Cognitive Impairment In Relation to On-Road Driving

by

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Abstract

On-road driving is a habitual and automatic task for many Canadians. The commute to work, dropping children off at school, or a simple grocery run require a driver to perform a very complex task: driving a vehicle. Driving has become such an automatic behaviour for many that the behaviour itself often goes unnoticed and is even taken for granted. Once the driving performance becomes adversely affected due to aging, vision loss, or illness people tend to lose a sense of freedom and even parts of their identity. Impairment related to on-road driving can come in many different shapes and forms. Driving is a complex cognitive behaviour that is an essential part of everyday life and can be broken down into many subcomponents, each of which can uniquely impact road safety. Cognitive Skills are the core skills used by our brains to think, problem solve, learn, and remember. If a driver is impaired, either due to short-term or long-term cognitive impairment associated with either chronic illness, aging, drug or alcohol consumption, these cognitive skills that are needed for driving are adversely affected - causing impairment and the inability to perform the overall driving behaviour accurately, efficiently and safely.

Study 1 of this thesis looked at aging and medication interferences in older drivers as a wide range of motor, sensory, and cognitive skills that are imperative for driving are affected in older adults. The application of tablet-based cognitive tasks (TBCT) was used in identifying unsafe drivers in a population of healthy and at-risk for driving older adults. It was hypothesized that older drivers will perform worse on the cognitive tasks and the TBCT will be found predictive for on-road driving performance. Overall, results showed that there was a high accuracy and reliable prediction of unsafe drivers using the TBCT in a sample of older adults. This showed the efficacy of a widely available screening tool that can be applied in other cognitively impaired

populations such as drug users.

These results lead to the completion of the second study of this thesis. When it comes to driving impairment, drug related cognitive impairment in relation to on-road driving has been increasingly reported during the past decade. The consumption of cannabis and cocaine is associated with a range of mental and physical effects that can impair overall driving behaviour. The hypothesis of this study was to identify driving-related cognitive-performance deficits that are impacted by recreational drug use, mainly associated with cannabis and cocaine in comparison to healthy controls. Over 300 individuals performed the tablet-based cognitive tasks battery (TBCT) that showed in study 1 to be related to on-road driving performance and are designed to test response speed, memory processes, perceptual-motor skills, and decision making. Data from a control group with healthy non-drug using adults was collected for Study 2 as well. Overall, the drug groups showed deficits in all tasks compared to both control groups. There were significant differences between the cannabis and cocaine groups where cannabis users were faster, and performed better on some aspects of the decision-making and perceptual-motor tasks. The results show the unique effects of cannabis and cocaine on human performance relating to driving and have important implications for road safety associated with driver impairment and will be investigated in future studies.

The results of these two studies suggest that there are crucial cognitive performance differences when it comes to different forms of impairment and on-road driving. The results also suggest that there might be different blueprints of impairment that can be associated with different drugs, combinations of drugs, medication consumption, or cognitive decline related to aging.

Further studies will explore these possibilities and will be addressed in the discussion section of this thesis (Chapter 4).

Preface

This thesis is an original work by Michelle Veronika Tomczak, under the supervision of Dr. Anthony Singhal. Data for this thesis was collected with the approval of the University of Alberta Research Ethics Board, project number 00072733.

Both studies presented in this thesis were designed by Michelle Tomczak, Reyhaneh Bakhtiari and Anthony Singhal. Data was collected by Michelle Tomczak, Reyhaneh Bakhtiari, Stephen Langor, Aaron Granley, Farah Visram, and Alice Atkin, and was analyzed by Michelle Tomczak and Reyhaneh Bakhtiari.

Dedication

This thesis is dedicated to my family

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CHAPTER 1: Introduction to Cognitive Impairment and On-Road Driving

1.1 Introduction

Theories of cognitive functioning and driving impairment due to age related disease, Traumatic Brain Injury (TBI), or recreational drug use agree that driving is a combination of complex psychological and motor processes that heavily rely on cognitive functioning (Theunissen et al, 2021; CCMTA, 2018; Filbey, Aslan & Calhoun, 2013). Age related cognitive decline and deterioration in gross motor skills are associated with an increase in accident risk connected to automobile fatalities (Dubinsky, Stein & Lyons, 2000). Theories explaining temporary and permanent impairment in relation to driving also argue that cognitive functioning and cross motor skills are adversely affected (Hoe, Cameron & Lee, 2003; Filbey et al., 2013). Despite various diagnoses related to cognitive impairment affecting the nervous system differently, much of the literature agrees that it can be very dangerous if at-risk drivers continue driving post-diagnosis without adequate screening (Anstey, Horswill, Wood, & Hatherly, 2012; Ott et al., 2013). People facing cognitive decline often portray challenged attention, memory, judgment, and motor skills (Groeger, 2000; Hoe et al., 2003). Driving is not only a cognitive ability, but also a physical activity. In order to perform safe on road driving, flexibility, proprioception, adequate reaction time, and proper coordination are all required (Morgan, 2018).

Therefore, any form of cognitive impairment is associated with diminishing driving abilities that can lead to increased risk for automobile collisions, injury, and death (CCMTA, 2018; Morgan, 2018). Thus, a critical question arises: How do we assess driving performance of individuals facing cognitive decline due to aging, injuries or other forms of impairment? When it comes to driving assessments, researchers and professionals agree that screening tools need to be

reliable and well tested in order to become standardized on a provincial and federal level (CCMTA, 2018).

Transport Canada reports that current driving assessments are limited, and lack evidence-based research and screening procedures (Transport Canada, 2018). There is an urgent need for tools aiding physicians and Canadian law enforcement to identify risky drivers that are either impaired due to permanent cognitive decline (e.g., dementia, Alzheimer's disease, TBI), or due to temporary impairment (e.g., recreational drugs) (Hoe et al., 2003; Stolwyk et al., 2019). The following chapter will review commonly used clinical screening tools characterized by cognitive subtests as well as neuropsychological assessments. Further, the paragraphs leading up to the clinical assessment review will elaborate on skills related to on-road driving and an explanation of patient populations commonly in need of screening assessments.

1.2 On-road Driving

Driving a vehicle in order to travel from point A to point B is the main form of transportation for most North American citizens and therefore is seen as a critical part of many individuals' lives and their sense of independence (Dubinsky, Stein & Lyons, 2000; Schwanen, Banister, & Bowling, 2012). Multiple domains can account for cognitive dysfunction, hence, interference with an individual's driving capacity can be observed in a wide area of clinical populations, even in nonclinical groups (Brown et al., 2005; Stolwyk et al., 2006). Due to this multi-domain capacity neuropsychologists and neuropsychiatrists are often consulted and relied on to assess and recommend future driving scenarios or cessation for individuals at risk (Wheatley, Carr, & Marottoli, 2014). As Anstey et al. described, driving is a very complex task that does not only require

cognitive abilities but also visual perception, a variety of physical abilities, emotional control and executive function (2012).

With driving being such a complex task, a study by Morgan reports that for each mile driven, a driver approximately makes twenty major decisions while only having 0.5 seconds of reaction time to avoid potential accidents (2018). Therefore, cognitive functioning in relation to on-road driving extends to the assessment of neuromuscular functions. Multiple motor deficits such as sensorimotor adaptation, instance gait and balance, and motor control sequencing are often observed across different motor domains while aging (Anstey et al., 2009; Wood et al., 2008). Further, flexibility of the neck and trunk are also reduced with age, leading to the inability to assess the road environment properly (Morgan, 2018). Multiple driving studies agree that the following cognitive behavioral skills are necessary to perform risk free on-road driving: attention, problem solving, processing speed and reaction time in relation to external events, visual- spatial memory and perspective, behavioral control, critical capacity, self-criticism and risk management (Anstey et al., 2012, CCMTA, 2019; Bernstein et al., 2019).

1.3 Driving and Impairment

Drug impaired driving has been a criminal offence in Canada since 1925 and impaired driving is the leading cause of criminal death and injury in Canada (CCMTA, 2018). Theories of cognitive functioning and driving impairment due to age related disease or recreational drug use agree that driving is a combination of complex psychological and motor processes that heavily rely on cognitive functioning (Wood et al., 2013; CCMTA, 2018). Further, age related cognitive decline and deterioration in cross motor skills are associated with an increase in accident risk connected to automobile fatalities (Lyman et al., 2001). Theories explaining temporary and per-

manent impairment in relation to driving also argue that cognitive functioning and gross motor skills are adversely affected (Anstey et al., 2012). Despite specific groups of recreational drugs affecting the nervous system differently, much of the literature agrees that it is not safe to drive under the influence of drugs. People consuming psychoactive substances (e.g., cannabis and cocaine) display deficits in attention, memory, judgment, and motor skills (Gouzoulis-Mayfrank et al., 2012). Therefore, drug-induced cognitive impairment is associated with diminishing driving abilities that can lead to increased risk for automobile collisions, injury, and death (Groeger, 2000; Anstey et al., 2012).

1.4 Assessing Driving Ability

Based on the previous definition of on-road driving, the complexity of the overall driving task is clearly notable. Many skills are needed to adequately and risk-free perform on-road driving. Occupational therapists are primarily responsible for performing comprehensive driver screening assessments in North America. Commonly, a physician or clinician will perform a pre-road screening and assessment to detect areas of concern before deciding if an on-road test and further assessments are needed (Asimakopulos et al., 2012). Despite these guidelines and recommendations, doctors are often inconsistent in the methods by which they use to determine when to recommend a driving-test, further screening, or even complete driving cessation (Betz, Jones, Petroff, & Schwartz, 2013; Molnar et al., 2005). The following paragraphs will look at the three main ways of assessing and studying driving performance: 1) An on-road driving test with a driving instructor and/or occupational therapist, 2) an in-office driving assessment consisting of various clinical and/or non-clinical subtests, and 3) simulator driving.

1.4.1 The Standardized Road Test

Current and past literature research studies have examined driving performance through an on-road driving test. These on-road driving tests are often standardized and can function as a baseline measure of a patient's overall driving performance. A driving test is often administered before further cognitive screening is completed, however, many clinicians refer for an on-road driving test post-diagnosis and post clinical assessment. A professional driving instructor is commonly blinded to diagnoses and office test results and standardized assessments are mostly performed and during daylight hours under good road conditions (Bakhtiari, Tomczak, et al., 2020; Hoe, Cameron & Lee, 2003). A categorical rating of participants' overall driving ability (pass, marginal, or fail) commonly serves as the outcome measure and several variables are assessed. For instance, a specific road-test example that was used by Bakhtiari et al. was the DriveABLE on-road evaluation (DORE) developed by Drivable (2020). The total driving distance was 16.2 km and took approximately 30-40 minutes in an automatic vehicle with dual-braking. DORE is a scientifically developed on-road evaluation designed to test for decline in cognitive skills needed for safe driving (Berndt, May & Clark, 2007; Dobbs et al., 1997). This on-road assessment was developed by identifying driving errors that distinguish cognitively impaired drivers from a healthy control group (Dobbs et al., 1997). Based on the severity and frequency of these competence-defining errors a scoring system was created and applied.

To protect the competent driver, the scoring system explicitly excludes errors that are made by experienced, healthy drivers and not associated with general cognitive decline related to aging. Kowalski and Tuokko described this test as the most well-developed of the standardized road tests for medically at-risk drivers (2007). Both cognitive and trainable mistakes due to bad

driving habits were evaluated while performing various common driving maneuvers. The course included right hand turns, left hand turns, traffic circles, lane changes, traffic lights, yield signs, stop signs and a precise manual and scoring sheet was used by the driving instructor to rate each checkpoint with the participants' performance using a point system. Each driving mistake (e.g. lane change creating a hazardous situation) results in a pre-defined score, which are accumulated at the end of the on- road assessment session, and is compared to each class threshold to define the final fail, borderline or pass result (Bakhtiari et al., 2020).

1.4.2 In-office/In-lab Driving Assessments

Simultaneously assessing various domains such as cognition, motor performance, and vision is key to appropriately assessing driving performance. Besides on-road driving assessments with trained driving instructors, in-office assessments have gained increasingly more popularity during the past decade. Computers and evolving technology make it easier for clinicians to administer clinical assessments related to driving performance in-office. These computerized assessments are time and cost-effective and can aid as predictors for on-road driving. Overall, computerized tests are mainly used to assess attention and reaction times in a timely manner (Ott et al., 2013). Furthermore, a wide area of driving literature is now specialized in the predictability of certain assessments, therefore examining sensitivity and specificity of assessment batteries can be recommended to identify potentially unsafe older drivers or impaired drivers (Ott et al., 2013; Asimakopulos et al., 2012; Bakhtiari et al., 2020). In office assessments can look differently depending on the diagnosis of a patient, or the cognitive skills that need to be tested. Most driving studies consist, or partially consist of standardized in-office assessments such as the Visual Field Test, Trail-Making Test Part A and B, and Maze Drawing. As mentioned before, these as-

sessments are often administered with pen and paper or through a standardized computer based assessment.

1.4.3 Simulator Driving Assessment

Driving simulators are one of the primary tools studying on-road driving performance. Simulators provide a safe testing environment that is time and cost effective, and easily controlled and replicable. Due to technological advancements, state of the art driving simulators have been developed where individuals are able to sit in a real automotive vehicle with real life kinematic and road-conditions. Many aspects of driving can be assessed through driving simulators and researchers have been focusing on studying human factors such as driving behaviour in relation to aging, recreational drug and alcohol use, or human ergonomics during different weather conditions or night-time driving (Chang, 2015). For instance, a study by Chan and Singhal (2015) examined emotions in relation to driving. This study used a simulator driving scenario assessing dependent measures such as overall speed, driver's lane maintenance, and steering wheel rate. Depending on the simulator technology and research goal, many variables can be simultaneously measured.

1.5 Neuropsychological and Cognitive Assessments Related to On-Road Driving

Clinical standardized assessments play a crucial role when it comes to assessing on-road driving performance and cognitive skills related to driving. Various types of assessments have been studied and many different opinions exist about statistical analysis, predictability and proper usage of specific construct variables that these assessments entail. At-risk populations are often screened for cognitive decline or injury-related performance decline, however, a wide area of literature is trying to identify predicted abilities of certain assessments in order to pre-screen cer-

tain at-risk populations. These pre-screens are often used to predict possible performance decline related to on-road driving, hence making more precise decisions about on-road driving tests and overall driving cessation. Most clinical assessments are still to date administered with pencil and paper, however, a growing number of clinical institutions also offer computerized neuropsychological testing where administration is often more cost-effective and reliably standardized.

In a study by Bernstein et al. different variables related to patient impairment were associated with an increase in likelihood of broad driving recommendations by clinicians (2019). After controlling for diagnoses, three significant predictors emerged: higher frequency of individualized recommendations, greater caregiver presence, and greater number of recommendations given. All three characteristics generally predicted frequency of all individual driving recommendations. This study also looked at possible variables that might influence clinicians' decisions to refer patients for further driving assessments - variables that were identified as predictors are "diagnoses, higher frequency of individualized recommendations, and greater caregiver presence" (Bernstein et al., 2019).

