?*

Never Very Rarely Occasionally Quite Often Very Often

7) Do you find you forget whether you've turned off a light or a fire or locked the door?*

Never Very Rarely Occasionally Quite Often Very Often

8) Do you fail to listen to people's names when you are meeting them?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

9) Do you say something and realize afterwards that it might be taken as insulting?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

10) Do you fail to hear people speaking to you when you are doing something else?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

11) Do you lose your temper and regret it?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

12) Do you leave important letters unanswered for days?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

13) Do you find you forget which way to turn on a road you know well but rarely use?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

14) Do you fail to see what you want in a supermarket (although it's there)?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

15) Do you find yourself suddenly wondering whether you've used a word correctly?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

16) Do you have trouble making up your mind?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

17) Do you find you forget appointments?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

18) Do you forget where you put something like a newspaper or a book?*

○ Never ○ Very Rarely ○ Occasionally ○ Quite Often ○ Very Often

19) Do you find you accidentally throw away the thing you want and keep what you meant to throw away – as in the example of throwing away the matchbox and putting the used match in your pocket?*

Never Very Rarely Occasionally Quite Often Very Often

20) Do you daydream when you ought to be listening to something?*

Never Very Rarely Occasionally Quite Often Very Often

21) Do you find you forget people's names?*

Never Very Rarely Occasionally Quite Often Very Often

22) Do you start doing one thing at home and get distracted into doing something else (unintentionally)?*

Never Very Rarely Occasionally Quite Often Very Often

23) Do you find you can't quite remember something although it's "on the tip of your tongue"?*

Never Very Rarely Occasionally Quite Often Very Often

24) Do you find you forget what you came to the shops to buy?*

Never Very Rarely Occasionally Quite Often Very Often

25) Do you drop things?*

Never Very Rarely Occasionally Quite Often Very Often

26) Do you find you can't think of anything to say?*

Never Very Rarely Occasionally Quite Often Very Often

Appendix C: Attentional Failures during Driving Questionnaire (AFDQ)

1) Please enter your Participant ID number: *

2) When entering a roundabout or intersection, you fail to notice vehicles that are not straight ahead.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

3) When preparing to turn onto a main road, you pay so much attention to the traffic on the main road that you nearly run into the car in front of you.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

4) On a busy street, you fail to notice a ‘Stop’ or ‘Yield’ sign, almost hitting a car that has the right of way.*

Never Hardly Ever Occasionally Frequently Quite Often Nearly All the Time

5) When checking the rear-view or side mirrors, you fail to promptly notice that the car in front of you brakes.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

6) You fail to promptly notice vehicles and pedestrians in your way when driving along a busy downtown street.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

7) You continue to follow the traffic, without noticing that the light at an intersection has turned red.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

8) You are looking for a specific point at the road, and you fail to promptly notice that the car in front of you brakes.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

9) When you are talking on a phone, you fail to promptly notice that there is a vehicle or pedestrian in your way.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

10) You start to cross the intersection once the oncoming vehicles are moving, but then realize that your light has not turned green yet.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

11) Before switching lanes, you are so focused on the traffic in the lane that you wish to join and you fail to notice promptly that the vehicle in front of you brakes.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

12) You fail to notice an animal coming onto the road and you nearly hit the animal.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

13) You are so focused on the road ahead that you fail to promptly notice a car in the next lane attempting to merge into your lane.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

14) During a right turn, you fail to notice a cyclist or pedestrian who is entering the crosswalk from the right side, and you almost hit the person.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

15) You do not notice a vehicle driving by your side until it passes you.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

16) You fail to notice road signs when they are not straight ahead.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

17) Another driver honks at you making you realize that the traffic light has turned green.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

18) Your attention is captured by visual characters of surrounding vehicles (e.g., vehicle design, license plate, decorative object) that you fail to notice road information such as traffic signs and pedestrians.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

19) You fail to check the rear-view or side mirrors before pulling out or changing lanes.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

20) Roadside advertisements capture your attention while driving that you fail to promptly notice that the vehicle in front of you is slowing down.*

Never Hardly Ever Occasionally Quite Often Frequently Nearly All the Time

Appendix D: Arnett Inventory of Sensation Seeking

1) Please enter your Participant ID number: *

2) I can see how it would be interesting to marry someone from a foreign country.*

Very well Somewhat Not very well Not at all

3) When the water is very cold, I prefer not to swim even if it is a hot day.*

Very well Somewhat Not very well Not at all

4) If I have to wait in a long line, I am usually patient about it.*

Very well Somewhat Not very well Not at all

5) When I listen to music, I like to be loud.*

Very well   Somewhat   Not very well   Not at all

6) When taking a trip, I think it is best to make as few plans as possible and just take it as it comes.*

Very well   Somewhat   Not very well   Not at all

7) I stayed away from movies that are said to be frightening or highly suspenseful.*

Very well   Somewhat   Not very well   Not at all

8) I think it's fun and exciting to perform or speak before a group.*

Very well   Somewhat   Not very well   Not at all

9) If I were to go to an amusement park, I would prefer to ride the rollercoaster or other fast rides.*

Very well   Somewhat   Not very well   Not at all

10) I would like to travel to places that are strange and far away.*

Very well   Somewhat   Not very well   Not at all

11) I would never like to gamble with money, even if I could afford it.*

Very well   Somewhat   Not very well   Not at all

12) I would have enjoyed being one of the first explorers of an unknown land.*

Very well   Somewhat   Not very well   Not at all

13) I like a movie where there are a lot of explosions and car chases.*

Very well   Somewhat   Not very well   Not at all

14) I don't like extremely hot and spicy foods.*

Very well   Somewhat   Not very well   Not at all

15) In general, I work better when I'm under pressure.*

Very well   Somewhat   Not very well   Not at all

16) I often like to have the radio or TV on while I'm doing something else, such as reading or cleaning up.*

Very well Somewhat Not very well Not at all

17) It would be interesting to see a car accident happen.*

Very well Somewhat Not very well Not at all

18) I think it's best to order something familiar when eating in a restaurant.*

Very well Somewhat Not very well Not at all

19) I like the feeling or standing next to the edge on a high place and looking down.*

Very well Somewhat Not very well Not at all

20) If it were possible to visit another planet or the moon for free, I would be among the first in line to sign up.*

Very well Somewhat Not very well Not at all

21) I can see how it must be exciting to be in a battle during a war.*

Very well Somewhat Not very well Not at all

Appendix E: Screening Questionnaire

1) First name:*

2) Last name:*

3) Email address: *

4) Phone number *: *

5) If you are interested in participating in future research at the Human Factors and Applied Statistics Lab, please indicate below.*

I am interested in participating in your future research; please contact me when opportunities become available.

I am NOT interested.

Demographics and Driving Experience

6) What is your age? *

7) What is your sex? *

Male

Female

8) Indicate your height (in cm or feet):*

9) Are you pregnant?*

Yes

No

10) Do you ordinarily wear corrective lenses (e.g. glasses, contact lenses) of any kind?
*

Yes - Glasses or Lenses

No

11) If you do have corrected vision, are you able to wear contact lenses during the experiment?*

Yes

No

12) Do you currently hold a valid government issued driver's license?*

Yes

No

13) What are your current driver's licenses? (Select that all apply)*

- [ ] Full license (e.g. G license in Ontario)
- [ ] Learner’s license (e.g. G1 and G2 licenses in Ontario)
- [ ] Motorcycle (M, M1 and M2 in Ontario)
- [ ] I don't have a driver's license
- [ ] Other licenses (e.g. from another country) - Please specify:: ______ *

14) When did you obtain your FULL driver’s license? (MM / YYYY)*

______

15) Please provide the city and province where you drove most often, over the last year:*

City:: ______

Province:: ______

16) Over the last year, how often did you drive a car or other motor vehicle?*

- ○ Every day or almost every day
- ○ A few days a week
- ○ A few days a month
- ○ A few times a year or less
- ○ Never

17) Over the last year, how often did you drive in a busy urban area?*

- ○ Every day or almost every day
- ○ A few days a week
- ○ A few days a month
- ○ A few times a year or less

- Never

18) Over the last year, how often did you drive in the Bathurst and Bloor area of downtown Toronto?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

19) Over the last year, how many kilometers did you drive? (Hint: from Toronto to Montreal one way ~540 km) *

- Under 5,000 km
- Between 5,001 km and 10,000 km
- Between 10,001 km and 20,000 km
- Between 20,001 km and 30,000 km
- Between 30,001 km and 40,000 km
- Over 40,001km
- None
- I don't know

20) Over this winter, how often did you ride a bike as a transportation tool?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times or less during the given period

- Never

21) Over the rest of the year (including summer), how often did you ride a bike as a transportation tool?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times or less during the given period
- Never

22) Over this winter, how often did you ride a bike as a recreational tool?*

- Every day
- A few days a week
- A few days a month
- A few times or less during the given period
- Never

23) Over the rest of the year (including summer), how often did you ride a bike as a recreational tool?*

- Every day
- A few days a week
- A few days a month
- A few times or less during the given period
- Never

24) What is your level of fluency in English?*

- Elementary proficiency

- Limited working proficiency
- Minimum professional proficiency
- Full professional proficiency
- Native or bilingual proficiency

25) Have you attended any driving related experiment before?*

- No
- Yes - Specify:: ____________ *

26) Compared with others your age, how would you rate your overall vision? (If you wear glasses or contacts, rate your corrected vision when you are wearing them.)*

- Excellent
- Good - Specify your condition: ____________ *
- Average - Specify your condition: ____________ *
- Fair - Specify your condition: ____________ *
- Poor - Specify your condition: ____________ *

27) Compared with others your age, how would you rate your overall hearing?*

- Excellent
- Good - Specify your condition: ____________ *
- Average - Specify your condition: ____________ *
- Fair - Specify your condition: ____________ *
- Poor - Specify your condition: ____________ *

28) Compared with others your age, how would you rate your overall memory?*

○ Excellent

○ Good - Specify your condition: [ ] *

○ Average - Specify your condition: [ ] *

○ Fair - Specify your condition: [ ] *

○ Poor - Specify your condition: [ ] *

29) Do you have any neck restriction?*

○ No

○ Yes - Specify:: [ ] *

Appendix F: Participant Recruitment Poster

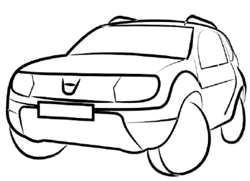
Mechanical & Industrial Engineering
UNIVERSITY OF TORONTO

Participants Needed

For an Instrumented Vehicle Study on Driving Behaviour
April – May 2019

The Human Factors and Applied Statistics Lab invites you to participate in an **on-road driving experiment** studying driving behaviour.