Studies as such are crucial to driving research as blunt driving restrictions are most often an inappropriate decision due to the adverse impact that driving reduction and cessation has on a patient's life and their environment. In summary, there is a crucial need for time-effective, efficient, cost-effective and reliable screening protocols recommended based on proper diagnoses and predictors to identify at-risk and safe drivers (Bernstein et al., 2019).

1.5.1. Cognitive Assessments

Based on literature, there are various clinical assessments that are frequently used to identify at-risk drivers, or to screen for driving related cognitive impairment (Stav et al., 2008). The following paragraphs will look at commonly used cognitive tests followed by more specialized neuropsychological testing. Because driving is a complex task simultaneously using vision, cognition, and motor performance, it is best predicted by assessment batteries capturing all of the domains necessary for safe driving.

Visual Assessments are a vast area in driving research as visual acuity is one of the key variables to safe on-road driving. In a study by Stav et al., visual clinical assessments were administered to all study participants and included visual field testing, visual contrast sensitivity, and acuity (2008). Specific vision testing machines are commonly used such as a Stereo Optical, Inc. vision testing machine (Optec® 2500) where specific subtests are incorporated, such as *The Functional Acuity Contrast Test (FACTTM)* (Ginsburg, 1984) with contrast sensitivity slides. The FACTTM contrast sensitivity slides increase in five different spatial frequencies (A to E) and each slide contains nine levels of decreasing contrast. With increasing age, the ability to discern between objects of similar contrast decreases and Bernstein et al. discovered that the contrast sensitivity slide-B alone accounted for 26% of the variance in the outcome measure (2008). Corresponding cutoffs for further action are visual field defects, visual acuity greater than 20/70, spatial span and visuo-spatial span. All of these variables proved to be predictive of the capacity to resume driving, in line with the observation that visuo-spatial learning is strongly involved in driving (Savida et al., 2017; Bernstein et al., 2008).

Further, the ***Rapid Paced Walk Test*** (Marottoli, 1994) is a commonly used cognitive assessment in assessing driving performance. This test is a 10-foot distance assessment where participants have to walk back and forth at a comfortable pace and are timed from picking up their first step to when the last foot crosses the finish line. The Rapid Pace Walk time for participants showed a strong independent correlation (r = -.454, p b .001) of all the significant measures retained from the domain of motor performance related to driving in a study by Ott and colleagues (2013). The cut off for the Rapid Paced Walk test is commonly set at 9 seconds and scoring is time-effective and efficient (Ott et al., 2013).

The Digit-Span Task from the WAIS-R (Wechsler, 1997). The Digit-Span Task (DST), a subtest from the Wechsler Memory Scale-Revised (WMS-R) (Weschsler, 1987), is used to assess attention, short-term memory, and working memory. The Digit Span test is a subtest that is also used for the Wechsler Adult Intelligence Scale (WAIS) and the Wechsler Memory Scales (WMS). Participants are being read a sequence of numbers and are then asked to repeat the exact numbers back to the examiner, either in forward (span) order, or in reverse (backward span) order. The DST is commonly used in driving research to assess working memory. Higher scores indicate better performance on the task, and participants have a maximum of two chances to succeed at each level (Bernstein et al., 2019).

The Motor-Free Visual Perceptual Test (MVPT) is a widely used standardized test of visual perception that is independently assessed of motor ability. Various forms of shape discriminations are used to identify issues with visual perception. Different aspects of visual-perceptual abilities have been shown to impact on-road driving performance in older drivers referred for driving assessment (Mazer, Korner-Bitensky, & Sofer, 1998; Novak et al., 2010). Overall per-

formance of the MVPT is measured as the number of correct responses on the task such that higher values represent a better performance.

The *Mini Mental State Exam (MMSE)* (Folstein, Folstein, & McHugh, 1975) is a measure of global cognition (Ott et al., 2013). This test is a quick screening tool to assess a quantitative evaluation of cognitive impairment. The questions assess orientation to time and place, immediate recall, short-term verbal memory, calculation, construct ability, and language. Possible scores range from 0 to 30, where 0 indicates severe cognitive impairment and 30 indicates no impairment. The MMSE has been reported to correlate to on-road driving, however, more recent findings show that using the current cut-off point of ≤ 24 on the MMSE is not always sensitive to predict on-road performance in older adult drivers (Crizzle et al., 2012). A study by Crizzle et al. offers strong evidence to support the current best practice of not using the MMSE in isolation to predict on-road performance, but rather to use it as an additional screening tool in a greater battery of tests (2012).

The Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005) is commonly used as a screening tool for mild cognitive impairment (MCI) and early Alzheimer's disease. The MoCA assesses short-term memory recall, visuospatial abilities, executive function, attention, language, and abstract reasoning. One of the subtests of the MoCA is the *Clock Drawing* test. Scores range from 0 to 30, with lower scores indicating more cognitive impairment, the cut-off usually sits at 21. Either the MoCA or MMSE are commonly used in driving studies, a combination of both in one research project is rare. Furthermore, the MoCA is often used in driving research to pre-screen participants for cognitive decline or dementia, especially older adults (Kwok et al., 2015).

Another common clinical based assessment is a measure of overall driving knowledge and often includes administering a “rules of the road test” and a “traffic sign test”. ***Measures of driving knowledg*e** are tested for driving studies, however, the variables often emerge as non-significant predictors of driving performance (Stav et al, 2008).

1.5.1.1. Tablet-Based Cognitive Tasks (TBCT)

The Tablet-Based Cognitive Tasks (TBCT) were designed and developed by DriveABLE/ Impirica to run as a continuous series of tasks administered on a tablet screen position in a flexible stand. The TBCT include four consecutive tasks: i) Reaction Speed: participants are asked to press a button as fast as possible after a visual cue (two stages, 15 trials in each stage), ii) Decision Making: participants are asked to press a ‘Go’ button after a visual cue while avoiding moving obstacles. A ‘Stop’ button is available as an additional control in obstacles avoidance (two stages; stage one had one set of obstacles and the second stage had two sets of obstacles, 20 trials in each stage), iii) Memory: participants are asked to draw a previously presented geometric shape (four stages with four trials in each stage). The number of shapes to recall, shape complexity, and the mask duration increased over stages. The fourth and final task is a iv) Bi-manual Perceptual-motor: participants were asked to follow a target circle using the iPad in a steering wheel fashion while avoiding fixed and surprise moving obstacles (four stages with each stage increasing in speed).

All tasks of the TBCT; Reaction Speed, Decision Making, and Bi-manual perceptual-motor tasks were adapted from the DriveABLE Cognitive Assessment Tool (DCAT). The DCAT is a reliable measure of cognitive processes needed for safe driving and predicts actual on-road performance in cognitively impaired drivers (Dobbs et al., 2013). The DCAT was developed based

on a number of standardized neuropsychological tests, including the Visual Field Test, Rabbitt Card Sort, Rod and Frame Test, Sitting- Rising Test, Cognitive Reflection Test, and span of Attentional Field, Speed of Attention Shifting, Corsi Block Tapping Test were collected. The subtasks of the DCAT were tasks designed to be used in conjunction with a touch-screen and a 3-button base and allow for easier administration (Dobbs, 1997).

In designing the TBCT, the cognitive screening tests were selected to cover the majority of the required cognitive domains needed for driving (CCMTA, 2018); divided attention (the ability to attend to two or more stimuli at the same time, evaluated in bi-manual perceptual-motor task), selected attention (the ability to selectively attend to one or more important stimuli while ignoring competing stimuli, evaluated in reaction speed and decision making tasks), sustained attention (the capacity to maintain attentional activity over a period of time, evaluated by bi-manual perceptual-motor task), short-term memory (the temporary storage of information that is currently being processed in a person's mind, evaluated by memory task), working memory (the ability to manipulate information with time constraints/taking in and updating information to solve problems, evaluated by all four tasks), complex reaction time (the time taken to respond differentially to two or more stimuli or events, evaluated by re- action speed and decision making tasks), tracking (the ability to visually follow a stimulus that is moving or sequentially appearing in different locations, evaluated by bi-manual perceptual-motor task), visuospatial abilities (processes dependent on vision such as the recognition of objects, the ability to mentally rotate objects and determination of relationships between stimuli based on size or color, evaluated by decision making task), executive functioning (capabilities that enable an individual to successfully engage in independent, purposeful, and self-serving behaviours, evaluated by all four tasks), and

visual information processing (the processing of visual information beyond the perceptual level, evaluated by all four tasks).

The TBCT is administered by a trained and DriveABLE certified evaluator. Each task includes a demonstration and or practice that is controlled by the administrator who provides feedback and answers any questions the participants may have. Test scripts are standardized as are test prompts and feedback.

TBCT dependent measures

Once the TBCT is administered and all four tasks are completed, 29 measures are extracted. From the response-speed task the percentage of trials that participants started early (% Premature go), did not respond at all (% Lack of response), and average reaction time (Reaction time) in each stage were extracted. From the decision making task the percentage of trials that participants started early (% Premature go), the percentage of trials success- fully passing the moving obstacles (% Success), contacting the moving obstacles from the front side (% Early collision), contacting the moving obstacles from a side other than front side (% Late collision), the number of times pressing the 'Go' button (Go Count), the average duration of each trial (Duration), the average number of obstacles that passed after the visual cue and before finishing passing the obstacles (Obstacle count), the average number of missed opportunity (Missed opportunity count) in each stage were extracted. From the memory task the duration of task completion (Duration), and the percentage of correct shape retrieval (% correct shape) were extracted. From the perceptual-motor task the percentage of time in- side the target (% Time inside target), and the percentage number of times fixed (% Fixed obstacles avoided) and surprise obstacles avoided (% surprise obstacles avoided) were extracted.

1.5.2 Neuropsychological Assessments

Cognitive assessments are used to evaluate important brain functions such as memory, concentration, language, processing speed, etc., whereas neuropsychological assessments are used to examine cognitive consequences of brain damage or brain disease. When it comes to driving performance, neuropsychological tests are of great importance screening for specific diagnosis and post-rehabilitation performance. In general, neuropsychologists appeared to be more likely to recommend that patients change their driving habits (e.g., limit distractions while driving, drive with lower frequency) and less likely to recommend that patients stop driving altogether (Stolwyk et al., 2019; Bernstein et al., 2018). These results may be indicative of neuropsychologists' recognition of the profound effect that driving cessation may have on patients' independence and well-being (Stolwyk et al., 2019; Reger et al., 2004). It appears that many neuropsychologists prefer that patients receive an evaluation of their driving ability before concluding that the patient should stop driving altogether. Impaired performance on at least one neuropsychological assessment tool component is commonly regarded as sufficient to trigger physician intervention and further testing (e.g., road-testing recommendation) (Ott et al., 2013; Stolwyk et al., 2019).

The following paragraph will now add onto previously presented clinical assessments used for driving screens. Following the previously alluded cognitive measures, neuropsychological assessments related to on-road driving are now being identified.

The Brain Injury Visual Assessment Battery for Adults (biVABA) is a screening tool used to assess visual processing ability following adult onset brain injury. It is a quick and easy to administer tool that includes distant reading (visual acuity), contrast sensitivity, visual atten-

tion and scanning (Ott et al., 2013). The biVABA assessment is often used as a tool to pre-screen for potential driving impairment and to provide an indication of underlying component skills in the area of cognition, perception, and executive functioning. Based on final scores further testing can be recommended (Saviola et al., 2018).

NEURO Symbol Digit Modalities Test (SDMT) (Smith, 1982), is a commonly used screening tool to assess neurological dysfunction assessing attention, perceptual speed, motor speed and visual scanning and is often used to scan for cognitive decline in relation to aging or TBI (Kiely, Butterworth, Watson, & Wooden, 2014). The SDMT is able to detect cognitive impairment in a short time-frame and is therefore of particular interest to clinicians. In relation to on-road driving, processing speed is commonly assessed by the oral version of the SDMT with the main construct being the number of correct responses provided within a time limit of 90 seconds (Saviola et al., 2018).

The Color and Stroop Test is a neuropsychological assessment commonly used to assess the ability to inhibit cognitive interference that occurs when the processing of one stimulus impedes the simultaneous processing of a second stimulus. This test asks participants to read out words describing colours such as “yellow” and “red”, however, the words are written in different coloured fonts making it more difficult to read the actual letters while disregarding the font colour. A study by Collet, Petit, Priez & Dittmar, examined drivers' performance when confronted with a critical crash avoidance situation showing that performance of the Stroop test and physiological biomarkers were indicative of their management in high risk situations (2005).

The Useful Field of View (UFOV®) (Goode et al., 1998). The UFOV was developed to assess visual difficulties that older adults commonly experience with everyday tasks such as dri-

ving. The UFOV is an online evaluation measuring the brain's ability to take in and react to information at a single glance and is one of the most extensively researched and promising predictor tests for a large range of driving outcome measures and predictors (Ott et al., 2013). Overall driving ability and crash risk seem to be predicted by the scoring on the UFVO. The UFVO total score is a measure of cognitive processing speed, divided attention, and selective attention (Goode et al., 1998).

An additional crucial assessment used to measure cognitive performance include ***Trail Making Test, Part A and B*** (Reitan & Wolfson, 2004). The TMT Parts A and B assesses overall cognitive functioning. This test has two parts: Trails A, requires the individual to connect a sequence of 25 numbers in order, and Trails B requires the individual to alternately connect a sequence of 25 numbers and letters (e.g. 1-A-2-B-3-C, etc.) (Reitan & Wolfson, 2004). The trails can be used independently of each other or can be administered together in any order. The TMT Parts A and B are often used in the screening for driving fitness. In a study by Ott et al., participants completed Trails B first and then Trails A, a simpler paper- and- pencil task than Trails B (2013). The time to complete the test (maximum time set at 180 seconds) and total error score were recorded. Maximum time for the Trails B test is commonly set at 300 seconds and those who are unable to complete the task within this time are given a score of 301. A total error score is often recorded for Trails B. Two additional cognitive tests (Trail-Making Test Part A (Trails A) and Maze Drawing) were examined as predictors of driving outcomes selected from an evidenced-based review (Wood et al., 2013; Ott et al., 2013). This review showed that Trails B was the most informative, with a sensitivity of 0.58 and a specificity of 0.78, yielding a correct classification rate of 0.71 and an area under the curve (AUC) of 0.68 (Wood et al., 2013).

Moreover, Trails A and Trails B are more highly correlated with road test scores than the MMSE, a measure of global cognition (Saviola et al., 2018). Further, Ott et al. discovered that in a sample of currently active older drivers with and without cognitive impairment, measures of cognition, particularly the Trail Making Test Part B were more highly correlated with driving scores than other measures of function (2013).

Maze Drawing Tasks were developed to assess attention, visuo-constructional ability, and executive functions of planning and foresight. Maze drawing assesses multiple cognition functions and often serves as a proxy measure for basic street navigational skills (Saviola et al., 2018). These tasks are often administered with pencil and paper, however, computerized maze tasks are becoming increasingly more popular. Two different maze drawing tasks were administered in a study by Ott et al. (2013), one using paper and pencil and via a computer. First, the ***Snellgrove Maze Task (SMT)*** was completed using pencil and paper and a practice maze was administered before the larger, more-complex maze. The SMT was scored for time to complete and the number of errors and predictor variables were the totals for drawing time and total error scores. Maximum completion time was 180 seconds per maze and overall error rates seemed predictive for at-risk driving (Ott et al., 2013; Saviola et al., 2018).

The Clock Drawing Test (CDT) aims to screen cognitive impairment and dementia through constructs of spatial dysfunction and the assessment of executive functioning (Folstein, Folstein, & McHugh, 1975). The cognitive decline can be seen when patients are able to perceive the instructions to “draw a clock and set the time 10 minutes past 11 o’clock”, however, acting on it seems particularly difficult. The Clock Drawing test is commonly used in driving literature and

results have shown its predictability of on-road driving performance (Folstein, Folstein, & McHugh, 1975; Ott et al., 2013).

Digit Symbol Matching Task **(DSM)** (Salthouse, 1994) is a computerized version of the Digit symbol substitution test. Based on Salthouse's (1994) adaptation of the Wechsler Digit Symbol Subscale as previously described (Anstey et al., 2006), a series of symbols were displayed under a row of digits (1-9) forming a legend for the task at the top of the screen. A number and a symbol are then displayed underneath that row and participants have to judge whether the symbol matching the number was the same as the symbol matched to that number in the legend via pressing true or false. Several trials are presented and the average response time and number of correct responses is recorded (Salthouse, 1994; Anstey et al., 2006).

In addition to the clinical assessments presented in this paper it is important to mention that many other tests are frequently administered to assess driving. Some of these assessments are not standardized yet and fewer researchers have been studying them, nevertheless, some of these assessment batteries show promising results, such as the Assessment of Driving-Related Skills (ADReS), DriveABLE Cognitive Driving Assessment (DCAT), Visual Selective Attention Test (VSAT), or the Physician's Guide to Assessing and Counseling Older Drivers as well as guides and aids for clinicians (Bakhtiari et al., 2020; Morgan, 2018; Ott et al., 2013).

1.5.3 Physical Assessments

In many countries, physical pre-screenings and mandatory driving assessments are key to identifying older at risk drivers. In Alberta for instance, it is the law, at age 75, 80, and every two years after, to renew a driver's license based on a general practitioner's medical report. A doctor assesses a patient's vision, neck and head flexibility, overall mobility, as well as other sensual

perception markers (hearing, reflexes, and different forms of attention) (CCMTA, 2018). Physical assessments often entail cognitive and neuropsychological screening tools such as the Rapid Paced Walk Test or the Snellen Eye Chart. Based on the overall medical report, patients can be referred for further on-road driving assessments if needed. Driving-prescreening can be requested at any age based on medical diagnosis or rehabilitation and is not only reserved for older adults.

1.6 Different Forms of Impairment

There are various populations with specific clinical diagnoses that are at high risk of being involved in vehicle accidents, such as patients diagnosed with dementia, traumatic brain injury, or multiple sclerosis (Dubinsky, Stein, & Lyons, 2000; Schultheis, Garay, Millis, & DeLuca, 2002; Asimakopulos et al., 2012). Depending on these exact patient populations, specific cognitive domains are often associated with different kinds of impairment (e.g., visuo- spatial impairment or cross-motor impairment) (Schanke & Sundet, 2000).

1.6.1 Permanent Cognitive Impairment

Post-recovery and after a temporary driving cessation has been in place, returning back to on-road driving is a common goal for many traumatic brain injury (TBI) survivors. As mentioned before, being able to drive is associated with increased life satisfaction as well as community integration and a sense of belonging (Novack et al., 2010, Schwanen, Banister, & Bowling, 2012). Around 40% to 70% of individuals with TBI return to driving at some stage during recovery and a great focus of driving research in regards to brain injury is to successfully identify predictors of on-road driving ability (Novack et al., 2010; Coleman et al., 2002; Ponsford et al., 2014). Several studies have provided evidence for an association between deceased performance of reaction

time, divided attention, and perceptual speed, as well as visual processing, various spatial and perceptual measures, cognitive flexibility executive functioning, and self-awareness in various environments, and poor on-road driving performance post TBI (Ponsford et al. 2014; Novak et al., 2006).

In order to evaluate the readiness to return to on-road driving after a traumatic brain injury, formal and comprehensive on-road assessments that integrate a wide range of skills are needed (Stolwyk et al., 2019). Detailed and individually tailored rehabilitation programs specific to driving have to address specific skill deficits to help individuals during rehabilitation and facilitate a safe return to driving post-injury and recovery (Stolwyk et al., 2019).

1.6.2 On-Road Driving and Aging

Normal cognitive aging is associated with cognitive decline affecting driving competency (Wood et al., 2008). The process of aging entails various psychological and physiological changes and is often shown through an overall decreased processing speed combined with increased forgetfulness in a short and long term memory association (Raz, 2000). Transport Canada reported that 34.4% of licensed Canadian drivers are over the age of 55 and actively driving while driver fatalities increase after the age of 65 and more fatalities are caused by male older drivers compared to female older drivers (Transport Canada, 2017; Efflein, 2018).

The most affected sensory function in older adults is vision due to the deterioration of the visual field resulting in a decrease of visual sensory information processing (Nusbaum, 1999; Sekuler and Bennett, 2000**)**. Once visual acuity worsens, stationary and moving objects cannot be perceived accurately and efficiently which has been linked to an increase in crashes in older adults (Wood, 2013). Older adults commonly report visual difficulties in daily tasks that are also

related to problems they experience while driving, such as decreased visual processing speed, sensitivity to light, dynamic vision, near vision and visual search, problems driving at night due to decreased night time vision, etc. (Kline et al., 1992; Efflein, 2018).

As Morgan predicted, many older adults will most likely have to retire from driving at one point in their lives due to "life expectancy exceeding driving fitness expectancy" (Morgan, 2018) in the United States. Research shows that at around 70 years of age and older fatal crash rates increase significantly and are highest for individuals 85 years of age and older (Morgan, 2018). However, literature also suggests that age alone is not a very reliable variable that predicts on-road driving, hence, age-related changes related to physical and cognitive abilities can equally affect a safe driving performance (Jones et al., 2015). Therefore, these high mortality rates can not only be associated with aging alone, but with overall fragility associated with the decline in physical and cognitive abilities. As older drivers increasingly rely on driving and their own personal vehicle transportation, it is becoming more important to use and develop time and cost-effective screening tools that are valid and reliable, easily accessible and preferably standardized to properly screen and assess driving skills and crash work of older adults. Based on existing research, it is crucial to perform statistical analysis controlling for age when it comes to cognitive impairment and cognitive assessments in relation to driving.

1.6.3 Temporary Cognitive Impairment

Besides the populations mentioned above, increasingly more research is focusing on other populations that need to be assessed for their driving performance. For instance, recreational drug and alcohol users are being studied while displaying "short term" driving impairment (Hoe et al., 2003). Besides cognitive decline being correlated with age, literature suggests that the spe-

cific form of cognitive impairment such as drug induced cognitive impairment can adversely affect driving performance (Wood et al., 2008; Lyman et al., 2001). Further, literature also displays differences between short-term and long-term drug users where neuropathological changes are taken into account and how these changes may adversely affect the overall driving performance, either while under the influence, or during wear off stages (Hoe et al., 2003; Ramaekers et al., 2004). A presentation by Tomczak et. al (2019) showed that participants under the influence of cannabis and/or cocaine performed worse on a battery of cognitive assessments predictive for on-road driving (Bakhtiari et al., 2020, Tomczak et al., 2019). Controlled and observational studies looking at the impairment caused by recreational drug use are increasingly observed when it comes to driving research.

1.6.3.1 Recreational Drugs & Alcohol

Recreational drug and alcohol use is a crucial topic when studying cognitive impairment. Users often desire the rewarding effects and feeling of alcohol and drugs leading to continuous use often resulting in addiction. The nucleus accumbens, a brain structure located in the basal forebrain, is linked to other brain structures involved in dopamine and serotonin release related to recreational drug use. The following paragraphs will elaborate the effects of alcohol and common recreational drugs (cannabis/THC, cocaine, opioids, ecstasy) on the human body and central nervous system (CNS). Each drug impacts the brain and CNS differently, and long-term misuse of recreational or prescription drugs can adversely affect essential organs.

Cannabis

The chemical compound 9-tetrahydrocannabinol (Δ9-THC), also commonly known as THC or cannabis is a recreational drug that influences the endocannabinoid system (ECS) in the

human body. The endocannabinoid system is a neuromodulatory system that plays important roles in the central nervous system (CNS) development and is involved in brain plasticity facilitating and responding to endogenous and environmental issues (Lu and Mackie, 2015). There are many cannabinoid receptors in the brain and throughout the entire body. These receptors regulate synthesis and degradation of endogenous chemical compounds that are called endocannabinoids (Iversen, 2003). 2-arachidonoyl glycerol (2-AG) and arachidonoyl ethanolamide (anandamide) are the most researched endogenous cannabinoids and are naturally produced by the human body (Lu and Mackie, 2015; Buzsaki, 2006). CB1 and CB2 receptors are the most abundant receptors where CB1 receptors are most commonly found in the brain and CB2 receptors are present throughout the remaining body. However, exogenous cannabinoids, such as tetrahydrocannabinol (THC), interact with these cannabinoid receptors which results in a mind altering state and in a perceived "high" leading to a depressing effect of the CNS (Lu and Mackie, 2015; Iversen, 2003).

Another commonly studied compound in cannabis is CBD. Cannabidiol (CBD) is a naturally occurring cannabinoid component of cannabis and it does not cause intoxication or the "high" that is perceived when THC is consumed (Lu and Mackie, 2015). CBD has been related to many health benefits that are currently intensively studied and investigated. CBD also binds on CB1 receptors in the brain and works as an antagonist to THC meaning it inhibits the chemical reaction of THC in the brain, lessening the psychoactive effects of THC (Buzsaki, 2006). Due to the increased social consumption of cannabis and THC products, biological and physical processes in regards to THC and the human body have extensively been studied. Frequent THC consumption, especially during young adolescence, has also been linked in some studies to schizo-

phrenia in young adults and the alteration of brain oscillations and synaptic connections (Lu and Mackie, 2015; Iversen, 2003).

When it comes to cannabis consumption and cognitive performance it is clear that cannabinoids induce short term and possible long term disruptions in attention, working memory, sensory-motor integration, and many other psychosis-related behavioural effects (Skosnik et al., 2015). Focusing on impairment related to THC consumption, these impairments have commonly been observed: Decreased reaction time, slower tracking, decrease in psychomotor skills and visual functions plus decreased attention spans (Berghaus et al., 2005; Radhakrishnan et al., 2014).

Further, several studies have found that long term administration of THC decreased performance on decision making tasks. Infrequent and frequent users portrayed adversely affected memory performances with acute users showing a greater decrease in performance accuracy (Ramaekers et al., 2004; Groeger, 2000). Cognitive abilities in regards to decision making also decreased in acute users. Further, studies have found that risky decision making and sensitivity to reward are increased in long term users suggesting that cognitive impairment caused by THC are most commonly associated with decreased memory scores and verbal learning (Groeger, 2000). Rodent and non-human primate research suggests that reaction time, memory, and overall learning abilities are adversely affected when THC is consumed short-term and long-term (Fattore and Fratta, 2010).

Based on a variety of studies it can be said that executive functioning and subdomains are influenced differently in long term and short term users (Fattore and Fratta, 2010; Downey et al., 2010). Planning, problem solving, time tracking, reasoning, and reaction time are affected and

more research is needed looking at long term and short term consumption in combination with abstinence and various levels of THC consumption. Drug abstinence is an important topic in the literature as it seems to be evident that recovery of executive functions is observed while individuals refrain from THC consumption for an extensive period of time leading to possibilities of optimizing recovery and treatment of addictions (Hopper et al., 2015).

Cocaine

Cocaine is classified as a stimulant. Consumption of cocaine results in serotonin flooding postsynaptic neuron channels and fully stimulating the CNS. Cocaine users usually insufflate ("snort") or inject the powdered cocaine through the nasal caves, intravenously, or smoke "crack" in a glass pipe. Recreational cocaine is commonly used because of its intense euphoric effects leaving the user in an energetic fulfilled state that lasts between 30 and 45 minutes. Individuals often report feeling more alert, energetic but also paranoid and shaky. Cocaine users crave a quick mood enhancement and addiction is often inevitable due to its fast on-set and 30 minutes wear off phase (Snyder, 1996). Cocaine produces physiological effects such as increased heart rate, large pupils, and sweating. A meta-analysis of studies with participants with chronic cocaine use found that sustained attention, impulsivity, verbal learning/memory, and working memory were the most impaired abilities (Potvin et al., 2014). Chronic cocaine users also show impairments in response inhibition, memory (recall) to a moderate degree, working memory (with limited evidence), cognitive flexibility (mild impairment), performance monitoring, and psychomotor responses, but selective attention is not impaired. Acute cocaine users have improved inhibitory control, and psychomotor responses (only when taken intranasally), but memory is not affected (Spronk, van Wel, Ramaekers, & Verkes, 2013). Acute use of stimulants (e.g., meth-

amphetamine, amphetamine, cocaine) is associated with side effects such as lack of coordination, sensory disturbances, disorientation, restlessness, lapses of attention, difficulty reacting appropriately in order to safely control a vehicle, increased risk taking, overconfidence in driving skills, drowsiness or rebound fatigue (as the effects wear off) (Marillier & Verstraete, 2018). While cocaine may improve attention at lower doses, cocaine causes cognitive impairment and impulsivity at higher doses and during the rebound fatigue stage. Therefore, cocaine is seen by some users as an avenue to improve driving ability when tired, and does in fact reverse some of the cognitive deficiencies in sleep-deprived persons (Marillier & Verstraete, 2018). Cocaine induces similar physical effects as cannabis such as heightened nervousness, increased alertness, and decreased concentration. However, reckless or reduced driving ability is reported more frequently for cocaine users, and cautious or normal behaviour was reported more for cannabis users (MacDonald et al., 2008).

Opioids

Opioids are considered drugs that reduce pain and are often classified as painkillers, prescribed or illicit. Opioids decrease the levels of the neurotransmitter GABA leading to an increase in dopamine causing the user to feel more at ease and less stressed. Many prescription pills such as OxyContin, Percocet, Vicodin, and fentanyl as well as the street drug heroin fall under the Opioid umbrella term (Snyder, 1996). In order to relieve pain, opioids have a relaxing effect on the central nervous system; pupils constrict, breathing rate slows down, increased body temperature and an overall feeling of relaxation. Due to the combined effect on the brain and CNS, opioids are considered highly addictive and heroin addictions often end fatally (Synder, 1996).