Location:	University of Toronto St. George Campus (Downtown)
Duration:	Approximately 3 hours
Compensation:	$50 for full-participation



- **Must have had a valid G driver's license (or equivalent) for at least 3 years**
- **Must drive at least few days per week**
- **Ages 35 – 54**

To apply, fill out our short questionnaire:
http://bit.ly/on-roadstudy

For more information, please contact:
nkaya@mie.utoronto.ca

Appendix G: Participant Recruitment Email Scripts

Email Example Script #1:

Hi ….,

Thank you for taking the time to fill out our screening survey. We are pleased to inform you that you qualify for our driving study at the University of Toronto. The study will take place on the weekend (Saturday or Sunday) during three time slots, 10:00 am or 1:00 pm.

The experiment will take up to 3 hours and will require you to answer some surveys before and after the drive. You will be driving in our instrumented car while we collect data from the vehicle, a head-mounted eye-tracker and some physiological sensors placed on your body (chest and left foot sole). After the drive, you will be asked to perform two attention related laboratory tasks. For more details, you can have a look at the attached consent form. You will be compensated at $15/hr for your time. We can reimburse your parking as long as there will be a receipt/ticket you can give us when you return to your car.

The following slots are open:

Saturday April … @ 10:00 AM

Sunday April … @ 10:00 AM

Sunday April … @ 1:00 PM

--- and subsequent weekends until we have enough participants.

If you are still interested in participating, please reply to this email confirming four things:

a) That you are between the ages 35-54

b) That you hold a valid G license issued at least 3 years ago

c) That you are able to drive legally without wearing glasses (contacts are allowed)

d) Your preferred day and time slot

Also, eye makeup has been shown to interfere with our eye tracker system, so please refrain from wearing any makeup when you come to participate. We also recommend that you do NOT wear a dress as this type of clothing might make it inconvenient to place physiological sensors on your chest.

We will call and confirm with you the week before your scheduled slot.

Thank you and kindly,

Nazli E. KAYA

MASc Candidate

HFASt Lab, Mechanical & Industrial Engineering

University of Toronto

nkaya@mie.utoronto.ca

Attachment of the email #1: Participant Consent Form

Email Example Script #2:

Hi,

This is the confirmation mail that you will have the driving experiment on Saturday/Sunday ... at .... The meeting location is in front of 150 College Street (see the attached document). Give us a call at the number (..) once you arrive so that we can pick you up from downstairs.

On the day, don't forget to bring your current driving license. The experiment will take up to 3 hours and we can reimburse your parking as long as there will be a receipt/ticket you can give us.

If you can't make it, please notify us as soon as possible. Thanks again for your participation.

Kindly,

Nazli E. KAYA

MASc Candidate

HFASt Lab, Mechanical & Industrial Engineering

University of Toronto

nkaya@mie.utoronto.ca

Attachment of the email #2: Meeting Location Document

HFASt Lab Driving Experiment: The experiment will start in the room RS 313 (Rosebrugh Building). The address is 164 College St, Toronto, ON, M5S 3E2. The closest subway station is Queen's Park on the yellow line. The picture below is the view of the meeting location from College Street.

Once you arrive the location, please give us a call at the number (..). We will pick you up from the door as shown below.

Email Example Script #3:
Hi,
This is a reminder email that you have your driving experiment tomorrow at (10:00 am / 1:00 pm / 4:00 pm). The meeting location is in front of 150 College Street (see the attached document). Please arrive on time and give us a call from the number (…).
Once again, don't forget to bring your current driving license!! The experiment will take up to 3 hours and we can reimburse your parking as long as there will be a receipt/ticket you can give us.
If you can't make it, please notify us as soon as possible!! See you tomorrow.
Kindly,
Nazli E. KAYA
MASc Candidate
HFASt Lab, Mechanical & Industrial Engineering
University of Toronto
nkaya@mie.utoronto.ca
Attachment of the email #3: Participant Consent Form and Meeting Location Document

Appendix I: Participant Consent Form

Participant Consent Form

Title of Study: Driver Behaviour and Physiology in Urban Setting
Investigators: Nazli Eser Kaya (647-519-6063; nkaya@mie.utoronto.ca)
Prof. Birsen Donmez (416-978-7399; donmez@mie.utoronto.ca)

You are being asked to take part in a research study. Before agreeing to participate in this study, it is important that you read and understand the following explanation of the proposed study procedures. The following information describes the purpose, procedures, benefits, discomforts, risks and precautions associated with this study. To decide whether you wish to participate in or withdraw from this research study, you should understand enough about its risks and benefits to be able to make an informed decision. This is known as the informed consent process. Please ask the investigator to explain any words you don't understand before signing this consent form. Make sure all your questions have been answered to your satisfaction before signing this document.

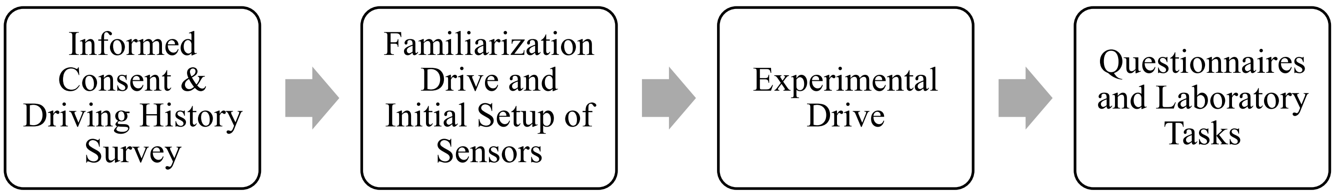
Purpose

This study **funded by NSERC** aims to understand driver behaviour in urban settings. You will be asked to:

1. Wear the eye-tracking measurement device
2. Drive on urban streets while following turn-by-turn directions given by the researcher
3. Fill out a series of questionnaires
4. Perform basic perception tasks in front of a computer

Procedure

There are four parts to this study:



1) **Informed Consent and Driving History Survey:** You have been asked to read this consent form. Please feel free to ask the researcher any questions you may have. A photocopy will be made of your driver's license for insurance purposes. You will also be asked to provide details about your driving history such as driving frequency, experience and previous traffic penalties.

2) **Familiarization Drive and Initial Setup of Sensors:** First, you will be familiarized with the features of the instrumented vehicle, then you will drive the vehicle while the researcher in the passenger seat guides you through a 5-10-minute-long preset route. This route will depart from the University of Toronto and arrive at the experiment start point. We will answer any questions you have about the system during and after this familiarization drive. You will not be recorded during this drive.

At the end of the familiarization drive, we will ask you to wear the following device. We will then calibrate it, which will take about 5 minutes:

  a. Eye tracking headset that measures where you look (worn like glasses)

If you need help with the placement, the researchers will help you physically, with your consent.

3) **Experimental Drive:** You will then be asked to drive another preset route, which will take about 30 minutes to complete. You will be given a break in the middle. You will be asked to fill out a questionnaire about your perceptions of this drive once during this break and once at the end of the drive. During this drive, you will again be guided through the route by turn-by-turn instructions given by the researcher in the passenger seat. Sensors and cameras will record your glance position and video data along with data from the vehicle like speed and lane deviation.

4) **Questionnaires and Laboratory Tasks:** After the experimental drive, you will be asked to fill out questionnaires related to your driving habits, behaviour, and personality. You will also perform two laboratory tasks in front of a desktop computer measuring basic perception, each 5-minute long.

The experiment is expected to last up to three hours.

Risks

We want to make you aware of three possible risks:

1. The first potential risk is that of a collision. The risk is minimal because all driving for the experiment will be done on streets with speed limits of 50 km/h or less. In case of an emergency, the vehicle is equipped with a secondary brake that can be depressed from the passenger seat. **However, you should not depend on the experimenter for safe driving.** During the experiment, you will be closely monitored for any signs of discomfort and you are asked to notify the experimenter if you begin to feel uncomfortable driving. Further, the experimenter will stop the experiment if you exhibit any unsafe driving behaviors. A first aid kit will be carried in the vehicle at all times. In case of collision, you will be covered by University of Toronto insurance. You will not be asked to violate any laws, and you should not. **You will be held responsible for any tickets issued for illegal actions while the vehicle is under your control.** We will not provide any of the recorded data to law enforcement officers.
2. You will be wearing the following instrument which may cause some discomfort.
    a. Eye tracking headset that measures where you look
3. There may be some minor psychological and/or emotional risks associated with completing laboratory tasks, such as a feeling of poor performance. All information obtained during the study will be held in strict confidence and you will be identified with a study number only. You will not be told how well you are doing in any of the tasks compared to others. We are not interested in your ability to perform the tasks in particular but the relation between task performance and driving behaviours in a general sense.

Benefits

There are several benefits to participating in this study. The most important benefit is your contribution to research in traffic safety, which will guide the development of methods to enhance traffic safety. You will also gain experience with academic research and be able to use and test out a state-of-the-art instrumented vehicle.

Compensation

The experiment is expected to last for approximately three hours. You will be receiving payment at the rate of $15/hr. Hence, the expected total compensation is $45 ($15/hr x 3hr). You may withdraw at any time. If a withdrawal should occur, you will be compensated on a pro-rated basis at $15 per hour for your involvement to that point. Compensation will be pro-rated to the next half-hour increment.

Confidentiality

All information obtained during the study will be held in strict confidence. You will be identified with a study number only, and this study number will only be identifiable by researchers working on this project. No names or identifying information will be used in any publication or presentation. No information identifying you will be transferred outside the research facilities for this study. The photocopy of your driver's license will be stored separately from your experimental records for the sole purpose of keeping a record for vehicle insurance.

The research study you are participating in may be reviewed for quality assurance to make sure that the required laws and guidelines are followed. If chosen, (a) representative(s) of the Human Research Ethics Program (HREP) may access study-related data and/or consent materials as part of the review. All information accessed by the HREP will be upheld to the same level of confidentiality that has been stated by the research team.

Please be advised that we make video recordings of experimental trials. The recordings will be stored securely in digital format. The videos will be seen for data analysis purposes by the investigator, as well as the co-investigator's and faculty supervisor's research assistants and research collaborators. Some section of these videos might be used for publication, where your face and identity won't be recognizable.