Ecstasy

Ecstasy and its various forms have gained multiple street names during the past few decades. Often described as “Molly”, “speed”, or “MDMA”, ecstasy is commonly consumed in pill or powder form. Ecstasy is a stimulant and high levels of serotonin and dopamine are released causing heightened levels of joy, an energy rush, as well as extensive feelings of love and empathy. While serotonin and dopamine are flooding synapses, cortisol levels also increase leading to restlessness, sweating, and enhanced sensory perception. An ecstasy high can last between three to four hours and is often followed by feelings of depression, fatigue, and loneliness triggering further addictive patterns (Snyder, 1996).

Alcohol

Alcohol is classified as a depressant meaning its neurobiological effects depress the CNS and vital processes of the brain slow down resulting in impaired cognitive functioning. Besides working as a depressant, initial levels of alcohol increase dopamine levels leaving an individual with feelings of joy, happiness and overall life satisfaction. This combination of having a depressed stress response in the body and high levels of dopamine can be a dangerous addictive combination. Dopamine is a neurotransmitter responsible for mood regulation, attention and motivation. Once blood alcohol concentration (BAC) increases, heart rate and breathing rate slow down leading to feeling less stressed and more relaxed. Due to rising dopamine levels, alcohol is a highly addictive drug and frequent consumption can lead to damaged neuronal connections slowing down overall processing speed in relation to attention. Long-term alcohol abuse can cause severe liver damage and organ failure (Harper, 2009). When it comes to measuring alcohol levels while driving, smart breathalyzers are commonly used. These devices are usually small

and hand-held collecting user-initiated voluntary readings and have been available commercially since 2013. This technology reliably infers blood alcohol concentrations (BACs) from a driver's exhaled breath (Aschbacher, K., Hendershot, C.S., Tison, G. et al. 2021).

1.6.4 Demographical Data and Recreational Drug Usage

Based on the World Drug Report of 2017, roughly 271 million people, equivalent to 5.5% of the global population, had used drugs in the previous years. Worldwide data shows a higher prevalence of the use of opioids in Africa, Asia, Europe and North America and the use of cannabis in North America, South America and Asia compared to previous years (Elflein, 2018). The North American opioid overdose crisis continuously grows and has reached new heights in 2019. With more than 15,300 opioid overdose deaths recorded in Canada between January 2016 and December 2019, fentanyl and its analogues remain the key problem of the synthetic opioid crisis in North America. The most widely used drug besides alcohol continues to be cannabis globally, with an estimated 188 million people having used the drug worldwide in 2017. Besides differences in overall drug consumption based on nationalities, there are also significant differences between ethnic groups in North America; the rate of drug use is highest among the First Nations and/or indigenous peoples population (10.6%) and those reporting mixed race (11.2%), followed by African Americans (7.7%), Hispanics (6.8%), whites (6.6%). The lowest rates are found among the Asian population. (3.2%).

According to Canadian statistics, within the year 2017 the overall percentage of Canadians who used cannabis was 14.8%, followed by cocaine/crack at 2.5% and hallucinogens and ecstasy sitting around 1% (Elflein, 2018). There are also significant differences based on gender and drug consumption as men are more likely than women to use almost all types of illicit drugs.

”Illicit" refers to use of illegal drugs, including marijuana and the misuse of prescription drugs. Elflein (2018) reported that in most age groups men have higher rates of addiction to alcohol and recreational drugs than women do, however, both groups are just as likely to develop a substance use disorder. Further work by Patrick et al. (2012) has shown that socio economic status (SES) and different drug use are correlated; smoking tobacco in young adulthood or adolescence was associated with lower childhood SES, however, alcohol consumption and cannabis use in young adulthood were correlated with higher SES during childhood. The indicators for family background SES were parental education, overall wealth and household income, however, further studies investigating the relationship between SES in childhood and adulthood connecting to drug consumption need to be completed (Patrick et al., 2012).

Various rapid on-site drug screening kits have been developed in the past decade to detect drugs via saliva or urine on site. Saliva testing is commonly preferred over urine analysis. Oral fluid testing has become the most convenient rapid on-road site drug testing method because of its fast, convenient and non-invasive characteristics (Xu et al., 2019). Further, research has been done to analyze and evaluate the efficacy of rapid on-site screening tests for detection of drug consumption such as cocaine, cannabinoids, amphetamine and methamphetamine, and MDMA. These rapid tests are not only used by law enforcement but also by occupational health physicians (Rosso, 2013).

1.6.5 Cannabis and Cocaine Consumption in Relation to Driving Performance

1.6.5.1 THC and Driving Performance

Reviewing THC and driving research portrays that performance in driving simulation decreases with increased levels of THC in the bloodstream (Asbridge et al., 2012). Various studies analyzing simulator variables that were collected while individuals were impaired report that individuals have a fairly difficult time controlling speed, are unable to maintain a safe distance to vehicles preceding them, and commonly straddling the solid and barrier line (Asbridge et al., 2012; Downey et al., 2012). Furthermore, insufficient stopping during night time driving was observed whereas no differences assessing insufficient stopping were observed during day time simulations. Simulated and on-road driving studies report impaired perceptual processes such as difficulties monitoring the speedometer and maintaining speed; response to stimuli, such as stopping and accelerating after a stop sign or traffic lights (Downey et al., 2012; Sewell et al., 2010). In a study by Asbridge and colleagues (2012) high and low THC conditions were compared in combination with low, high and no alcohol conditions reporting that individuals consuming high amounts of THC and alcohol were unable to control their speed and unable maintaining a safe distance to vehicles proceeding them suggesting critical impairment and the inability to drive a vehicle. Furthermore, speed limit violations increased with the increase of alcohol consumption in the low and high THC groups (Downey et al., 2012).

Significant differences between regular cannabis users and non-regular users were also reported such as regular users showing more signalling errors and greater impairment in relation to high THC consumption. However, non-regular users had slower acceleration from stop signs or traffic lights but faster reaction time in the high THC conditions suggesting a more cautious

approach to driving (Downey et al., 2012). Overall, some of the driving simulator variables were fairly unaffected across conditions. Another study by Sewell and colleagues (2010) found that driving simulator performance was significantly compromised in the THC and alcohol combined conditions, particularly in the night-time simulations. Generally, regular cannabis users displayed more driving errors than non-regular cannabis users and Asbridge and colleagues (2011) stressed that further research in this domain is needed as acute and short term users greatly differentiate in cognitive and driving performances when it comes to THC consumption, and THC and alcohol combined.

It is important to notice that multiple studies have also examined the interactive effects of THC and alcohol in various combinations and have shown varied results. Synergistic and additive effects of combined drugs can either elevate or decrease the level of cognitive impairment (Bramness et al., 2010). In highly controlled and counter balanced studies of the interaction between THC and alcohol it was found that there is an additive effect with some evidence suggesting increased levels of THC and alcohol often leading to a synergistic effect (Liguori et al., 2002; Ramaekers et al., 2004; Lukas and Orozco, 2001). The interaction seems less additive at lower levels of THC and alcohol, however, individual performances on cognitive assessments and physiological experiences vary depending on the individual consuming THC, familiarity with the drug, tolerance, weight and body water-fat content (Ballard and De Wit, 2011; Iversen, 2003).

When the consumption of THC is studied alone, without the combination of alcohol, driving impairment can be observed in various forms; reaction time is often slowed, tracking of speedometers and other attention related variables are adversely affected (Berghaus et al., 1995; Sewell, 2010). These findings in regards to THC impairment and simulator driving have been

observed in several studies within the last three decades (Sewell et al., 2010; Liguori et al., 2002; Ramaekers et al., 2004; Lukas and Orozco, 2001). However, another interesting spectrum of variables to observe while measuring simulator driving performance are neural brain oscillations. Only limited studies have been done looking at the relationship between brain oscillations and driving simulator variables. The following paragraphs will look at simulated driving while EEG measures were obtained.

1.6.5.2 Cocaine and Driving Performance

As previously explained, cocaine is a CNS stimulant and if consumed in high doses, it can also work as a local anesthetic (Efflein, 2018). Cocaine use and driving literature is limited, however, more studies are looking at physical and cognitive effects long term cocaine use can have on the human body and brain. As previously mentioned, chronic cocaine use can have many dangerous side effects ranging from great sense of euphoria, hallucinations, respiratory failure to psychosis and cerebral hemorrhage. Individuals often become violent and euphoria can lead to destructive and impulsive behaviour (Marillier & Verstraete, 2018). More importantly, adverse reactions have been reported after long-term cocaine use even when no measurable drug levels were found in the blood. All the adverse short-term and long-term effects of cocaine on the CNS and body may negatively affect safe driving performance.

Due to euphoric states experienced during a cocaine high, impairment may lead to speeding behaviour, increased risk taking, short-term memory loss and increased reaction time. Some of the signs of driving impairment that may have been caused by cocaine that have been observed are speeding, causing collisions, losing control of the vehicle, high-risk behavior, turning in front of other vehicles, inattentive driving and poor impulse control. Once cocaine wears off,

fatigue, depression and shivering can also lead to impaired driving (Marillier, & Verstraete, 2018; MacDonald et al., 2008).

As Chapter 3 will show, cannabis and cocaine are commonly consumed together. When it comes to drug impairment and on-road driving, polysubstance use (PSU) is commonly observed but not as readily studied as single drug consumption. The combination of various drugs, often consumed with or without alcohol, may affect the CNS differently and depending on habitual or occasional substance abuse, physiological and neuro cognitive effects may vary. (Ignaszewski, 2021).

1.7. Challenges when Assessing (Impaired) Driving

Due to the complexity of on-road driving tests and in-office assessments, challenges and limitations often arise. Overall, consistency is most crucial when it comes to driving assessments as the main goal is to increase a patient's quality of life as well as their overall safety (Bernstein et al., 2019). Furthermore, a lack of precise literature outlining recommended clinical and neuropsychological recommendations has led to an increase in non-standardized assessments and guidelines. Non-standardized assessments are valid to explore, however, they often lack validity and credibility resulting in poor driving evaluations. Another challenge when it comes to assessing driving skills is the presentation of many different (clinical) populations that are commonly identified as at-risk drivers. For instance, individuals with TBI, dementia, epilepsy, or healthy aging seniors often require modified assessments tailored to their diagnosis or cognitive abilities. This means assessment times are often cut short or divided into blocks which can lead to confounding results (Savia et al., 2017).

Furthermore, an additional challenge when assessing driving performance via in lab assessments, speed-accuracy trade offs can be seen. The speed–accuracy trade-off (SAT) phenomena dates back to first research by Wickelgren in 1977. SAT is the fundamental concept of accuracy being traded off in a given task by speed, meaning an increase in reaction time related to memory performance, perceptual and cognitive performance can be observed. This means that most individuals perform less accurately when they move or react faster. Measuring cognitive performance in healthy and impaired individuals commonly supports the speed-accuracy trade-off and will be further elaborated on in the result and discussion section in Chapter 4.

When it comes to clinical settings, acute care rarely allows the possibility of conducting hour-long assessments, whereas in a rehabilitation centre or specialized driving evaluation centre, it is more common to have the equipment and time necessary for extensive driving assessments (Asimakopulos et al., 2012). Additionally, older drivers with impaired driving skills are likely to present multiple deficits. Due to the dynamic nature of the driving task, it is not likely that a single assessment tool will adequately identify at-risk drivers (Savia et al., 2017).
Lastly, PSU affects the majority of the substance-using population as one drug dependence most commonly leads to further dependences and addiction (Crummy et al., 2020; Ignaszewski, 2021). Precise toxicology reports and self-report measures can often portray a challenge for researchers due to reliability and cost issues.

In conclusion, assessing cognitive impairment in relation to on-road driving is a vastly researched area, nevertheless, more research is needed to identify more consistent patterns of assessing different forms of cognitive assessments in relation to drug impairment (Chapter 3) and aging (Chapter 2). Chapter two of this thesis will present a study that was completed in 2019 and

published in 2021 assessing cognitive performance of older drivers and at-risk drivers. Different performance patterns were identified via a machine learning approach.

CHAPTER 2:

Application of tablet-based cognitive tasks to predict unsafe drivers in older adults

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Abstract

Background: Due to aging and medication interferences, a wide range of motor, sensory, and cognitive skills that are imperative for driving are affected in older adults. Though on-road tests are most indicative of driving ability, they are costly, stressful, time-consuming, and risky. Application of tablet-based cognitive tasks is investigated in identifying unsafe drivers in a population of healthy and at-risk for driving older adults. **Method:** Forty-nine older adult participants aged 54 to 81 (M = 78.08, SD = 9.78) that were screened by their physicians as "at-risk for driving impairment", and forty-eight control participants aged 54 to 81 years (M = 65.85, SD = 6.93) completed an on-road driving test and a set of tablet-based cognitive tasks (composed of reaction speed, decision making, memory, and bi-manual perceptual-motor tasks). Accuracy and reliability of predicting unsafe drivers based on the cognitive tasks were investigated using different trichotomous classifiers. **Results:** Trichotomous naive Bayes demonstrated the highest overall accuracy performance of 73%, a sensitivity of 69%, and a specificity of 75%. The rate of misclassified unsafe drivers was 19%, and the rate of misclassified safe drivers was 8%. **Conclusion:** High accuracy and reliable prediction of unsafe drivers using cognitive-only tasks in a sample of older adults population demonstrate the efficacy of a widely available screening tool that can be applied in other cognitively impaired populations such as drug users.

1. Introduction

As baby boomers age and geriatric care improves, there are more elderly people living independently than ever before (Cameron et al., 2017). As a result, the number of older adult drivers has increased considerably posing a challenge to the traffic system (Anstey et al., 2005; Foley et al., 2002; Koppel and Berecki-Gisolf, 2015). In Canada, in 2012, one in seven Canadians were older than 65 years (5 million), and this ratio is expected to increase to almost one in four (9 million) by 2030 (Employment, Social Development Canada, 2016), which has a similar trend in the United States (Mather et al., 2015). Several studies show that the number of crashes and mortality rates increase by age (Cameron et al., 2017; Koppel et al., 2011; Lee et al., 2003). In Canada (2016) the mortality rate for people aged 75 and older is similar to young adults (18–20 years of age), representing the highest rate of 10% (IRTAD, 2018; CCMTA, 2017). These studies focus on the risk older adults impose on their own and others, and are the basis for more restriction and screening measures for older adults. However, for many individuals, the ability to drive is a key element for living independently as driving cessation commonly results in social isolation, depression, and a decline in general physical health, mental health, and overall quality of life (Chihuri et al., 2016; Windsor et al., 2007). There is an adverse impact of revoking an older adult's driving license that must be taken into careful consideration. Both the physician-patient relationship and physician-family relationships suffer after these life-changing decisions are made. This often results in an increase in stress for caregivers and family relationships can suffer greatly (CCMTA, 2017; Molnar et al., 2005).

Although chronological age per se is not, and should not be a prohibitive factor for driving (Hakamies-Blomqvist et al., 2002; Siren and Haustein, 2015) senescence is usually associated with overall cognitive decline, a broad range of medical conditions (e.g. cardiovascular diseases (Viamonte et al., 2010), diabetes (Cox et al., 2003), musculoskeletal disorders (Jones et al., 1991), Alzheimer's diseases (Brown et al., 2005)) and various medications to cure or control them that may interact with each other and affect fitness to drive.

Cognitive decline is one of the most common conditions in older adults that has been attributable to dementia and associated pathologies (Wingo et al., 2019). In the Canadian province of Alberta, individuals must complete a driver's medical exam at age 75, 80, and every two years after, but this age varies across provinces (AMA, 2018). Disagreement regarding the age, time interval, and procedure for assessing driving competency in older adults also exists in the United States and European countries (Lococo et al., 2017; Mitchell, 2008). Other than older adults, commercial drivers and individuals with specific health conditions (e.g., neurological conditions, mild cognitive impairment) must complete a driver's medical examination periodically depending on their health conditions (CCMTA, 2017).

Considering the rapidly growing rate of older adults, and the need for regular screenings, this will be a considerable cost and stressor for the patient's family. Therefore, there is a need for an intermediate cost and time efficient tablet-based assessment tool that can reliably discriminate between most of the safe and unsafe drivers and leave the remainder (those with in-between performance) for further functional assessment (AMA, 2018; CCMTA, 2017).

In the past decade, many screening tools have been developed and extensively studied to replace on-road assessments with a faster, cheaper, more-widely available and secure tablet-based evaluation assessment. In Wood et al. (2013), the ability to predict risky drivers based on the sensitivity (the proportion of unsafe drivers correctly classified or true positive rate [TPR]), specificity (the proportion of safe drivers correctly identified or true negative rate [TNR]) using several screening tests was evaluated as. The multi-disciplinary test battery: TPR=80%, TNR=73%, the hazard perception test: TPR=75%, TNR=61%, the hazard change detection test: TPR=70%, TNR=61%, and the Mini-Mental State Examination (MMSE): TPR=65%, TNR=37%. By combining several cognitive and physical tasks of the hazard perception test, color vision, and, a measure of walking speed in (Jones Ross et al., 2014), and the hazard perception test to the multi-disciplinary driving battery in (Wood et al., 2013), a sensitivity, specificity of TPR=82%, TNR=69%, and TPR=85%, TNR=78% was reported for identifying safe and unsafe drivers in older adult populations respectively. In cognitively healthy, licensed older drivers, the combination of the hazard perception test, color vision, and, a measure of walking speed from the Roadwise Review, resulted in TPR=82% and a TNR=69% for predicting unsafe drivers (Jones Ross et al., 2014). The combination of the hazard perception test, leg strength, visual acuity, visual search and working memory, and number of medications taken could identify unsafe drivers with TPR=71%, and the TNR=75% in cognitively impaired older adults (Jones Ross et al., 2015). Visual acuity, physical flexibility, and knowledge of road signs were found to be the best predictive set of tests for the on-road fitness to drive outcome in (Urlings et al., 2018).

Aging results in decline of sensory and motor skills which leads to driving incompetency (Choi et al., 2017). In addition to evaluating cognitive skills, the mentioned studies measured various

sensory-motor domains such as leg strength measure of the Roadwise Review (Staplin and Bella, 2006), motion sensitivity, color choice reaction time, postural sway, and a measure of driving exposure to predict safe or unsafe on-road driving performance. Therefore, generalizing these evaluation approaches to other populations that are impacted by cognitive decline such as clinical patients and drug users is not possible. In this study, a series of tablet-based cognitive tasks (TBCT) were developed. An older version of these tasks implemented on a touch-screen and a 3-button base were able to successfully discriminate between safe and unsafe drivers in cognitively impaired drivers (Choi et al., 2015; Dobbs, 2013; Dobbs et al., 1998; Korner-Bitensky and Sofer, 2009).

The main purpose of the study reported in this paper was to examine the potential of a series of tablet-based cognitive tasks (TBCT) as a reliable predictor of on-road driving performance in a population of older adults, including healthy individuals and those at-risk for further cognitive impairment. To this end, we evaluated the driving performance of participants using an established on-road test specifically designed to focus on cognitive abilities. In this test, errors that are usually considered during on-road exams and practiced by many "experienced" drivers (e.g., speeding) are differentiated from those resulting from cognitive decline such as drifting into other lanes, and inappropriate responding to other stimuli (Dobbs, 2013). Furthermore, we conducted a series of cognitive tests that measure different skills necessary for driving and implemented on an iPad. This recently developed TBCT allows fast, cheap, and portable screening of unsafe drivers. Finally, a machine learning classifier approach was used to predict the safe and unsafe on-road drivers based on their performance on the cognitive tasks.

2. Methods

2.1 Participants

We compared data from two separately recruited populations. The first consisted of forty-eight older adult control participants (22 females and 26 males) who were recruited from Edmonton, Alberta, Canada. The inclusion criteria were an active driving record (each participant was actively driving within the past six months), a valid driver's license, and aged 55 years and older. Participation was voluntary and the sample age ranged from 54 to 81 years (M = 65.85, SD = 6.93). The second consisted of forty-nine older adult participants (20 females and 29 males) aged 54 to 81 (M = 78.08, SD = 9.78) that were recruited from the Canadian Back Institute (CBI). These older adults were referred by their health care providers to CBI for a functional driving assessment after being screened by their physicians as "at-risk for driving impairment." The individuals subsequently volunteered to participate in our study.

This study was conducted according to the Declaration of Helsinki (1996), was approved by the University of Alberta Health Research Ethics Board, and performed in compliance with relevant laws and institutional guidelines. All participants gave informed consent. Each assessment took approximately three hours. Forty-three participants completed the assessment over the course of two days within a maximum of a four day interval, except for one participant who did the tasks in a fourteen day interval. Fifty participants completed all assessments in one setting, and the performance date for four participants could not be found. On-road and cognitive assessments

were counterbalanced accordingly in both situations. Control participants were compensated $30 CDN for their participation, and the functional driving assessment expense was waived for the at-risk group as compensation. The data for three participants were fully/partially removed as these participants had difficulty understanding the task, felt anxious during the task performance, or wanted to abort the task prematurely. Two participants in each group were younger (54.5) years old and removing their data did not significantly change the results so they were not excluded from the study. Table 1 contains the demographic and on-road driving data. Based on the results from the standard on-road evaluation test, those who drive safely or dangerously are grouped as Pass or Fail, respectively. The participants whose driving errors were toward the upper end, but did not exceed the range for healthy normal drivers are categorized in the borderline group. Reassessment in six months' time or sooner is strongly recommended for this group, if medical status or function changes or is expected to change (more details in Section 2.3.1).

2.2 Procedure

Both groups performed the DriveABLE on-road evaluation (DORE) with a professional driving instructor that was blind to which group the participants were in, and a set of tablet-based cognitive tasks, that were presented in counterbalanced order. The TBCT were designed to test reaction time, decision-making, memory, and perceptual-motor skills.

Table 1
Demographic data, and driving performance

	Control	At-risk
Age ($M \pm SD$)	65.85 ± 6.93	78.08 ± 9.78
Total number	48	49
Gender (f/m)	22/26	20/29
Driving Pass	45	19
Driving Borderline	0	4
Driving Fail	2	24
Driving N/A	1	2

2.3 Tasks

2.3.1 DriveABLE On-Road Evaluation (DORE)

All but three participants, who were absent (due to weather conditions or schedule interferences), completed a day-time on-road driving assessment with a trained driving instructor. The performance of these participants is included for the group comparison during the TBCT for the first phase of the analysis. The total driving distance was 16.2 km and took approximately 30-40 minutes in an automatic vehicle with dual-braking. DORE is a scientifically developed on-road evaluation designed to test for decline in cognitive skills needed for safe driving (Berndt et al., 2007; Dobbs et al., 1998). DORE was developed by identifying driving errors that distinguish cognitively impaired drivers from a healthy control group (Dobbs et al., 1998). Based on the severity and frequency of these competence-defining errors a scoring system was created. Further analyses and studies demonstrated its efficacy (Dobbs, 2013). To protect the competent driver, the scoring system explicitly excludes errors that are made by experienced, healthy drivers and not associated with competence decline. Kowalski and Tuokko described this test as the most well-developed of the standardized road tests for medically at-risk drivers (Kowalski and Tuokko, 2007). The driving instructor was blind to the group status of participants and the previous performance on the other tasks in the study. The driving instructor sat in the passenger seat and provided turn-by-turn driving instructions. Both cognitive and trainable mistakes due to bad driving habits were evaluated while performing various common driving maneuvers. The course included right hand turns, left hand turns, traffic circles, lane changes, traffic lights, yield signs, and stop signs. A precise procedure manual and scoring sheet was used by the driving instructor

to rate each checkpoint with the participants' performance using a point system. Each driving mistake (e.g. lane change creating a hazardous situation) results in a pre-defined score, which are accumulated at the end of the on-road assessment session, and is compared to each class threshold to define the final fail, borderline or pass result.

2.3.2 Tablet-Based Cognitive Tasks (TBCT)

These tasks were designed and developed by DriveABLE to run as a continuous series and included: i) Reaction Speed: participants pressed a button as fast as possible after a visual cue (two stages, 15 trials in each stage), ii) Decision Making: participants pressed a 'Go' button after a visual cue while avoiding moving obstacles. A 'Stop' button is available as an additional control in obstacles avoidance (two stages; stage one had one set of obstacles and the second stage had two sets of obstacles, 20 trials in each stage), iii) Memory: participants drew a previously presented geometric shape (four stages with four trials in each stage). The number of shapes to recall, shape complexity, and the mask duration increased over stages. The fourth and final task was a iv) Bi-manual Perceptual-motor: participants followed a target circle using the iPad in a steering wheel fashion while avoiding fixed and surprise moving obstacles (four stages with each stage increasing in speed). There was a minor update for the TBCT after evaluating the performance of the 10th participant. Before this update, the number of trials in the first stage of the reaction time and decision making tasks was 10 instead of 15, and the complexity and speed of memory and bi-manual perceptual-motor tasks were slightly different.

The Reaction Speed, Decision Making, and Bi-manual perceptual-motor tasks were adapted from the DriveABLE Cognitive Assessment Tool (DCAT) that can reliably measure the cognitive

processes needed for safe driving and predict actual on-road performance in cognitively impaired drivers (Dobbs et al., 1998). To develop appropriate tasks for the DCAT, performance measures of various standard neuropsychological tests, including the Visual Field Test, Rabbitt Card Sort, Rod and Frame Test, Sitting-Rising Test, Cognitive Reflection Test, and span of Attentional Field, Speed of Attention Shifting, Corsi Block Tapping Test were collected. The top six tasks that have the best predictive ability to discriminate between unsafe and safe drivers were chosen. These tasks were altered to take advantage of a touch-screen and a 3-button base and allow for easier administration (Dobbs, 1997). The current reaction speed task is a modified version of the Attentional Shifting Task (Robbins, 2007). The decision making task is related to the spatial judgment task. The memory task is a heavily modified version of the Corsi block test (Kessels et al., 2000). The Bimanual perceptual-motor task is a new addition to the DCAT that was chosen for its similarity to a driving task, and its ability to capture perceptual-motor coordination.

In designing the TBCT, the cognitive screening tests were selected to cover the majority of the required cognitive domains needed for driving (CCMTA, 2017); divided attention (the ability to attend to two or more stimuli at the same time, evaluated in bi-manual perceptual-motor task), selected attention (the ability to selectively attend to one or more important stimuli while ignoring competing stimuli, evaluated in reaction speed and decision making tasks), sustained attention (the capacity to maintain attentional activity over a period of time, evaluated by bi-manual perceptual-motor task), short-term memory (the temporary storage of information that is currently being processed in a person's mind, evaluated by memory task), working memory (the ability to manipulate information with time constraints/taking in and updating information to solve problems, evaluated by all four tasks), complex reaction time (the time taken to respond differen-

tially to two or more stimuli or events, evaluated by reaction speed and decision making tasks), tracking (the ability to visually follow a stimulus that is moving or sequentially appearing in different locations, evaluated by bi-manual perceptual-motor task), visuospatial abilities (processes dependent on vision such as the recognition of objects, the ability to mentally rotate objects and determination of relationships between stimuli based on size or color, evaluated by decision making task), executive functioning (capabilities that enable an individual to successfully engage in independent, purposeful, and self-serving behaviours, evaluated by all four tasks), and visual information processing (the processing of visual information beyond the perceptual level, evaluated by all four tasks).

The TBCT was performed by a trained and DriveABLE certified evaluator. Each task includes a demonstration and or practice that is controlled by the administrator who provides feedback and answers any questions the participants may have. Test scripts are standardized as are test prompts and feedback.

2.4 TBCT dependent measures

For each participant 29 measures were extracted from the TBCT. For the memory and bi-manual perceptual-motor tasks, the measures were calculated by averaging the performance of each participant over all trials of all stages. However, during the response speed and decision making tasks, participants' performance improved significantly by repeating the tasks, and getting familiar with the speed of lines and the box. This was evident by plotting participants' performances (e.g. reaction time or success rate) versus trial number, which shows there is a learning curve in their responses. To minimize response variations, the extracted measures in these two tasks were

calculated by averaging from trial #8 in stage 1 (trial #6 in stage 2) to the last trial of that stage. These numbers were determined by visually inspecting the response across trials, as shown in Fig. 1.

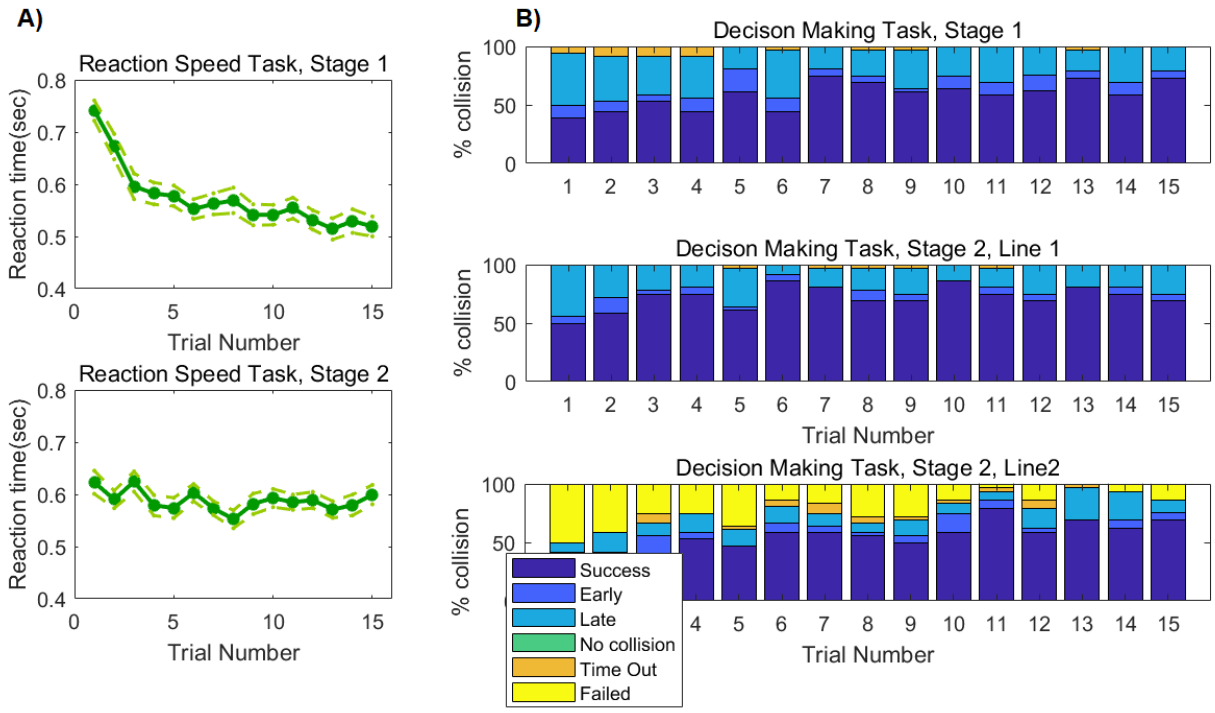

Fig. 1. Performance of the control group across trials. A) Reaction time in the reaction speed task, stage 1, and 2. B) Collision type in the decision making task, stage 1, and 2. By visual inspection, trials #8 in stage 1, and trial #6 in stage 2, of both reaction speed and decision making tasks, were chosen as a trial from which stable performance is observed in the participants.