Faces will be blurred in all photographs & videos used in publications or presentations. Please indicate below if you give us permission to also show videos of your face in public presentations:

( ) I consent to having my video non-blurred used for public presentations
( ) I DO NOT consent to having my video non-blurred used for public presentations

Participation
Your participation is voluntary, and you may refuse to participate, may withdraw at any time, and may decline to answer any question or participate in any parts of the procedures/tasks – all without negative consequences. If you choose to withdraw at any point during the driving experiment, your data will be deleted, and the experimenter will drive you back to the laboratory. Only your name will be kept on record for your participation in this experiment. If you choose to participate in this study, the responses you have already given for the screening questionnaire, including your age, sex, and driving frequency, may be used in data analysis.

Location
The laboratory portion of the experiment will be conducted in the Human Factors and Applied Statistics Lab, located at Rosebrugh Building (RS), 164 College Street, Toronto, ON M5S 3G8. The on-road portion of the experiment will take place within downtown Toronto.

Questions
You can contact the Office of Research Ethics at ethics.review@utoronto.ca, or 416-946-3273, if you have questions about your rights as a participant. If you have any general questions about this study, please call Nazli E. Kaya at (⋯) or email nkaya@mie.utoronto.ca.

Results
To request a copy of the published results of this study, please email nkaya@mie.utoronto.ca with subject line "Research Results". A link to the published results of this study will also be made available at https://hfast.mie.utoronto.ca/ under "Publications".

Consent

I have had the opportunity to discuss this study and my questions have been answered to my satisfaction. I consent to take part in the study with the understanding that I may withdraw at any time. If required, I also consent to physical interaction with the researchers to place the eyetracker. I consent to the use of my video data for data analysis purposes and blurred in photographs and videos for publications and/or presentations. I have received a signed copy of this consent form. I voluntarily consent to participate in this study.

______________________________	____________________	____________________
Participant’s Name (please print)	Signature	Date

I confirm that I have explained the nature and purpose of the study to the participant named above. I have answered all questions.

Nazli E. Kaya ______________________	____________________	____________________
Investigator’s Name	Signature	Date

Appendix J: Pre-drive Survey

1) Please enter your Participant ID number: *

2) Please enter your birth year: *

3) How safe a driver do you consider yourself?*

Very Unsafe ... Very Safe

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10

4) In the past five years, how many times have you been stopped by a police officer and received a WARNING (but no citation or ticket) for a moving violation (i.e. speeding, running a red light, running a stop sign, failing to yield, reckless driving, etc.)? *

5) In the past five years, how many times have you been stopped by a police officer and received a CITATION OR TICKET for a moving violation? *

6) In the past five years, how many times have you been in a VEHICLE CRASH where you were the driver of one of the vehicles involved? *

7) **Follow - up question from question #5*

How many of these vehicle crashes involved a:

pedestrian?:

cyclist?:

8) When did you obtain your first driver's license (after your knowledge test)? (MM / YYYY)

9) Over the last year, how often did you drive a car or other motor vehicle?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

10) For how long do you typically drive a car or other motor vehicle per day (in terms of hours)?*

11) Please indicate your current vehicle brand and type:

12) Over the last year, how many kilometers did you drive? (Hint: from Toronto to Montreal one way ~ 540 km)*

- Under 5,000 km
- Between 5,001 km and 10,000 km
- Between 10,001 km and 20,000 km
- Between 20,001 km and 30,000 km
- Between 30,001 km and 40,000 km
- Over 40,0001 km

- None
- I don't know

13) Over the last year, how often did you drive in ANY downtown area?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

14) Over the last year, how often did you drive in downtown Toronto?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

15) Over the last year, how often did you drive in the Bathurst and Bloor area of downtown Toronto?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

16) Do you drive a motorcycle?*

Yes

No

17) When did you obtain your full motorcycle's license (M, M1, and M2 in Ontario)?*

18) Over this winter, how often did you ride a bike as a transportation tool?*

Every day or almost every day (Specify):: *

A few days a week (Specify):: *

A few days a month (Specify):: *

A few times or less during the given period (Specify):: *

Never

19) Over the rest of the year (including summer), how often did you ride a bike as a transportation tool?*

Every day or almost every day (Specify):: *

A few days a week (Specify):: *

A few days a month (Specify):: *

A few times or less during the given period (Specify):: *

Never

20) Over this winter, how often did you ride a bike as a recreational tool?*

Every day or almost every day (Specify):: *

A few days a week (Specify):: *

A few days a month (Specify):: *

- A few times or less during the given period (Specify):: ____ *
- Never

21) Over the rest of the year (including summer), how often did you ride a bike as a recreational tool?*

- Every day or almost every day (Specify):: ____ *
- A few days a week (Specify):: ____ *
- A few days a month (Specify):: ____ *
- A few times or less during the given period (Specify):: ____ *
- Never

22) Do you have a family member & close relative who rides a bike frequently?*

- Yes - Specify:: ____ *
- No

23) Over the last year, how often did you ride a bike in the Bathurst and Bloor area of downtown Toronto?*

- Every day or almost every day
- A few days a week
- A few days a month
- A few times a year or less
- Never

24) Over the last year, how often did you walk in the Bathurst and Bloor area of downtown Toronto?*

- Every day or almost every day
- A few days a week
- A few days a month

- A few times a year or less
- Never

25) Please describe the highest level of formal education you have completed:*

- Some high school or less
- High school graduate
- Some college
- College graduate
- Some graduate education
- Completed graduate or professional degree (e.g. Masters, LCSW, JD, Ph.D., MD, etc.)

26) Are you: (Please select all that apply)*

- [ ] A full time student
- [ ] A part time student
- [ ] Unemployed
- [ ] Retired
- [ ] Employed full time
- [ ] Employed part time
- [ ] A full time caregiver (e.g. children or elder)
- [ ] A part time caregiver (e.g. children or elder)
- [ ] None of the above

27) Are you right-handed?*

- [ ] Yes

☐ No

☐ Ambidextrous (both)

28) How often do you play computer games?*

☐ Every day or almost every day

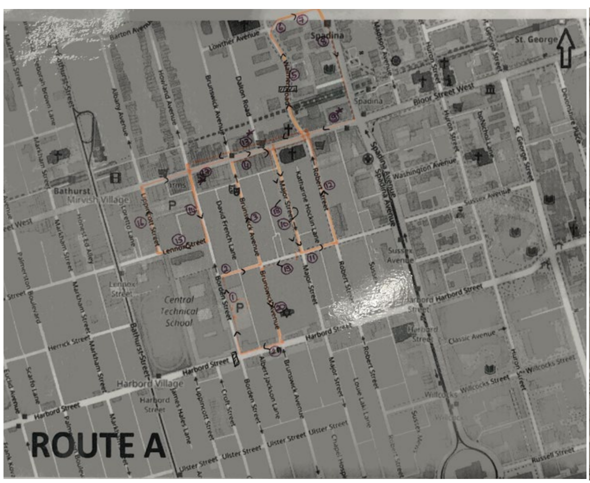
☐ A few days a week

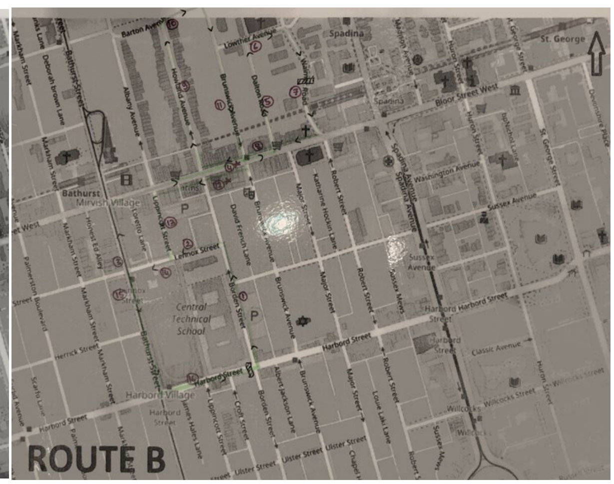
☐ A few days a month

☐ A few times a year or less

☐ Never

Appendix K: Pre-determined Routes A and B





Appendix L: Turn-by-turn Direction Scripts for Routes A and B

Script for Route A

1. At the stop sign turn right
2. At the next stop sign turn left
3. At the intersection with traffic signal, turn right

4. At the next traffic signal, turn left
5. At the stop sign turn right
6. (At the next stop sign) keep right
7. At the traffic signal, turn right
8. At the next signal, turn right
9. After the traffic signal, turn left (next to this facility building)
10. At the stop sign, turn left
11. At the next stop sign, turn left
12. At the traffic signal, turn left
13. After the traffic signal, turn left at the next intersection
14. At the stop sign, turn right
15. At the next stop sign, turn right
16. At the intersection (or at the stop sign), turn right
17. After the traffic signal, take the first right
18. At the stop sign, turn right
19. At the next stop sign, turn left
20. At the next signal, turn right
21. Just before the pedestrian crossing, turn right

Script for Route B

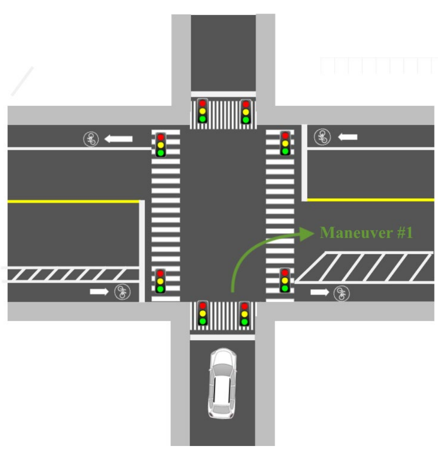
1. At the second stop sign, turn left
2. At the traffic signal, turn right
3. At the next traffic signal, turn right
4. After the traffic signal, take the first left

5. At the stop sign, turn right
6. At the next stop sign, turn right
7. At the signal, turn right
8. After the traffic signal, take the first right
9. At the stop sign, turn right
10. At the next stop sign, turn right
11. At the traffic signal, turn right
12. After this intersection (Bloor& Howland), turn left (where the aroma espresso is)
13. At the stop sign, turn right
14. At the signal, turn left
15. At the next traffic light, turn left
16. At the pedestrian crossing, turn left

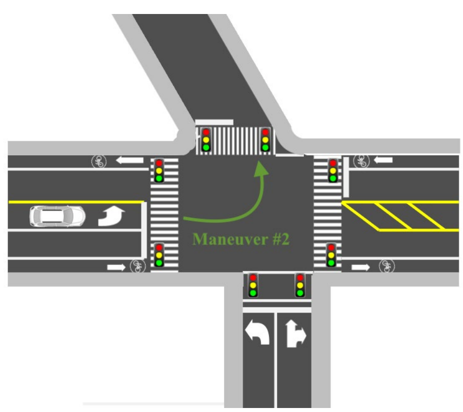
Appendix M: Investigated Maneuver Sketches

(All sketches facing north)

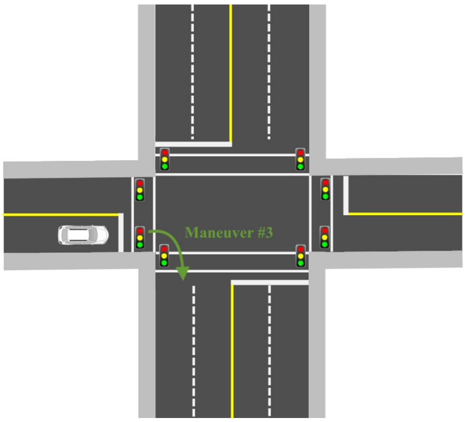
Turn 1: Brunswick & Bloor



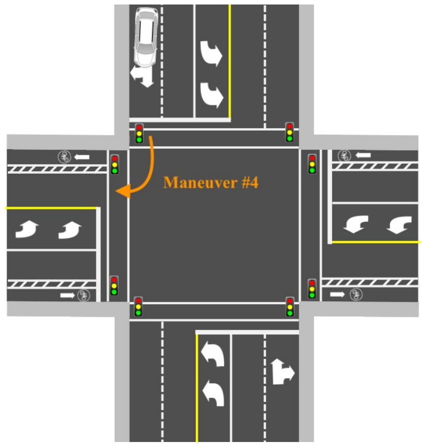
Turn 2: Bloor & Walmer



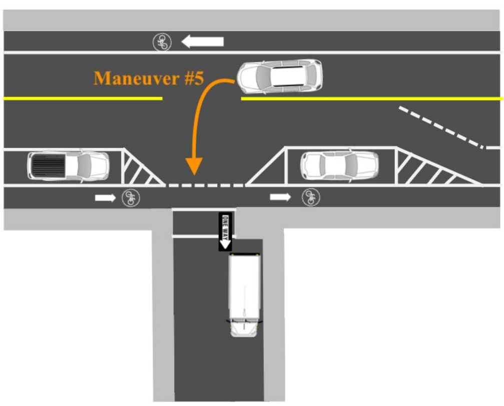
Turn 3: Lowther & Spadina



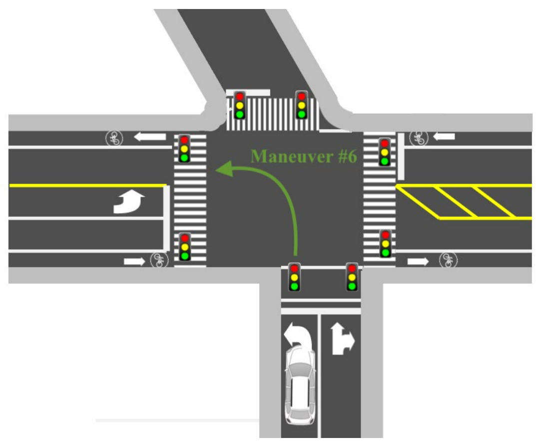
Turn 4: Spadina & Bloor



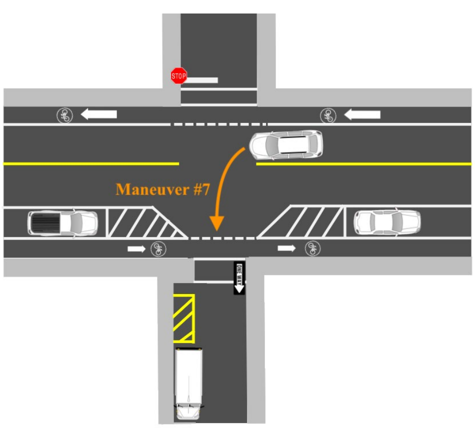
Turn 5: Bloor & Major



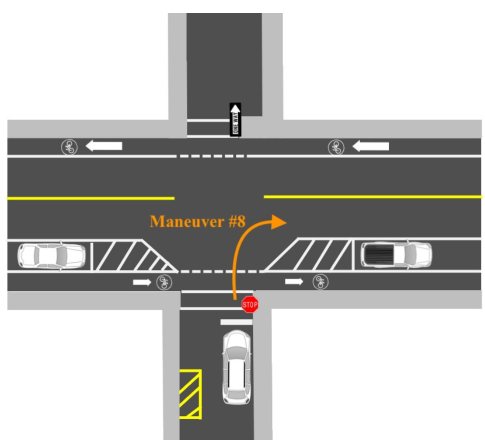
Turn 6: Robert & Bloor



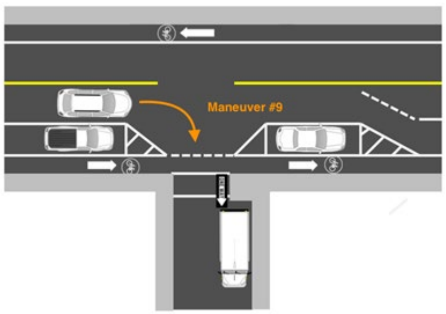
Turn 7: Bloor & Borden



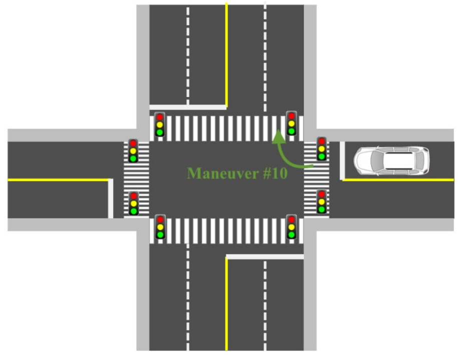
Turn 8: Robert & Bloor



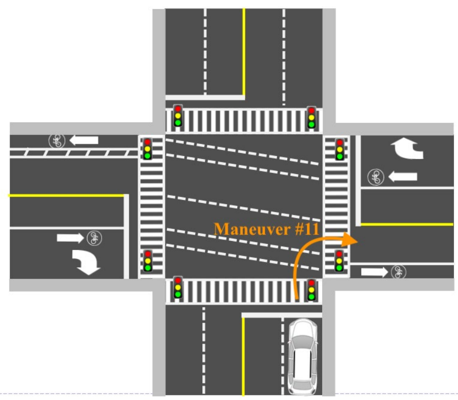
Turn 9: Bloor & Major



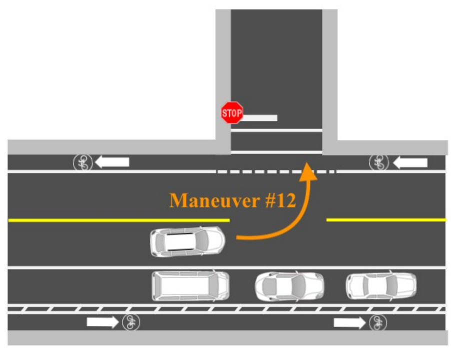
Turn 10: Lennox & Bathurst



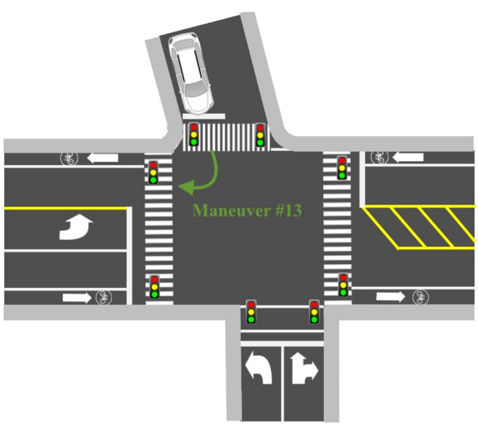
Turn 11: Bathurst & Bloor



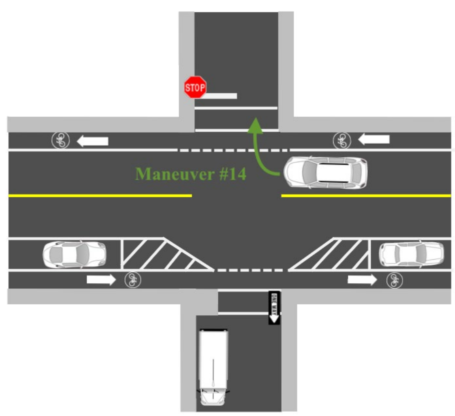
Turn 12: Bloor & Dalton



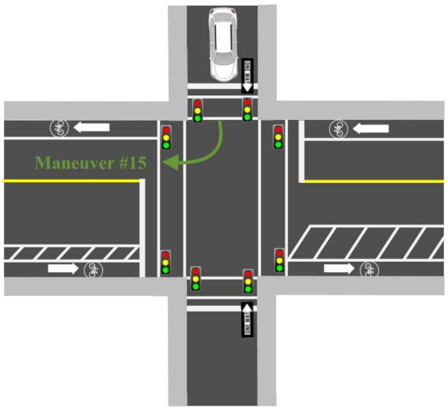
Turn 13: Walmer & Bloor



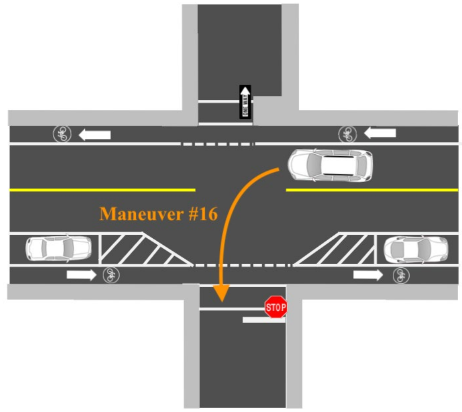
Turn 14: Bloor & Howland



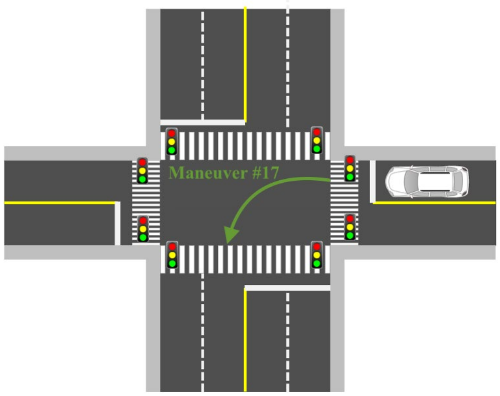
Turn 15: Brunswick & Bloor



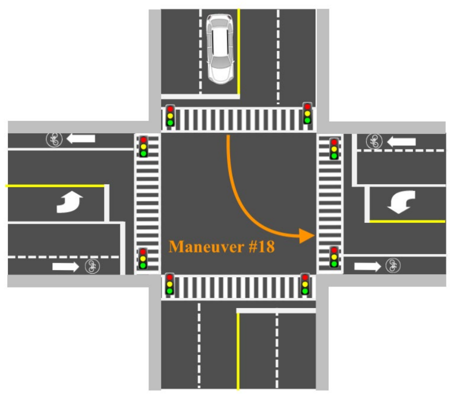
Turn 16: Bloor & Lippincott



Turn 17: Lennox & Bathurst



Turn 18: Bathurst & Harbord



Appendix N: Python Code of Multiple Object Tracking (MOT) Task

```
import sys, os
from messagescreens import  *
from psychopy.gui import DlgFromDict

# == Trial variables ==
n_real = 50
n_prac = 2

# == Processing power or frames per second ==
FPS = 144

# == Directory to save file to ==
save_directory = r"H:\Attentiondata_2019\MOT_excel_results"

class MOTobj:
    def __init__(self, default_color=WHITE):
        # -- Radius of the circle objects
        self.radius = obj_radius
```

```
        # -- Object positions attributes
        self.x, self.y = choice([n for n in range(int(boundary["left"]), int(boundary["right"]))
                                 if n not in range(x - self.radius, x + self.radius)]), \
                         choice([n for n in range(int(boundary["up"]), int(boundary["down"]))
                                 if n not in range(y - self.radius, y + self.radius)])
        # -- Velocity set so that it's random within a range but NOT ZERO
        self.dx, self.dy = choice([dx for dx in range(min_spd, max_spd) if dx not in [0]]), \
                           choice([dy for dy in range(min_spd, max_spd) if dy not in [0]])

        # -- Set the circle object neutral state color
        self.color = default_color
        self.default_color = default_color

        # -- Timer attributes
        self.timer = 0
        self.flash = True

        # -- State attributes for mouse selection control
        self.state = ""
        self.isClicked = False
        self.isSelected = False

    def change_color(self, color):
        self.color = color

    def in_circle(self, mouse_x, mouse_y):
        # -- Return boolean value depending on mouse position, if it is in circle or not
        if math.sqrt(((mouse_x - self.x) ** 2) + ((mouse_y - self.y) ** 2)) < self.radius:
            return True
        else:
            return False

    def state_control(self, state):
        # -- Neutral or default state with no form of mouse selection
        if state == "neutral":
            self.color = self.default_color
            self.state = "neutral"
            self.isClicked = self.isSelected = False
        # -- Hovered state if mouse is hovering over circle object
        if state == "hovered":
            self.color = hover_col
            self.state = "hovered"
            self.isClicked = self.isSelected = False
        # -- Clicked state if mouse click DOWN while in object
        if state == "clicked":
            self.color = click_col
            self.state = "clicked"
            self.isClicked = True
            self.isSelected = False
        # -- Selected state if mouse click UP on a "clicked" object
        if state == "selected":
            self.color = select_col
            self.state = "selected"
```

```
            self.isClicked = False
            self.isSelected = True

    def detect_collision(self, mlist):
        # -- Object positions in x and y coordinates change in velocity value
        self.x += self.dx
        self.y += self.dy
        # -- If the object reaches the window boundary, bounce back
        if self.x < self.radius or self.x > win_width-self.radius:
            self.dx *= -1
        if self.y < self.radius or self.y > win_height-self.radius:
            self.dy *= -1
        # -- If the object bounces off each other, run the Brownian motion physics
        # objects need to be from the same list, otherwise the objects
        # can pass through each other if they're from a different list
        for a in mlist:
            for b in mlist:
                if a != b:
                    if math.sqrt(((a.x - b.x) ** 2) + ((a.y - b.y) ** 2)) <= (a.radius + b.radius):
                        brownian_motion(a, b)

    def draw_circle(self, display=win):
        # -- Function to draw circle onto display
        pg.draw.circle(display, self.color, (int(self.x), int(self.y)), self.radius)

    def flash_color(self):
        # -- Function to flash color
        if self.timer == FPS:
            self.timer = 0
            self.flash = not self.flash

        self.timer += 3

        if self.flash:
            self.color = self.default_color
        else:
            self.color = GREEN

    def shuffle_position(self):
        """Shuffle the position of circles"""
        self.x = choice([n for n in range(int(boundary["left"]), int(boundary["right"]))
                        if n not in range(x - self.radius, x + self.radius)])
        self.y = choice([n for n in range(int(boundary["up"]), int(boundary["down"]))
                        if n not in range(y - self.radius, y + self.radius)])


def generate_list(color):
    """function to generate new list of objects"""
    distractor_list = []
    for nd in range(num_distractor):
        d = MOTobj()
        distractor_list.append(d)
```

```
    target_list = []
    for nt in range(num_targ):
        t = MOTobj(color)
        target_list.append(t)

    return distractor_list, target_list


def delay(t):
    """function to stop all processes for a time"""
    pg.time.delay((t*1000))  # multiply by a thousand because the delay function takes milliseconds


def record_response(response_time, response_score, time_out_state, log):
    # record the responses
    header_list = [response_time, response_score, time_out_state]
    # convert to string
    header_str = map(str, header_list)
    # convert to a single line, separated by commas
    header_line = ','.join(header_str)
    header_line += '\n'
    log.write(header_line)


def guide_user(master_list, distractor_list, target_list):

    timeup = False
    submitted = False
    need_to_select_4 = False
    guiding = True
    animating = True
    Tsub = 0

    STL = []
    # -- Welcome message --
    guide_screen("start", master_list, STL)
    wait_key()

    # -- Fixation cross screen
    guide_screen("focus", master_list, STL)
    wait_key()

    # -- Present cross and circles screen
    guide_screen("present", master_list, STL)
    wait_key()

    t0 = pg.time.get_ticks()

    while True:
        pg.time.Clock().tick_busy_loop(FPS)  # =Set FPS

        win.fill(background_col)  # =fill background with background color
        mx, my = pg.mouse.get_pos()  # =get x and y coord of mouse cursor on window
```

```