Table 2 contains the list of dependent measures from each task. They are as follows. From the response-speed task the percentage of trials that participants started early (% Premature go), did not respond at all (% Lack of response), and average reaction time (Reaction time) in each stage were extracted. From the decision making task the percentage of trials that participants started

early (% Premature go), the percentage of trials successfully passing the moving obstacles (% Success), contacting the moving obstacles from the front side (% Early collision), contacting the moving obstacles from a side other than front side (% Late collision), the number of times pressing the 'Go' button (Go Count), the average duration of each trial (Duration), the average number of obstacles that passed after the visual cue and before finishing passing the obstacles (Obstacle count), the average number of missed opportunity (Missed opportunity count) in each stage were extracted. From the memory task the duration of task completion (Duration), and the percentage of correct shape retrieval (% correct shape) were extracted. From the perceptual-motor task the percentage of time inside the target (% Time inside target), and the percentage number of times fixed (% Fixed obstacles avoided) and surprise obstacles avoided (% surprise obstacles avoided) were extracted.

2.5. Statistical analyses

Table 2
Tasks and dependent measures from TBCT

Task	Measure	Description
Reaction speed (available for stage 1 & 2)	% Premature go	Percentage of releasing 'Start' button before the visual cue
	% Lack of response	Percentage of timeout trials
	Reaction time	Average reaction time to tap 'Stop' button after the visual cue
Decision making (available for stage 1 & 2)	% Premature go	Percentage of releasing 'Start' button before the visual cue
	% Success	Percentage of successfully navigating through the moving obstacles
	% Early collision	Percentage of hitting moving obstacles with the front side
	% Late collision	Percentage of hitting moving obstacles with a side other than front side
	Reaction time	Average time to tap 'Go' button after the visual cue
	Go count	Average number of times 'Go' button tapped
	Duration	Average duration between the visual cue and the end of trial
	Obstacle count	Average number of passed obstacles
	Missed opportunity count	Average number of missed opportunities
Memory	Duration	Average time to complete task
	% Correct shape	Percentage of shapes drawn correctly
Bi-manual perceptual motor	% Time inside target	Percentage of time inside the target
	% Fixed obstacles avoided	Percentage of fixed obstacles avoided
	% Surprise obstacles avoided	Percentage of surprise obstacles avoided

To investigate the association between performance on the TBCT and driving competency, a comparison between participants in at-risk and control groups while performing cognitive tasks was first investigated. We expected worse (slower and less accurate) performance during cogni-

tive tasks. It has been well established that cognitive abilities and driving skills deteriorate with chronological age (Anstey et al., 2012). As the age distribution is not similar in the control and at-risk groups (welch $t(86.55) = 7.11$, $p < .001$), a one-way analysis of covariance (ANCOVA) was used to examine differences in performance between the at-risk group and the control group on cognitive tasks.

Participants with borderline performance during the DORE were assigned to the pass group. Next, each of the measured cognitive variables were entered one-by-one into the logistic regression model to investigate their ability to predict safe drivers. Categorizing unsafe drivers as safe drivers presents risks for the traffic system and endangers themselves and other drivers, but since driving cessation of safe drivers isolates them and impacts their mental health, it is equally important not to prioritize and compromise one outcome measure for the other. Therefore, the threshold level was identified in a receiver operating characteristic (ROC) curve to minimize both the specificity (proportion of actually safe drivers that are correctly identified as safe drivers), and sensitivity (proportion of actually unsafe drivers that are correctly identified as unsafe drivers) measures.

As the same data was used for both model fitting and model evaluation in calculating the specificity and sensitivity of predictive ability of each variable, the preliminary bivariate analysis is a biased estimate of these measures. To have a better estimate of the accuracy of the TBCT the classifiers were trained and evaluated on a separate train and test data sets to discriminate between safe and unsafe drivers. For very few cases, participants' performance was not measured for all the TBCT. As sample size is an important factor when training classifiers, we used a class-

conditional mean imputation approach, wherein a participant's performance for a TBCT task was replaced with the average of its group performance (less than 2.2% of cases). This method is a straightforward approach to address missing data at the expense of ignoring correlations between different measures and also data variation (García-Laencina et al., 2010).

In total, 68 participants passed, and 26 failed the DORE. This is an unbalanced sample size (only 27% of cases belong to the fail group). Therefore, the classifiers' training algorithm favors correctly classifying safe drivers at the cost of misclassifying unsafe drivers. To overcome this problem, the Synthetic Minority Over-sampling Technique (SMOTE) was utilized to create synthetic samples from the minor class that is similar to other samples in that class to balance the dataset (Chawla et al., 2002). The overall accuracy is not an appropriate measure for evaluating the classifiers' performance in an unbalanced data set, especially for classifying the minority group (correctly identifying unsafe drivers) (Cuaya et al., 2011). Therefore, The ROC curve and confusion matrix was used. Leave-one-out-cross-validation was used to evaluate the classification performance in predicting safe vs. unsafe drivers. Classifiers' parameters were optimized based on internal 5-fold cross validation, over 5 repetitions.

Considering the importance of correctly identifying both safe and unsafe drivers, and the possibility of using an on-road test as a reference standard in identifying unsafe drivers (Kay et al., 2012), trichotomous classifier implementation was used to categorize the outcome into three classes: safe, unsafe, and undefined. The performance of the participants categorized in the undefined group during the TBCT was not discriminative enough to classify them as either a safe or unsafe driver, and and thus they are referred for on-road tests. Using a trichotomous classifier

decreases the classification error (incorrectly classifying safe drivers as unsafe, and unsafe drivers as safe), at the cost of a reduced explicit assessment outcome for all participants.

To design a trichotomous classifier, after training the classifiers, the thresholds that define the class label were optimized such that there would be less than 30% of cases in the undefined class, and the rate of incorrectly identifying safe drivers as unsafe (false positive rate (FPR)), and the rate of incorrectly identifying unsafe drivers as safe drivers (false negative rate (FNR)) are similar to each other. Classifiers that provided a continuous output measure rather than a binary outcome were chosen, so that the low and high thresholds for class labels {safe, undefined, unsafe} could be optimized based on the previously mentioned approach. Therefore, the classifiers that produce either probabilistic output value or voting proportion were chosen in this study (Bishop, 2016; Hastie et al., 2009). The chosen classifiers are from a variety of classifiers' families including a) linear classifiers, which are among the classifiers with simple structure: 1) linear discriminant (LDA), wherein a hyperplane is optimized to split the independent variable space into pass/fail, and 2) logistic regression classifier, where log-odds are calculated as a linear combination of independent variables. Then a logistic function is applied on this value to calculate the outcome probability of a pass/fail, b) decision trees in which a set of sequential binary decisions on the space of independent variables form a tree structure. Decision trees are fast and inexpensive to construct, easy to interpret, and can exclude the unimportant features. Two derivatives of decision trees were also used: 1) random forest that is an ensemble of multiple independently trained decision tree classifiers, whose outcome are aggregated using majority voting, and can withstand overfitting property of decision trees, and 2) gradient boosting models, in which at each stage a new decision tree is added to improve the performance of the existing model, c)

naïve Bayes classifier that is a probabilistic classifiers, and works based on the assumptions that input variables are independent of each other, though in practice, its efficacy has been proven even when this criteria is not met. A naïve Bayes classifier requires a small sample size for training, d) non-parametric classifier of k-nearest neighbors classifier (k-NN), where output membership is defined by voting of its k-nearest neighbors, and it is built under the assumption that similar things exist in close proximity.

In Fig. 2, the modified version of a confusion matrix (Fawcett, 2006) adopted for a trichotomous classifier output, and the application of low and high threshold in determining class outcome is depicted.

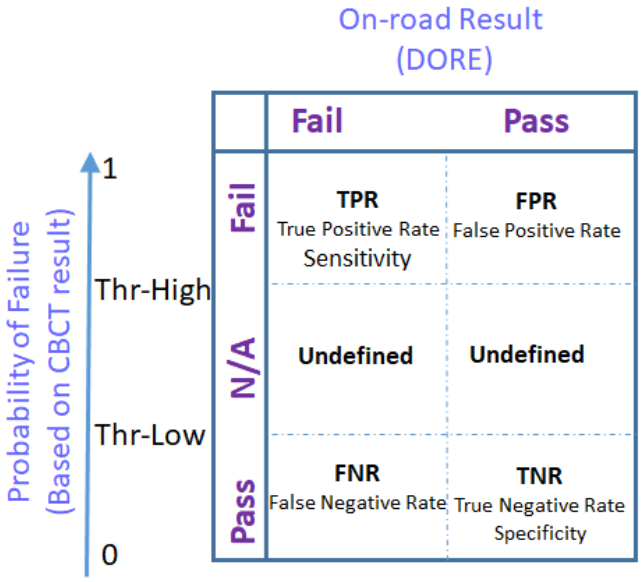

Fig. 2. Modified version of the confusion matrix adopted for trichotomous classifier

Hyperparameters for the classifiers are set as follows. In the random forest classifier: the number of randomly selected predictors = 2, in the k-NN classifier: the number of neighbors = 7, in the

gradient boosting model: the number of iterations = 50, the complexity of the tree = 1, the learning rate = 0.1, and the minimum number of training set samples in a node to commence splitting = 10. For logistic regression, LDA, decision tree and naïve Bayes classifiers, no hyperparameter tuning was involved. The calculation of outcome measures are as follows (Fawcett, 2006):

$$\text{Accuracy} = \frac{\text{Number of participants correctly classified as unsafe or safe driver}}{\text{Number of all participants}}$$

$$FPR = \frac{\text{Number of participants incorrectly classified as unsafe driver}}{\text{Number of participants passed the on minus road test}}$$

$$TPR = \text{sensitivity} = \frac{\text{Number of participants correctly classified as unsafe driver}}{\text{Number of participants passed the on minus road test}}$$

$$FNR = \frac{\text{Number of participants incorrectly classified as safe driver}}{\text{Number of participants passed the on minus road test}}$$

$$TNR = \text{specificity} = \frac{\text{Number of participants correctly classified as safe driver}}{\text{Number of participants passed the on minus road test}}$$

Calculation of behavioural measures from the TBCT was implemented in MATLAB, statistical analysis and classifier's training was performed in SPSS and R. The caret package (Classification And Regression Training) in R was used to classify the data (Kuhn, 2019).

3. Results

3.1 Group comparison

The cognitive skills measured during the TBCT were compared between the control and at-risk group. During the response speed task, at-risk participants showed more trials with no response, and started trials earlier than the visual cue more frequently. Overall, at-risk participants were slower in responding to the visual cue. In the decision making task, trials with successful performance were significantly less in the at-risk group. The at-risk group was slower in reacting to the visual cue, had longer durations for task trials, and portrayed greater difficulties with prema-

ture attempts. The participants in the at-risk group also had less ability to use the 'Go' and 'Stop' buttons to avoid obstacles. During the memory task, both the duration to create the drawing, and the retrieval rate was worse in the at-risk group. The number of surprise obstacles avoided was significantly less in the at-risk group than in the control group during the final bi-manual perceptual-motor task. The at-risk group had worse object avoidance performance than the control group and there was a clear trend for diminished target following performance in the at-risk group. Overall, the performance of the at-risk group in all of the cognitive tasks was significantly worse than the performance of the control group, even after statistically excluding age as an effect (Table 3).

Table 3
Performance on tablet-based cognitive tasks (TBCT). Group comparison, excluding age effect

Task	Measure	At-risk	CON	*p*-Val	Partial η^2	Leven's Var eq.
		Mean ± SD	Mean ± SD			
Reaction speed	% Premature go (stage 1)	10.1 ± 14.6	3.4 ± 7.0	–	–	–
	% Lack of response (stage 1)	16.8 ± 23.0	1.6 ± 4.2	.007	0.081	0.000
	Reaction time (stage 1)	0.6 ± 0.1	0.5 ± 0.1	.017	0.066	0.023
	% Premature go (stage 2)	10.6 ± 10.0	2.6 ± 5.0	.001	0.122	0.000
	% Lack of response (stage 2)	31.0 ± 29.7	5.4 ± 9.9	.003	0.099	0.000
	Reaction time (stage 2)	0.7 ± 0.1	0.6 ± 0.1	.032	0.054	0.005
Decision making	Duration (stage 1)	9.6 ± 2.3	8.3 ± 1.4	.018	0.062	0.00
	% Premature go (stage 2)	18.0 ± 16.0	6.5 ± 8.3	.029	0.055	0.00
	% Success (stage 2)	36.7 ± 21.4	63.0 ± 21.9	.008	0.078	0.70
	% Early collision (stage 2)	10.2 ± 7.1	5.0 ± 5.1	.017	0.064	0.12
	Go count (stage 2)	1.3 ± 0.3	1.7 ± 0.4	.005	0.09	0.14
Memory	Duration	18.4 ± 2.4	15.8 ± 1.6	.000	0.16	0.075
	% Correct shape retrieval	25.7 ± 15.0	54.4 ± 15.5	.000	0.26	0.11
Bi-manual perceptual motor	% Time inside target	31.0 ± 14.8	46.1 ± 14.3	.051	0.04	0.61
	% Surprise object avoided	75.2 ± 13.5	84.5 ± 12.9	.017	0.063	0.59

3.2. Predictability of cognitive measures to distinguish safe and unsafe drivers

The results of bivariate score tests for age and 17 cognitive measures that showed significant ($p <$ .05) predictive ability to distinguish safe and unsafe drivers is given in Table 4.

Age, reaction time, performance on decision making and memory tasks, and the target following ability are the best predictors for identifying unsafe drivers. Gender was not a predictor of fitness for driving in this sample.