selected_list = STL = []  # - list for all selected objects
selected_targ = []  # - list for all SELECTED TARGETS

for event in pg.event.get():
    if event.type == pg.QUIT:
        pg.quit()
        sys.exit()
    if event.type == pg.KEYDOWN:
        if event.key == pg.K_ESCAPE:
            pg.quit()
            sys.exit()
        if event.key == pg.K_SPACE:
            if animating:
                for target in target_list:
                    if target.isSelected and not target.isClicked:
                        selected_targ.append(target)
                        selected_list.append(target)
                for distractor in distractor_list:
                    if distractor.isSelected and not distractor.isClicked:
                        selected_list.append(distractor)
                if len(selected_list) == num_targ:
                    submitted = True
                else:
                    need_to_select_4 = True

    for obj in master_list:
        if obj.in_circle(mx, my):
            if event.type == pg.MOUSEMOTION:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("hovered")
            if event.type == pg.MOUSEBUTTONDOWN:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("clicked")

                if not obj.isClicked and obj.isSelected:
                    obj.state_control("neutral")
            if event.type == pg.MOUSEBUTTONUP:
                if obj.isClicked and not obj.isSelected:
                    obj.state_control("selected")

        elif not obj.in_circle(mx, my):
            if event.type == pg.MOUSEMOTION:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("neutral")
            if event.type == pg.MOUSEBUTTONUP:
                if obj.isClicked and not obj.isSelected:
                    obj.state_control("neutral")

t1 = pg.time.get_ticks()
dt = (t1 - t0)/1000

if animating:
```

```
            if dt < Tfl - Tfix:
                flash_targets(distractor_list, target_list)
            elif Tfl - Tfix <= dt < Tani - Tfl:
                for t in target_list:
                    t.state_control("neutral")  # this resets target color to match distractor's
                animate(distractor_list, target_list, master_list)
            elif Tani - Tfl <= dt < Tans - Tani:
                if need_to_select_4:
                    message_screen("not_selected_4")
                guide_screen("answer", master_list, selected_targ)
            elif Tans - Tani < dt:
                # guide_screen("timeup", master_list, selected_targ)
                timeup = True
        if timeup:
            guide_screen("timeup", master_list, STL)
            delay(feedback_time)
            guiding = False
        if submitted:
            guide_screen("submitted", master_list, STL)
            for obj in master_list:
                obj.shuffle_position()
                obj.state_control("neutral")
            delay(feedback_time)
            guiding = False
        if not guiding:
            guide_screen("finished", master_list, STL)
            wait_key()
            need_to_select_4 = False
            break


def practice_trials(master_list, distractor_list, target_list, CPT):
    """function for practice trials; goes through all the protocols but does not record subject responses"""
    completed_practice_trial_count = CPT

    # == Variables for controlling protocols ==
    reset = False
    submitted = False
    need_to_select_4 = False
    timeup = False

    # == Timer
    t0 = pg.time.get_ticks()

    # == Main loop
    while True:
        pg.time.Clock().tick_busy_loop(FPS)  # =Set FPS

        win.fill(background_col)  # =fill background with background color
        mx, my = pg.mouse.get_pos()  # =get x and y coord of mouse cursor on window

        selected_list = []  # - list for all selected objects
        selected_targ = []  # - list for all SELECTED TARGETS
```

```
# -- Quit controller
for event in pg.event.get():
    if event.type == pg.QUIT:
        pg.quit()
        sys.exit()
    if event.type == pg.KEYDOWN:
        if event.key == pg.K_ESCAPE:
            pg.quit()
            sys.exit()

        # -- Answer submission controller
        if event.key == pg.K_SPACE:
            if not reset:  # -- If the loop is not in the reset state
                # -- Add selected distractors and targets separately to compare answers
                for target in target_list:
                    if target.isSelected and not target.isClicked:
                        selected_targ.append(target)  # separate list for selected targets
                        selected_list.append(target)  # common list for both targ and dist
                for distractor in distractor_list:
                    if distractor.isSelected and not distractor.isClicked:
                        selected_list.append(distractor)

                if len(selected_list) == num_targ:  # if user selects the same number as there are targets
                    submitted = True  # allow for answer submission
                else:  # if user selects more or less than there are targets,
                    need_to_select_4 = True  # remind them to select the same number as there are targets

    for obj in master_list:
        if obj.in_circle(mx, my):  # -- If the mouse is within the circle
            if event.type == pg.MOUSEMOTION:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("hovered")
                    # print("Clicked state: ", obj.isClicked, "Selected state: ", obj.isSelected)
            if event.type == pg.MOUSEBUTTONDOWN:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("clicked")
                if not obj.isClicked and obj.isSelected:
                    obj.state_control("neutral")
            if event.type == pg.MOUSEBUTTONUP:
                if obj.isClicked and not obj.isSelected:
                    obj.state_control("selected")

        elif not obj.in_circle(mx, my):
            if event.type == pg.MOUSEMOTION:
                if not obj.isClicked and not obj.isSelected:
                    obj.state_control("neutral")
            if event.type == pg.MOUSEBUTTONUP:
                if obj.isClicked and not obj.isSelected:
                    obj.state_control("neutral")

# == Timer to calculate elapsed time ==
t1 = pg.time.get_ticks()
```

```
        dt = (t1 - t0)/1000

        if completed_practice_trial_count < n_prac:  # if the completed trial count is less than total trial count
            if not reset:  # normal state; return to this state if reset is passed, or is supposed to run
                if dt <= Tfix:  # fixation time
                    fixation_screen(master_list)
                elif Tfix < dt <= Tfl:  # flash targets
                    flash_targets(distractor_list, target_list)
                elif Tfl < dt <= Tani:  # animate/move the circles around the screen
                    for targ in target_list:
                        targ.state_control("neutral")
                    animate(distractor_list, target_list, master_list)
                elif Tani < dt <= Tans:  # stop moving the circles
                    if need_to_select_4:
                        message_screen("not_selected_4")
                    static_draw(master_list)
                    pg.display.flip()
                elif Tans < dt:  # timed out
                    timeup = True

            if submitted:  # if user successfully submits answer
                win.fill(background_col)
                msg_to_screen_centered("{:d} out of {:d} correct".format(len(selected_targ), len(selected_list)), BLACK,
large_font)
                pg.display.flip()
                delay(feedback_time)
                reset = True

            if timeup:  # if timed out, run this protocol
                message_screen("timeup")
                delay(feedback_time)
                reset = True

            if reset:  # reset state to reset the whole trial
                for obj in master_list:
                    obj.shuffle_position()
                    obj.state_control("neutral")
                completed_practice_trial_count += 1
                submitted = timeup = need_to_select_4 = reset = False
                t0 = t1
        else:  # if the user completes all the intended trial number
            win.fill(background_col)
            message_screen("prac_finished")
            pg.display.flip()
            wait_key()
            break


def real_trials(master_list, distractor_list, target_list, CRT, recorder):
    """function for real trials to record answer score, time and timed out state; same as practice trial except
    the user responses are recorded"""

    completed_practice_trial_count = CRT
```

```
reset = False
submitted = False
need_to_select_4 = False
timeup = False

t0 = pg.time.get_ticks()
while True:
    pg.time.Clock().tick_busy_loop(FPS)  # =Set FPS

    win.fill(background_col)  # =fill background with background color
    mx, my = pg.mouse.get_pos()  # =get x and y coord of mouse cursor on window

    selected_list = []  # - list for all selected objects
    selected_targ = []  # - list for all SELECTED TARGETS

    for event in pg.event.get():
        if event.type == pg.QUIT:
            pg.quit()
            sys.exit()
        if event.type == pg.KEYDOWN:
            if event.key == pg.K_ESCAPE:
                pg.quit()
                sys.exit()
            if event.key == pg.K_SPACE:
                if not reset:
                    for target in target_list:
                        if target.isSelected and not target.isClicked:
                            selected_targ.append(target)
                            selected_list.append(target)
                    for distractor in distractor_list:
                        if distractor.isSelected and not distractor.isClicked:
                            selected_list.append(distractor)

                    if len(selected_list) == num_targ:
                        submitted = True
                        # print("Answer submitted")
                        t_keypress = pg.time.get_ticks()
                    else:
                        need_to_select_4 = True

        for obj in master_list:
            if obj.in_circle(mx, my):
                if event.type == pg.MOUSEMOTION:
                    if not obj.isClicked and not obj.isSelected:
                        obj.state_control("hovered")
                if event.type == pg.MOUSEBUTTONDOWN:
                    if not obj.isClicked and not obj.isSelected:
                        obj.state_control("clicked")
                    if not obj.isClicked and obj.isSelected:
                        obj.state_control("neutral")

                if event.type == pg.MOUSEBUTTONUP:
```

```
                    if obj.isClicked and not obj.isSelected:
                        obj.state_control("selected")

                elif not obj.in_circle(mx, my):
                    if event.type == pg.MOUSEMOTION:
                        if not obj.isClicked and not obj.isSelected:
                            obj.state_control("neutral")
                    if event.type == pg.MOUSEBUTTONUP:
                        if obj.isClicked and not obj.isSelected:
                            obj.state_control("neutral")

        t1 = pg.time.get_ticks()
        dt = (t1 - t0)/1000

        if completed_practice_trial_count < n_real:
            if not reset:
                if dt <= Tfix:
                    fixation_screen(master_list)
                elif Tfix < dt <= Tfl:
                    flash_targets(distractor_list, target_list)
                elif Tfl < dt <= Tani:
                    for targ in target_list:
                        targ.state_control("neutral")
                    animate(distractor_list, target_list, master_list)
                elif Tani < dt <= Tans:
                    if need_to_select_4:
                        message_screen("not_selected_4")
                    static_draw(master_list)
                    pg.display.flip()
                    t_stop = pg.time.get_ticks()
                elif Tans < dt:
                    timeup = True

            if submitted:
                t_sub = ((t_keypress - t0)/1000) - animation_time
                record_response(t_sub, len(selected_targ), False, recorder)
                win.fill(background_col)
                msg_to_screen_centered("{:d} out of {:d} correct".format(len(selected_targ), len(selected_list)), BLACK,
large_font)
                pg.display.flip()
                delay(feedback_time)
                reset = True

            if timeup:
                record_response("timed out", "timed out", True, recorder)
                message_screen("timeup")
                delay(feedback_time)
                reset = True

            if reset:
                print("MOT trial number: ".format(completed_practice_trial_count))
                for obj in master_list:
                    obj.shuffle_position()
```

```
                obj.state_control("neutral")
            completed_practice_trial_count += 1
            submitted = timeup = need_to_select_4 = reset = False
            # timeup = False
            # need_to_select_4 = False
            # reset = False
            t0 = t1

    else:
        win.fill(background_col)
        message_screen("exp_finished")
        pg.display.flip()
        wait_key()
        recorder.close()
        break


def main():
    """Main loop"""

    # == Variables to count how many trials have been completed ==
    completed_real_trials = 0
    completed_practice_trials = 0

    # == Generate a list of objects ==
    list_d, list_t = generate_list(WHITE)
    list_m = list_d + list_t

    # == Dialogue box to enter participant information ==
    dlg_box = DlgFromDict(session_info, title="Multiple Object Tracking", fixed=["date"])
    if dlg_box.OK:  # - If participant information has been entered
        print(session_info)

        # == Prepare a CSV file ==
        mot_log = date_string + ' pcpnt_' + session_info['Participant'] + '_obsvr_' + session_info['Observer']
        save_file = os.path.join(save_directory + "\\" + mot_log + '.csv')
        log = open(save_file, 'w')
        header = ["response_time", "response_score", "timed_out"]
        delim = ",".join(header)
        delim += "\n"
        log.write(delim)

        # == Initiate pygame ==
        pg.init()

        # == Start guide ==
        guide_user(list_m, list_d, list_t)

        # == Start practice ==

        practice_trials(list_m, list_d, list_t, completed_practice_trials)

        # == Start real trials, recording responses ==
```

```
        real_trials(list_m, list_d, list_t, completed_real_trials, log)
        pg.quit()
        sys.exit()

    else:  # - If the user has not entered the participant information
        print("User has cancelled")
        pg.quit()
        sys.exit()


if __name__ == "__main__"
main()
```