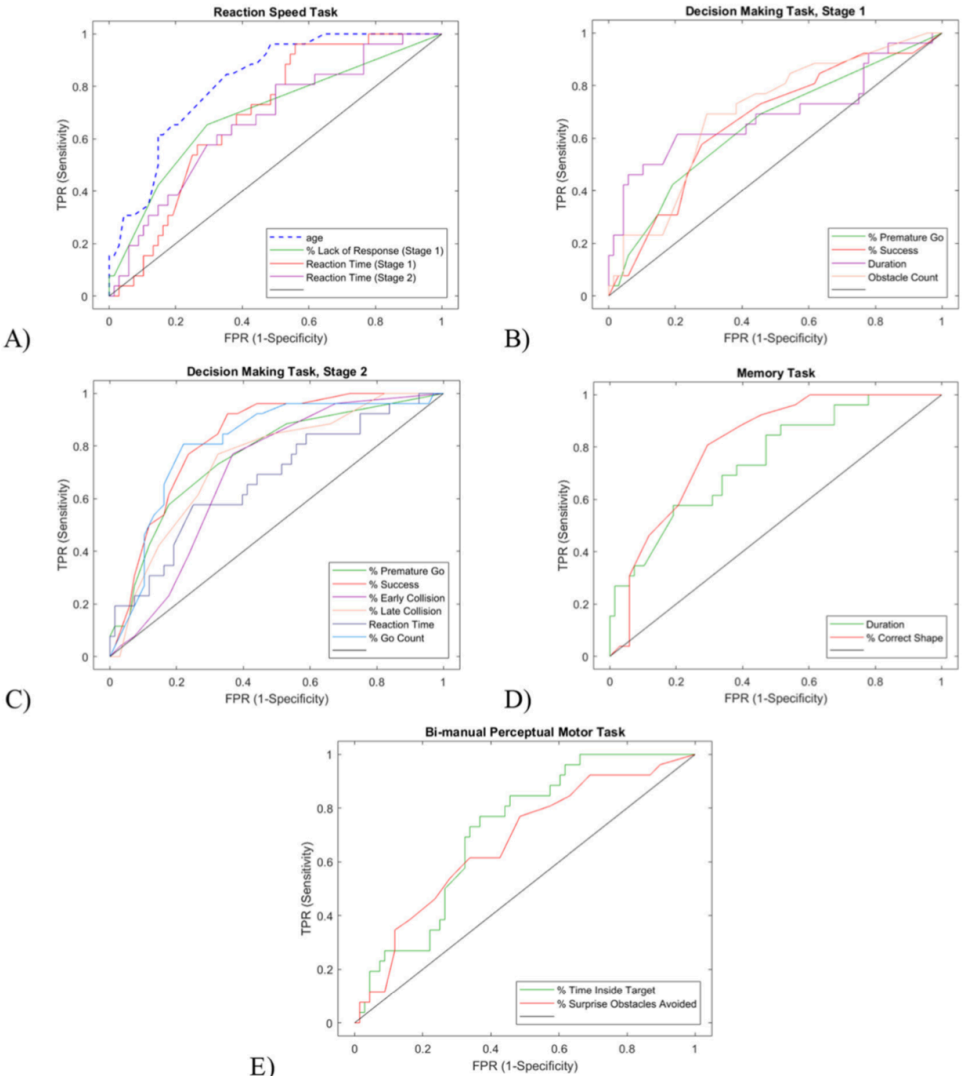

Fig. 3. Receiver operating characteristic curves (ROC) of predictive variables with $p < .05$ in bi-variate tests for predicting safe and unsafe drivers. A) age and reaction speed task, B) Decision making task, stage 1, C) Decision making task, stage 2, D) Memory task, E) Bi-manual perceptual motor task.

Table 4
Bivariate score tests of cognitive measures for predicting safe and unsafe drivers ($p < .05$)

Task	Measure	Accuracy (specificity, sensitivity)	Area under curve	Nagelkerke R^2	p-Val	Odds
Reaction speed	Age	71%(68%,81%)	0.82	0.36	.000	0.15
	% Lack of response (stage 1)	69%(71%,65%)	0.70	0.15	.01	1.05
	Reaction time (stage 1)	64%(62%,69%)	0.69	0.08	.028	77.7
	Reaction time (stage 2)	66%(68%,62%)	0.67	0.09	.016	352.6
Decision making	% Premature go (stage 1)	59%(54%,69%)	0.65	0.07	.03	1.0
	% Success (stage 1)	68%(72%,58%)	0.66	0.08	.026	1.0
	Duration (stage 1)	74%(79%,62%)	0.69	0.22	.000	1.7
	Obstacle count (stage 1)	70%(71%,69%)	0.70	0.13	.008	4.4
	% Premature go (stage 2)	69%(68%,73%)	0.76	0.21	.000	1.1
	% Success (stage 2)	76%(76%,77%)	0.83	0.37	.000	0.9
	% Early collision (stage 2)	67%(63%,77%)	0.70	0.1	.013	1.1
	% Late collision (stage 2)	70%(68%,77%)	0.74	0.17	.002	1.1
	Reaction time (stage 2)	70%(75%,58%)	0.67	0.13	.006	1.7
	Go count (stage 2)	78%(78%,81%)	0.81	0.31	.000	0.02
Memory	Duration	67%(66%,69%)	0.75	0.26	.000	1.7
	% Correct shape	73%(71%,81%)	0.81	0.30	.000	0.9
Bi-manual perceptual motor	% Time inside target	68%(66%,73%)	0.71	0.18	.002	0.9
	% Surprise object avoided	65%(66%,62%)	0.67	0.09	.018	0.9

3.3. Application of tablet-based cognitive tasks to predict unsafe drivers

In Table 5, the performance of various dichotomous classifiers is given. In this analysis, a decision threshold level optimized such that FPR and FNR (or similarly specificity and sensitivity values) would be as close as possible. The most accurate classification performance was achieved using naive Bayes classifier with accuracy of 80%, TPR = 81%, and a TNR = 79%.

Table 5
Dichotomous classifiers performance, with {safe, unsafe} outcome.

Classifier	Accuracy	FPR	FNR	TPR (sensitivity)	TNR (specificity)	Thr
Random forests	78%	22%	23%	77%	78%	0.40
Logistic regression	68%	32%	31%	69%	68%	0.30
Decision tree	63%	37%	38%	62%	63%	0.29
k-NN	73%	25%	31%	69%	75%	0.56
Gradient boosting model	76%	23%	23%	77%	76%	0.45
Naive Bayes	80%	21%	19%	81%	79%	0.75
LDA	73%	26%	27%	73%	73%	0.42

In Table 6, the performance of trichotomous classifiers after optimizing the decision threshold such that FPR and FNR would be similar to each other and the undefined area would be around

30% is given. Similar to the dichotomous naïve Bayes classifier, the trichotomous naïve Bayes classifier demonstrated the highest overall accuracy performance of 73%, and sensitivity of 69% and a specificity of 75%. Optimization of thresholds resulted in 11% unclassified cases, which was less than the acceptable level of 30%. Therefore, the FPR and FNR are not as low as other classifiers such as gradient boost tree that has lower overall accuracy of 57%, sensitivity of 58% and a specificity of 57%, but performed better at classification error.

Table 6
Trichotomous classifiers performance, with {safe, undefined, unsafe} outcome.

Classifier	Accuracy	FPR	FNR	TPR (sensitivity)	TNR (specificity)	Thr-high	Thr-low	Undefined
Random forests	56%	15%	11%	46%	60%	0.6	0.26	30%
Logistic regression	52%	16%	23%	31%	60%	0.93	0.09	30%
Decision tree	51%	18%	23%	38%	56%	0.81	0.14	30%
k-NN	54%	18%	15%	31%	63%	0.86	0.29	29%
Gradient boosting model	57%	13%	11%	58%	57%	0.73	0.16	30%
Naive Bayes	73%	19%	8%	69%	75%	0.92	0.01	11%
LDA	55%	18%	8%	61%	53%	0.65	0.09	30%

In Fig. 4, the ROC of the best three classifiers, naive Bayes, random forest, gradient boosting model is depicted in solid, dashed, and dotted lines, respectively. The green, blue, and red lines show the regions where the classifiers' prediction is safe, undefined, and unsafe. The value associated with the optimal threshold for dichotomous classifiers is shown in the blue circle.

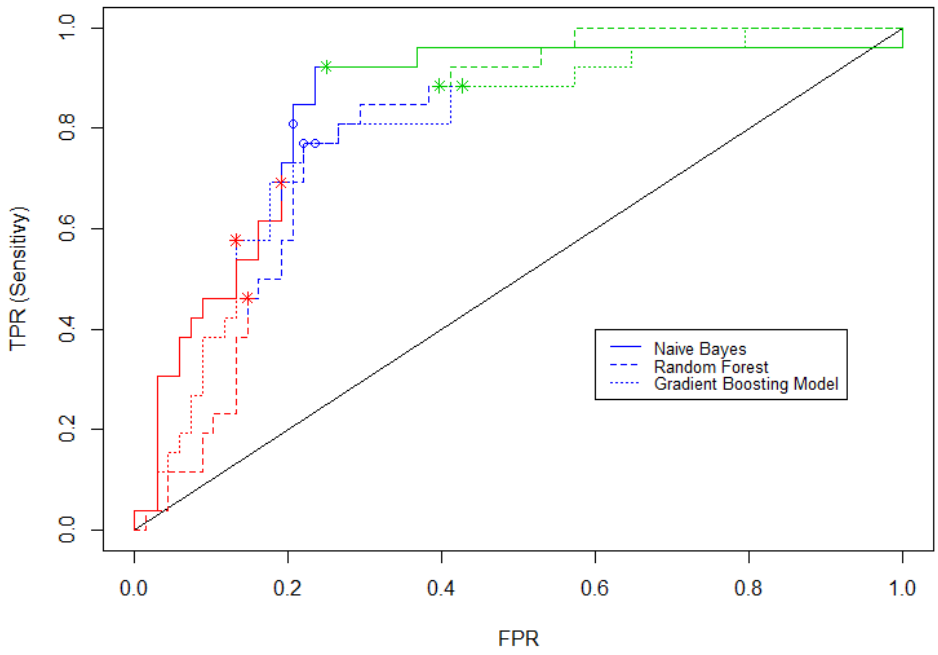

Fig. 4. Receiver operating characteristic curve (ROC) of the best three classifiers, naive Bayes, random forest, gradient boosting mode, are shown in solid, dashed, and dotted lines respectively. The green, blue, and red lines illustrate pass, undefined, and fail prediction regions in trichotomous classifiers respectively. The blue circles show the optimal threshold for dichotomous classifier.

4. Discussion

The purpose of this study was to further understand some of the major underpinnings of safe driving in an older adult population. As the number of older drivers increases, there is an urgent need for fast, widely accessible and affordable screening tools to reliably identify safe vs. unsafe drivers. In this study, we evaluated the performance of healthy older adults and at-risk for driving older adults on a series of TBCT and an on-road driving assessment evaluated by a professional

driving instructor. We took a machine learning approach to examine the relationship between performance during the TBCT and the on-road driving. Driving is a highly complex and multi-dimensional behaviour incorporating cognitive-perceptual-motor skills that must interact in an unpredictable, fast paced, and high-risk environment (CCMTA, 2017). Aging, medical conditions, drug influences, and substance abuse affect cognitive functioning as well as the ability to drive safely. Medical examinations are able to detect the presence or absence of specific diseases and assess the patient's overall health, but lack the ability to screen cognitive functioning associated with driving (Cameron et al., 2017; CCMTA, 2017; Molnar et al., 2005). It is important that individuals are fairly assessed so that driver's licenses are not revoked based solely on results from one medical diagnosis as there is little evidence of a direct relationship between medical conditions causing cognitive impairment and driving competency (McGwin, 2000). Unsworth and Chan, 2016 have shown that impaired cognitive functioning evidenced by Alzheimers' disease should not preclude driving, and further assessments are needed to analyze driving ability (Unsworth and Chan, 2016). There is a need to specifically design tasks to target cognitive skills needed for driving that have an accurate and reliable predictive ability to distinguish safe and unsafe drivers rather than identifying the cognitive domains with impaired performance. It should also be noted that, due to the complex nature of driving, it is possible to compensate for deficiencies in one domain with other domains. Therefore, reliable evidence-based assessment tools with a high sensitivity for both screening unsafe drivers and not unnecessarily limiting older adults' independence by revoking driver's licenses (resulting in isolation and an increased risk for mental health issues) are necessary (Lee et al., 2003).

In this study, the application of cognitive-only tablet-based tasks to identify safe and unsafe drivers in older adults was investigated. In developing a screening test for driving, it is crucial to have a reliable on-road driving test that only identifies errors related to cognitive decline so that the relationship between the TBCT and on-road driving can be established. The DriveABLE On-Road Evaluation (DORE) is a standardized, licensed, scientifically developed on-road assessment that was used to assess on-road driving competency in an older adult population. Unlike other on-road tests, the DORE tests for cognitive impairment rather than bad-habit errors that are common among healthy experienced drivers (Dobbs, 2013).

Compared to the healthy group, participants in the at-risk group performed more slowly, and less accurately on the TBCT, which demonstrates deterioration of the cognitive skills required for driving in this population. The cognitive impairments in this group are beyond the normal cognitive decline expected in older adults, which was successfully detected by TBCT, after the effect of age on performance was removed. However, it would be important to replicate the results of this study with a larger cohort of participants with a wider range of age and cognitive impairment. The results of bivariate score tests show that many of these TBCT measures from all the tasks have a high predictive ability to identify unsafe drivers. Our analysis suggests that age is a good predictor of decline in driving performance. Although this finding is in line with some of the previous studies showing higher mortality rate and accident rate in older adults (IRTAD, 2018), it should be noted that in the current study, the control and the at-risk for driving groups were not matched for age. That is, the participants in the at-risk group were significantly older than the control group. So, the group differences may partially explain the association between age and driving competency. Reduced ability with increasing age has been questioned in the re-

cent reviews (O'Neill, 2015), as explained the higher mortality rate in older adults is the result of body frailty in this age group, whereby they are affected more significantly during the accidents (Staplin et al., 2008). Although it has been shown that the number of crashes (even after controlling for kilometers driven) in older adults are significantly higher than other age groups, it is mainly due to their low exposure to driving (a compensatory approach by limiting driving to familiar neighborhood areas and avoiding riskier locations), which is known as low mileage bias. When compared with other age groups with similar average kilometers driven, there is no increased accident risk in older adults (Hakamies-Blomqvist et al., 2002; Langford et al., 2006).

Importantly, we revealed an exciting relationship with our classifier approach to investigate whether cognitive impairment as measured by TBCT corresponds with driving competency. We implemented a trichotomous classifier based on the performance of the participants during TBCT to classify them into three groups of safe, unsafe, and undefined drivers. This approach results in identifying profoundly dangerous and safe drivers with high accuracy, while referring the drivers with modest performance for further on-road assessments. The naive Bayes classifier outperformed other classifiers with an overall accuracy of 73%, followed by gradient boosting model and random forest that have an overall accuracy of 57% and 56% respectively. Naïve Bayes is one of the most efficient machine learning algorithms, which has superb classification performance in various complex real world applications despite its oversimplified assumption of independence among features (Zhang, 2004).