Appendix O: Written Instruction of Multiple Object Tracking (MOT) Task

<u>Welcome screen: this text is displayed when the experiment first begins</u>

"You will first see a cross at the center of the screen. Please focus your gaze to that cross.

There will be 8 circles appearing on the screen, 4 of which flash in GREEN.

All circles will start to move. Keep track of those 4 flashed circles.

When the circles stop moving, select which circles you've been tracking by clicking on them.

When you have made your selection, press the SPACEBAR to submit your selection.

Press F to start when you are ready.

If you need to stop, let the experimenter know."

<u>Welcome screen for real trials: this text is displayed after the practice rounds finish, and before the real trials begin:</u>

"The practice is now over.

Press the F when you are ready to continue to the real experiment.

Keep track of the 4 targets and submit your result by pressing the SPACE bar.

Remember to be as quick and accurate as you can!"

<u>Final screen: this text is displayed when the experiment finishes</u>

"The experiment is now over; let the experimenter know.

Thank you for participating!"

Appendix P: Python Code of Posner Task

```
from psychopy.visual import Window, Rect, ShapeStim, TextStim, Circle
from psychopy.core import wait
from psychopy.event import waitKeys, getKeys
```

```
from psychopy.gui import DlgFromDict
from random import choice
import time, sys, os

# ===== Number of trials =====
n_real = 100
n_practice = 10
p_valid = 0.8

# ===== Window size =====
win_width, win_height = 1920, 1080
win_dimension = (win_width, win_height)

# ===== Times and durations in seconds =====
# -- v sync is important to match participants' responses to the monitor's refresh rate
v_sync = 0.012  # (average of cue_diff)-t_cue

t_fix = 1.5 - v_sync
t_cue = 0.05 - v_sync
t_feedback = 0.7 - v_sync
t_target = 0.05 - v_sync  # for how long the target appears
t_answer = 1 - v_sync  # for how long to make an answer choice

# ===== Parameters for font, text and writing =====
font_size = 30

# ===== CSV file preparation ======
save_directory = r"H:\Attentiondata_2019\POSNER_excel_results"
session_info = {'Observer': 'Type observer ID', 'Participant': 'Type participant ID'}


# ===== Message texts ======
welcome_text = "You will see a screen with a white cross in the middle, and two boxes to the sides.\n\n" \
            "One of the boxes will briefly flash. Ignore this!\n\n" \
            "A circle will then appear in either left or right box.\n" \
            "Press the LEFT ARROW KEY when you see the circle in the left box.\n" \
            "Press the RIGHT ARROW KEY when you see the circle in the right box.\n\n" \
            "Press the correct keys as quickly and accurately as you can.\n\n" \
            "Press the SPACEBAR when you are ready to practice.\n\n" \
            "If you need to stop, let the experimenter know."

practice_finished_text = "The practice is now over.\n\n" \
             "When you are ready for the real trials, press the SPACEBAR to continue.\n\n" \
             "Remember to be as quick and accurate as you can!"

experiment_finished_Text = "The experiment is now over. Thank you for participating!\n\n" \
             "Please let the experimenter know"

# ===== Target radius in pixels =====
target_size = 30

# ===== Colours to be used =====
GREY = [128, 128, 128]
```

```
BLACK = [0, 0, 0]
WHITE = [1, 1, 1]
YELLOW = [255, 255, 0]
GREEN = [0, 255, 0]
RED = [255, 0, 0]

cue_color = YELLOW
background_color = GREY


def convertRGB(RGB):
    """function to convert RGB guns from 255-range values to normalised values for PsychoPy"""
    normalised_color = []
    for gun in RGB:
        normV = ((1/127.5)*gun)-1
        normalised_color.append(normV)

    return normalised_color


# ===== Display window =====
disp = Window(size=win_dimension, pos=(0, 0), color=background_color, colorSpace="rgb255", fullscr=False,
units="pix")
# - Fixation cross in the center of display
fixation_cross = ShapeStim(disp, lineWidth=7000, lineColor=convertRGB(BLACK),
fillColor=convertRGB(BLACK), vertices='cross')


class Box:
    """class to draw boxes, neutrally or to flash as cues"""
    def __init__(self):

        self.normal_color = convertRGB(BLACK)
        self.normal_line = 3

        self.cue_color = convertRGB(cue_color)
        self.cue_line = 8

        self.width = self.height = 200

        self.left_x = int(win_width * -0.25)
        self.right_x = int(win_width * 0.25)

    def default_draw(self):
        y = 0
        left_box = Rect(disp, pos=(self.left_x,y), width=self.width, height=self.height,
                        lineColor=self.normal_color, lineWidth=self.normal_line)
        right_box = Rect(disp, pos=(self.right_x,y), width=self.width, height=self.height,
                         lineColor=self.normal_color, lineWidth=self.normal_line)
        left_box.draw()
        right_box.draw()

    def cue(self, location):
```

```
        y = 0
        if location == "left":
            left_cue =  Rect(disp, pos=(self.left_x,y), width=self.width, height=self.height,
                            lineColor=self.cue_color, lineWidth=self.cue_line)
            right_box = Rect(disp, pos=(self.right_x, y), width=self.width, height=self.height,
                            lineColor=convertRGB(BLACK), lineWidth=self.normal_line)
            right_box.draw()
            left_cue.draw()

        if location == "right":
            left_box = Rect(disp, pos=(self.left_x, y), width=self.width, height=self.height,
                           lineColor=convertRGB(BLACK), lineWidth=self.normal_line)
            right_cue = Rect(disp, pos=(self.right_x,y), width=self.width, height=self.height,
                            lineColor=self.cue_color, lineWidth=self.cue_line)
            right_cue.draw()
            left_box.draw()


class Target:
    """class to draw targets"""
    def __init__(self, color, radius=target_size):
        self.color = color
        self.radius = radius

    def draw(self, location):
        y = 0
        if location == "left":
            x = int(win_width * -0.25)
            left_targ = Circle(disp, pos=(x, y), radius=self.radius, edges=32, lineColor=self.color, fillColor=self.color)
            left_targ.draw()
        if location == "right":
            x = int(win_width * 0.25)
            right_targ = Circle(disp, pos=(x, y), radius=self.radius, edges=32, lineColor=self.color, fillColor=self.color)
            right_targ.draw()


class Write:
    """class to display texts on screen"""
    def __init__(self, size):
        self.size = size

    def instructions(self, state):
        if state == "welcome":
            textscreen = TextStim(disp, text=welcome_text, color=convertRGB(BLACK), height=self.size)
            textscreen.draw()
            disp.flip()

        if state == "experiment finished":
            endscreen = TextStim(disp, text=experiment_finished_Text, color=convertRGB(BLACK), height=self.size)
            endscreen.draw()
            disp.flip()

        if state == "practice finished":
```

```
            pracscreen = TextStim(disp, text=practice_finished_text, color=convertRGB(BLACK), height=self.size)
            pracscreen.draw()
            disp.flip()

    def feedback_text(self, state):
        if state == "incorrect":
            fb_inc = TextStim(disp, text='Incorrect!', height=self.size, color=convertRGB(RED))
            fb_inc.draw()
        if state == "correct":
            fb_C = TextStim(disp, text='Correct!', height=self.size, color=convertRGB(GREEN))
            fb_C.draw()
        if state == "no response":
            fb_nr = TextStim(disp, text='Please make a choice!', height=self.size, color=convertRGB(BLACK))
            fb_nr.draw()


def record_response(cue_diff, validity, target_location, correct, RT, log):
    """function to record responses"""
    header_list = [cue_diff, validity, target_location, correct, RT]
    header_str = map(str, header_list)
    header_line = ",".join(header_str)
    header_line += "\n"
    log.write(header_line)


def default_screen():
    """function to display cross and neutral boxes"""
    fixation_cross.draw()
    Box().default_draw()


def cue_and_target(validity, target_location, record, log):
    """
    function to cue and present target
    cue onset and offset are used to calculate the v_sync of the monitor
    """
    if validity == "valid":
        if target_location == "left":
            fixation_cross.draw()
            Box().cue("left")
            cue_onset = disp.flip()
            wait(t_cue)

            default_screen()
            Target(convertRGB(BLACK)).draw("left")
            cue_offset = disp.flip()
            wait(t_target)

            default_screen()
            target_offset = disp.flip()

            cue_diff = cue_offset - cue_onset
```

```
    if target_location == "right":
        fixation_cross.draw()
        Box().cue("right")
        cue_onset = disp.flip()
        wait(t_cue)

        default_screen()
        Target(convertRGB(BLACK)).draw("right")
        cue_offset = disp.flip()
        wait(t_target)

        default_screen()
        target_offset = disp.flip()

        cue_diff = cue_offset - cue_onset

if validity == "invalid":
    if target_location == "left":
        fixation_cross.draw()
        Box().cue("right")
        cue_onset = disp.flip()
        wait(t_cue)

        default_screen()
        Target(convertRGB(BLACK)).draw("left")
        cue_offset = disp.flip()
        wait(t_target)

        default_screen()
        target_offset = disp.flip()

        cue_diff = cue_offset - cue_onset

    if target_location == "right":
        fixation_cross.draw()
        Box().cue("left")
        cue_onset = disp.flip()
        wait(t_cue)

        default_screen()
        Target(convertRGB(BLACK)).draw("right")
        cue_offset = disp.flip()
        wait(t_target)

        default_screen()
        target_offset = disp.flip()

        cue_diff = cue_offset - cue_onset

# -- Returns a list of which key is pressed in a predefined list
resp_list = waitKeys(maxWait=t_answer, keyList=['left', 'right'], timeStamped=True)
correct = 0
if resp_list is not None:
```

```
        response, t_keypress = resp_list[0]
        if response == target_location:
            correct = 1
        else:
            correct = 0

        RT = t_keypress - target_offset

        if correct == 1:
            Write(font_size).feedback_text("correct")
            disp.flip()
        elif correct == 0:
            Write(font_size).feedback_text("incorrect")
            disp.flip()

    else:
        Write(font_size).feedback_text("no response")
        disp.flip()
        RT = "no_response"

    if record:
        record_response(cue_diff, validity, target_location, correct, RT, log)


def trial(trial_number, record_answers, log):
    """trial loop function"""
    # == Number of specific condition trials, must be rounded
    n_valid_left = n_valid_right = round((trial_number*p_valid)/2)
    n_invalid_left = n_invalid_right = round((trial_number*(1-p_valid))/2)

    print("Num. of trials per condition: valid, left: {VL:d}; valid, right: {VR:d}, "
          "invalid, left: {IL:d}; invalid, right: {IR:d}".format(VL=n_valid_left, VR=n_valid_right,
                                                          IL=n_invalid_left, IR=n_invalid_right))

    # == count of total trials completed
    c_total = 0
    # -- Count of total conditional trials
    TOTAL_VALID_LEFT = TOTAL_INVALID_LEFT = TOTAL_VALID_RIGHT = TOTAL_INVALID_RIGHT
= 0

    # == Set to record answer to true or false for recording responses
    if record_answers:
        record = True

    else:
        record = False

    # == variable to make it easier to denote locations and validity
    left = "left"
    right = "right"
    valid = "valid"
    invalid = "invalid"
```

```
# == Pool of different conditions for fixed number of conditions across trials
pool = ["VL", "VR", "IL", "IR"]

while c_total < trial_number:
    print("SCP trial number: {:d}".format(c_total))

    # -- Display fixation screen
    default_screen()
    disp.flip()
    wait(t_fix)

    # -- Randomly pick a condition from the pool, and name it ticket (like picking a name from a hat)
    ticket = choice(pool)

    # print(pool)

    if ticket == "VL" and n_valid_left > 0:  # VL
        cue_and_target(valid, left, record, log)
        wait(t_feedback)

        n_valid_left -= 1
        c_total += 1
        TOTAL_VALID_LEFT += 1

        if n_valid_left == 0:
            pool.remove("VL")

    if ticket == "VR" and n_valid_right > 0:  # VR
        cue_and_target(valid, right, record, log)
        wait(t_feedback)

        n_valid_right -= 1
        c_total += 1
        TOTAL_VALID_RIGHT += 1

        if n_valid_right == 0:
            pool.remove("VR")

    if ticket == "IL" and n_invalid_left > 0:  # IL
        cue_and_target(invalid, left, record, log)
        wait(t_feedback)
        n_invalid_left -= 1
        c_total += 1
        TOTAL_INVALID_LEFT += 1

        if n_invalid_left == 0:
            pool.remove("IL")

    if ticket == "IR" and n_invalid_right > 0:  # IR
        cue_and_target(invalid, right, record, log)
        wait(t_feedback)
        n_invalid_right -= 1
        c_total += 1
```

```
            TOTAL_INVALID_RIGHT += 1

            if n_invalid_right == 0:
                pool.remove("IR")

    print("Total number of left: valid {TVL:d}, invalid {TIL:d}; right: valid {TVR:d}, invalid
{TIR:d}".format(TVL=TOTAL_VALID_LEFT, TIL=TOTAL_INVALID_LEFT, TVR=TOTAL_VALID_RIGHT,
TIR=TOTAL_INVALID_RIGHT))


def main():
    """main loop"""
    # == Box to enter subject and experimenter information ==
    dlg_box = DlgFromDict(session_info, title="Spatial Cueing Paradigm", fixed=["date"])

    if dlg_box.OK:  # - If participant information has been entered

        print(session_info)

        # == Prepare file to record responses ==
        date_Str = time.strftime("%b_%d_%H%M", time.localtime())  # add the current time
        file_prefix = date_Str + ' pcpnt_' + session_info['Participant'] + '_obsvr_'+session_info['Observer']
        save_file = os.path.join(save_directory + "\\" + file_prefix + ".csv")
        file = open(save_file, "w")
        header = ["cue_diff", "validity", "target_location", "correct", "response_time"]
        delim = ",".join(header)
        delim += "\n"
        file.write(delim)

        # == Welcome screen ==
        Write(font_size).instructions("welcome")
        waitKeys(keyList=['space'], timeStamped=False)

        # == Practice trials, not recording responses ==
        trial(n_practice, False, file)

        # == Practice over screen and key
        Write(font_size).instructions("practice finished")
        waitKeys(keyList=['space'], timeStamped=False)

        # == Real trials
        trial(n_real, True, file)

        # == Experiment over
        Write(font_size).instructions("experiment finished")
        waitKeys(keyList=['escape', 'space'])
        file.close()
        disp.close()
        sys.exit()
        # else:
        #     sys.exit()

    else:
```

```
        print("User has cancelled")
        disp.close()
        sys.exit()


if __name__ == "__main__":
    main()
```

Appendix Q: Written Instruction of Posner Task

<u>Welcome screen: this text is displayed when the experiment first begins</u>

“Welcome! Firstly, you are welcome to stop at any time; just let the experimenter know!

In this experiment, you will see a white cross in the middle, and two boxes to the sides.

Press the LEFT ARROW KEY when you see the black circle in the left box.

Press the RIGHT ARROW KEY when you see the black circle in the right box.

Every trial, you will see one of the boxes flashing. Do not respond to this, just ignore it!

Press the correct keys as quickly and accurately as you can.

Press the spacebar when you are ready to practice.”

<u>Real trial welcome screen: this text is displayed after the practice rounds finish, and before the real trials begin</u>

“The practice is now over.

Press the spacebar when you are ready to continue to the real experiment.

Remember to be as quick and accurate as you can!”

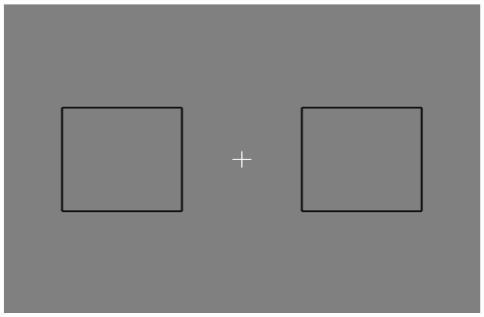
<u>Finished screen: this text is displayed when the experiment finishes</u>

“The experiment is now over; let the experimenter know.

Thank you for participating!”

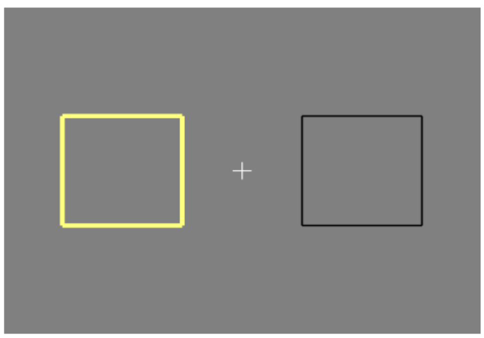
Appendix R: Procedure of Posner Task

Posner Task – Procedure



a) Fixation screen

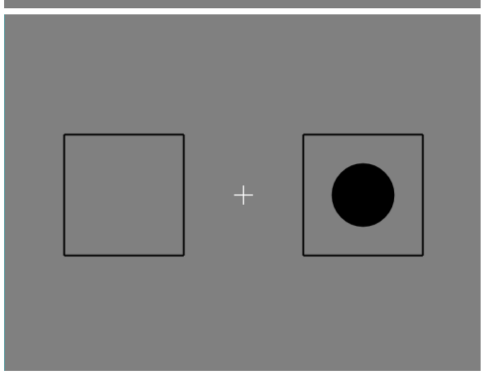
t = 0 - 1500 ms



b) Cueing:

t = 1500 - 1550 ms

One of the boxes will flash yellow as a cue, indicating the potential target location



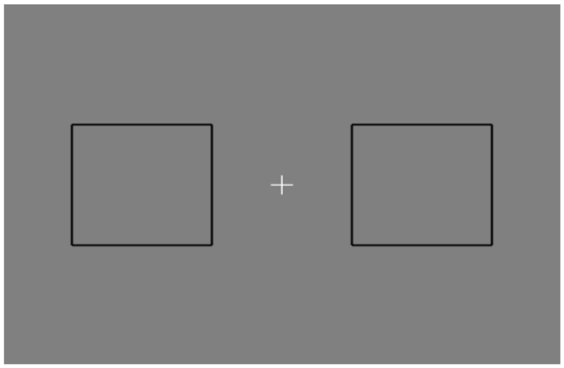
c) Target display

t = 1550 - 1600 ms

The **target** (black circle) appears

This trial is denoted as **invalid** since the cueing was on the opposite side.

If the black circle appeared on the left side, then it would be **valid**.



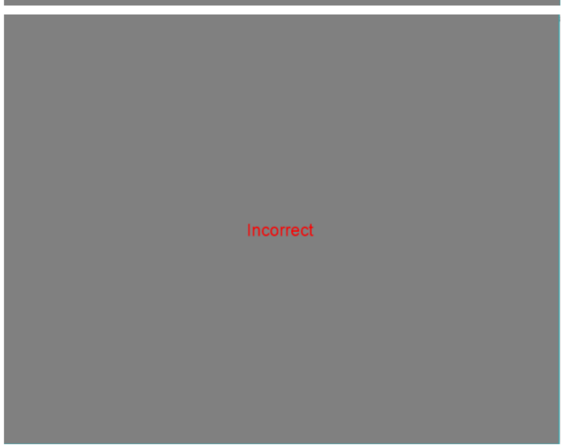
d) Responding to the target

t = 1600 - 2600 ms

e) Feedback prompt (Version 1)

t = 2600 - 3600 ms

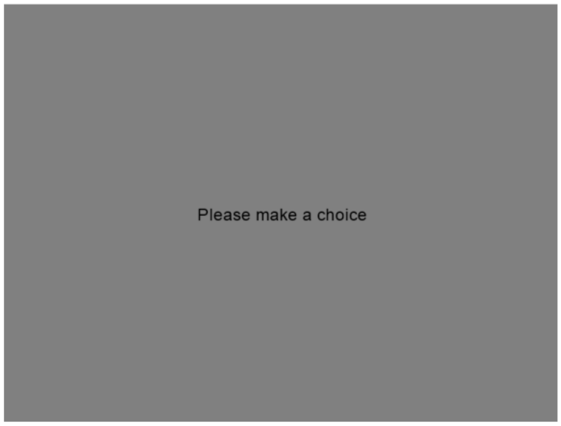
If the response i s correct



e) Feedback prompt (Version 2)

t = 2600 - 3600 ms

If the response is incorrect



e) Feedback prompt (Version 3)

t = 2600 - 3600 ms

If there is no response given

Appendix S: Emergency Vehicle Information Sheet

<u>Emergency vehicles</u>

Emergency vehicles (police, fire, ambulance and public-utility emergency vehicles) are easily identified when responding to an emergency through their use of flashing red lights (police may also use red and blue flashing lights), a siren or bell, or alternating flashes of white light from their headlamp high beams.

When an emergency vehicle is approaching your vehicle from any direction with its flashing red or red and blue lights, or siren or bell sounding, you are required to bring your vehicle to an immediate stop. When bringing your vehicle to a stop, you are required to bring your vehicle as near as is practical to the righthand curb or edge of the roadway.

If you are in an intersection and preparing to make a turn when an emergency vehicle is approaching, you should abandon the turn and clear the intersection by proceeding straight when safe to do so, then pull to the right and stop. This will clear the intersection and minimize the possibility of a collision with the emergency vehicle should it be passing you on the side you intended to turn towards.

Appendix T: NASA Task Load Index (TLX)

Definition of Task Demand Factor

Mental demand

How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the experiment task easy or demanding, simple or complex, exacting or forgiving?

Physical demand

How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Temporal demand

How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Performance

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

Frustration level

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Effort

How hard did you have to work (mentally and physically) to accomplish your level of performance?

NASA-TLX Mental Workload Rankings

For each of the pairs listed below, circle the scale title that represents the more important contributor to workload during the driving condition

Mental Demand	or	Physical Demand
Mental Demand	or	Temporal Demand
Mental Demand	or	Performance
Mental Demand	or	Effort
Mental Demand	or	Frustration
Physical Demand	or	Temporal Demand
Physical Demand	or	Performance
Physical Demand	or	Effort
Physical Demand	or	Frustration
Temporal Demand	or	Performance
Temporal Demand	or	Frustration
Temporal Demand	or	Effort
Performance	or	Frustration
Performance	or	Effort
Frustration	or	Effort

NASA-TLX Mental Workload Rating Scale

Please place an "X" along each scale at the point that best indicates your experience with the driving condition.

Mental Demand: How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc)? Was the mission easy or demanding, simple or complex, exacting or forgiving?

Low High

Physical Demand: How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the mission easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Low High

Temporal Demand: How much time pressure did you feel due to the rate or pace at which the mission occurred? Was the pace slow and leisurely or rapid and frantic?

Low High

Performance: How successful do you think you were in accomplishing the goals of the mission? How satisfied were you with your performance in accomplishing these goals?

Low High

Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low High

Frustration: How discouraged, stressed, irritated, and annoyed versus gratified, relaxed, content, and complacent did you feel during your mission?

Low High

Appendix U: Post-drive Survey

1) Please enter your Participant ID number: *

2) How close to your natural way of driving do you think your driving was in this experiment?*

1 _________________________[__]______________________________ 10

3) Do you think that you were driving more cautiously than you normally would due to being observed?*

1 _________________________[__]______________________________ 10

4) Do you think that you were driving more cautiously than you normally would due to being in an unfamiliar vehicle?*

1 _________________________[__]______________________________ 10

5) How cautious do you think you were towards pedestrians on the road during this driving experiment?*

1 _________________________[__]______________________________ 10

6) How cautious do you think you were towards cyclists on the road during this driving experiment?*

1 _________________________[__]______________________________ 10