Specificity and sensitivity using preliminary bivariate score tests evaluated on a similar train and test data, as in Table 4, results in values as high as 78% and 81% for Go Count, while logistic

regression classifier using age and 17 cognitive measures with the highest predictive ability, trained and evaluated on separate train and test data, as in Table 5, demonstrates reduced values of 68% and 69%. Separation of train and test data for evaluating classifiers performance is critical to have a reliable unbiased performance evaluation, which has been neglected in previous studies (Wood et al., 2013; Urlings et al., 2018). This should be taken into account when comparing the existing literature with the presented study.

Tablet-based tasks provide portable, affordable, fast, and widely accessible evaluation tools that have successfully been used for both assessment of cognitive impairment (e.g. after concussion (Fischer et al., 2016), after chemotherapy (Khan et al., 2019), in older adults (Fujiwara et al., 2019; Takahashi et al., 2020), in low- and middle-income countries (Willoughby et al., 2019)), and training purposes (e.g. in children with autism spectrum disorders (Quezada et al., 2019), and with developmental disabilities (Sung et al., 2020), and in older adults with amnestic mild cognitive impairments (Bekrater-Bodmann et al., 2019)). Moreover, tablet based tasks can measure large amounts of different behavioural performance measures compared to the paper-based or traditional neuropsychological tests. These multimodal performance measures can better capture the underlying cognitive processes, as well as classify and cluster existing patterns using machine learning algorithms.

Despite the aforementioned advantages of tablet-based tasks, there are few concerns that should be kept in mind when using tablet-based tasks especially as screening tools in older adults. As a result of extensive exposure of younger generations to touch-screen technologies and mobile apps, they have a better and faster grasp of working with tablet-based tasks. Therefore, caution-

ary steps should be taken when studying cognitive performance in a cohort of a wide age range to assure the measured responses reflect the subtle differences of cognitive skills, and not various levels of familiarity with task environments or technologies. This problem could be partly overcome with considering a separate training phase for each individual. Moreover, the sensitivity of capacitive touchscreens is less in individuals with very dry hands, or older adults (Zombie Finger and Touchscreens Consumer Reports, 2020). Applying a water-based moisturizer, or using a touchscreen stylus can be used to alleviate this problem.

As there is still no available gold standard for off-road testing to reliably predict on-road performance (Kay et al., 2012), the on-road assessments that are appropriately adjusted to evaluate driving competency in experienced drivers are considered to be the reference standard for identifying unsafe drivers. In this study, we demonstrated the application of a set of TBCT to reliably identify safe and unsafe drivers in more than 70% of the population (and referring the rest for further on-road evaluations). Considering the increasing number of older adults as a result of aging baby boomers and improvement in overall health and geriatric care, as well as large populations of other cognitively impaired groups such as drug users (Tomczak et al., 2019), developing similar TBCT will significantly improve screening process and safety measures.

4.1 Limitation

The fact that the TBCT with the applied machine learning approach successfully identified safe and unsafe drivers in a relatively small sample size of 94 older adults makes it a promising avenue for future studies. A larger and more diverse population would likely lead to more reliable performance accuracy. It should also be noted that this study is a case-control design. The partic-

ipants in the at-risk group have elevated rates of cognitive deficits which results in higher on-road failure rates, and increased sensitivity of the cognitive-tests (Altman and Bland, 1994; Wood et al., 2013). Moreover, the motivation in the two groups is not the same, as the control group was monetarily compensated, and the on-road driving test fees were waived for the at-risk group. As previously discussed, the average age in the at-risk group was higher than that of the control group, which may confound the results especially regarding the relationship between age and driving performance.

Due to scheduling difficulties, data for all participants could not be collected within the same day. As the on-road evaluation is stressful and tedious, it is expected the participants who did the on-road test and the CBCT on separate days performed differently from those who did all tasks during the same day. Further analysis, with day performance as an independent variable, shows that the on-road performance was not affected by this situation. However, performing tasks during one day or two days had a significant effect on some of the TBCT measures that were used in classifications (Table 4): Decision making: %Premature Go (stage 1), %success (stage 1), %success (stage 2), Reaction time (stage 2), Go count (stage 2), Bi-manual perceptual motor: %surprise object avoided. This methodological difference may confound the results and should be avoided in future data collections.

Nevertheless, a study of this nature is an important first step to elucidating the true relationship between cognitive performance outside of a vehicle and the likelihood of driving impairment. Such an approach will have wide reaching impact as impairment can manifest in many different

ways and for many different behaviours, particularly in the face of world-wide aging demographics and many newly implemented laws permitting recreational drug consumption.

CRediT authorship contribution statement

Reyhaneh Bakhtiari: Conceptualization, Data curation, Investigation, Formal analysis, Writing - original draft, Writing - review & editing, Validation. Michelle V. Tomczak: Data curation, Formal analysis, Writing - review & editing, Validation. Stephen Langor: Data curation, Formal analysis, Validation, Writing - review & editing. Joanna E.M. Scanlon: Writing - review & editing, Validation. Aaron Granley: Conceptualization, Methodology, Writing - review & editing, Validation. Anthony Singhal: Conceptualization, Writing - review & editing, Validation.

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Declaration of competing interest A.G. is an employee of and has ownership interest in DriveABLE Inc.

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CHAPTER 3: The Effects of Cannabis and Cocaine on Driving Related Tasks of Perception, Cognition, & Action

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Abstract:

Background and Objective: Consumption of cannabis and cocaine is associated with a range of mental and physical effects that can impair aspects of human behaviour. Driving is a complex cognitive behavior that is an essential part of everyday life and can be broken down into many subcomponents, each of which can uniquely impact road safety. With the growing movement of jurisdictions to legalize cannabis use, there is an increased focus on impairment and driving. The purpose of this study was to identify driving-related cognitive-performance deficits that are impacted by recreational drug use.

Design and Methods: With the assistance of law enforcement agencies, we recruited over 300 participants under the influence of various drugs including cannabis and cocaine. These individuals performed a battery of tablet-based cognitive tasks scientifically proven to be related to on-road driving performance and designed to test response speed, memory processes, perceptual-motor skills, and decision making. Data from a control group with healthy non-drug using adults was collected as well.

Results: Compared to controls, the drug groups showed deficits in all tasks. There were clear differences between the cannabis and cocaine groups where cannabis users were faster, and performed better on some aspects of the decision-making and perceptual-motor tasks. Finally, the participants who consumed both cannabis and cocaine performed most similarly to the cannabis group.

Conclusions: The results show distinct and combined effects of cannabis and cocaine on human performance relating to driving. These differential effects are likely related to the unique effects

of each drug on the human brain and how they distinctly contribute to mental states. The results have important implications for road safety associated with driver impairment.

Keywords: driving, cognitive impairment, recreational drugs

3.1 Introduction

A drug-impaired driving offence occurs, on average, every 3 hours in Canada each day (Perreault, 2016). Drug-related motor vehicle accidents are Canada's leading cause of death for individuals under 30 years of age. In North America, cannabis use is significantly increasing and about 13% of nighttime and weekend drivers have delta-9-tetrahydrocannabinol (THC), the main psychoactive component in cannabis, in their system. According to Beirness (2019), roughly 8% of drivers tested positive for recreational drugs such as cannabis. Drug use was most prevalent among drivers aged 20 to 24 (14%) and decreased with increasing age.

After alcohol, cannabis and cocaine are the two most frequently detected substances in drivers under the influence of drugs (Herrera-Gómez et al., 2020). Research shows that driving performance decreases with increased levels of cannabis or cocaine in the body (Ramaekers et al., 2004; Ramaekers et al., 2006). With the legalization of cannabis in Canada and many parts of the United States, drug-impaired driving has become more of a focus than ever before. Fatal accidents where at least one driver tested positive for THC increased by an average of 10% from 2013 to 2016 in the United States (Hansen et al., 2018). Drug-induced cognitive impairment is associated with diminishing driving abilities that can lead to increased risk for automobile collisions, injury, and death (Groeger, 2013). Cannabis is the most commonly detected illicit drug in drivers (Robertson et al., 2017). Furthermore, polysubstance use (PSU) affects the majority of the substance-using population as one drug dependence often leads to another, for instance to counterbalance coming off one substance, or choosing more affordable drugs over more expensive ones (e.g., THC over cocaine) when needed (Crummy et al., 2020; Ignaszewski, 2021).

Driving is negatively impacted by the active chemicals in cannabis (mainly THC) in a dose-dependent fashion but can vary between individuals based on differences in smoking technique, tolerance, and absorption of THC (Sewell et al., 2009). Besides cannabis, cocaine is also a widely consumed drug. Based on a 5-year review from drug recognition expert cases (DRE) in

the province of Quebec, cocaine (29%) is the third most prevalent illicit substance detected in impaired drivers following cannabis in second place (48%) (Vaillancourt et al., 2021). Furthermore, long-term cocaine consumption and associated cognitive impairment seems to yield increased accident risk during on-road driving where impaired drivers have a more excited and stimulated disposition when under the influence of cocaine (Scherer et al., 2016; Musshoff & Madea, 2010).

On-road testing is considered the most accurate and realistic method for evaluating the effect of drugs on driving performance. Micallef et al. (2018) found driving stability is significantly impaired after smoking cannabis. An increase in lane position variability, steering wheel position variability, and inappropriate line crossing was observed in a dose-dependent manner up to two hours after smoking cannabis (Robbe, 1994; Veldstra et al., 2015; Kalant & Centre for Addiction and Mental Health; Micallef et al., 2018). Lensch et al. (2020) found that overall risk perception is more adversely affected by cannabis than alcohol. There is limited to no research on how cocaine affects driving during actual driving conditions.

There is also limited research on how cocaine affects driving during simulated driving conditions. Brookhuis et al. (2000) reported that young adults under the influence of two stimulants, MDMA (Methylenedioxymethamphetamine = "ecstasy") and cocaine, showed increased risk-taking behaviour during a driving simulator performance. Further driving simulator research is needed to investigate the effect of cocaine on driving performance in a controlled environment.

Cannabis users experience feelings of euphoria, altered perception, and relaxation through psychotomimesis, creating a "high". Cocaine is a stimulant drug that induces physiological effects such as increased heart rate, pupil dilation, and sweating (Schwartz et al., 2010). Cocaine induces similar physical effects as cannabis such as heightened nervousness, increased alertness, and decreased concentration. THC impacts the nervous system by attaching to cannabinoid-1 (CB1) receptors that are densely distributed throughout the central nervous system (Green et al., 2003; D'Souza et al., 2004). On the other hand, cocaine mainly impacts the nervous system by blocking dopamine transporters, and by attaching to serotonin receptors. This explains the differences in the heightened feelings of intoxication experienced by drug users and also the

cognitive impairment difference between cannabis and cocaine users. However, reckless and/or reduced driving ability is reported more frequently for cocaine users, and cautious or normal behaviour is reported more for cannabis users (MacDonald et al., 2008).

Cannabis negatively impacts nearly all psychomotor and cognitive skills related to driving including reaction time, tracking, memory, decision making, divided and sustained attention, perception, body sway, and hand-eye coordination in a dose dependent manner (Kurzthaler 1999; Ramaekers et al., 2004; Capler et al., 2017; Berghaus et al., 1998a; Berghaus et al., 1998b). The effects are greatest and most numerous during the first hour after cannabis consumption and gradually fade after 3-4 hours (Berghaus et al., 1998a; Berghaus et al., 1998b; Ramaekers et al., 2004). While it was once thought that chronic cannabis users did not display the same degree of cognitive deficits of acute cannabis users due to their increased tolerance, recent studies have provided evidence that cannabis produces a similar degree of cognitive deficits in users irrespective of their cannabis use history (Ramaekers et al., 2016).

Unlike cannabis, cocaine consumption impacts cognitive abilities differently during the initial and relapse periods, and during low and high doses. Acute cocaine users have improved inhibitory control, psychomotor responses (only when taken intranasally), and attention at lower doses (Spronk et al., 2013). However, cocaine causes cognitive impairment and impulsivity at higher doses. This initial improvement in attention abilities reverse some of the cognitive deficiencies in sleep-deprived persons, and is therefore seen by some users as an avenue to improve driving ability when tired (Marillier & Verstraete, 2019). Acute use of stimulants (e.g., methamphetamine, amphetamine, cocaine) is associated with side effects such as lack of coordination, sensory disturbances, disorientation, restlessness, lapses of attention, difficulty reacting appropriately to safely control a vehicle, increased risk taking, overconfidence in driving skills, and drowsiness or rebound fatigue (as the effects wear off) (Marillier & Verstraete, 2019). A meta-analysis of studies with participants with chronic cocaine use found that sustained attention, impulsivity, verbal learning/memory, and working memory were the most impaired cognitive abilities (Potvin et al., 2014) (Spronk et al., 2013). Chronic cocaine users also show impairments in response inhibition, memory (recall) to a moderate degree, working memory (with limited evidence), cognitive flexibility (mild impairment), performance monitoring, and psychomotor re-

sponses, but selective attention is not impaired. Moreover, chronic cocaine use is associated with typified structural abnormalities in the brain (Wang, 2021). It is more short-lived and only lasts 30-40 minutes with an abrupt fading post-consumption (Gold et al., 1985; Snyder, 1996). Overall, cocaine seems to block the re-uptake of norepinephrine (NE) at adrenergic nerve endings resulting in NE neurons being inhibited by cocaine. Further, acute cocaine consumption seems to increase the overall beta receptor density in the brain (Gold et al., 1985; Langer et al., 1980). This may explain the cause of a very acute elevation of NE within the first 10 minutes after consumption and the following quick reduction of NE below normal levels leaving the user feeling a "wear off" effect or a "comedown" 20-30 minutes after consumption of cocaine (Gold et al., 1985; Langer et al., 1980). Cocaine is classified as a stimulant and psychological and neurophysiological adaptation in long-term users can be observed (Gawin, 1991). Consumption of cocaine results in serotonin and norepinephrine flooding postsynaptic neuron channels and fully stimulating the CNS. Cocaine users usually insufflate ("snort") or inject the powdered cocaine through the nasal cavities, intravenously, or smoke "crack" in a glass pipe. Physical symptoms of cocaine entail dilated pupils, and heart rate and blood pressure increase (Schwartz et al., 2010). Individuals often report feeling more alert, energetic but also paranoid (Gawin, 1991; Morton, 1999). Cocaine users crave a quick mood enhancement and addiction is often inevitable due to its fast onset and 30 - 40 minutes wear-off phase (Snyder, 1996; Gawin, 1991).

Despite ample evidence showing clear degradation of a driver's ability to drive safely under the influence of drugs, it remains unclear what cognitive processes are impacted the most and what the differences are between various drugs. The presented study aimed to investigate the influence of drugs of abuse on cognitive abilities that are paramount for driving. A set of tablet-based cognitive tasks that include Reaction Speed, Decision Making, Memory, and Bi-manual Perceptual-motor tasks were used to measure the cognitive processes needed for safe driving. These tasks were successfully used in a previous study to show their predictability for on-road driving behaviour in older adults (Bakhtiari et al., 2020). Performances of these tasks by participants under the influence of cocaine and/or cannabis were compared with healthy participants to identify a blueprint of impairment based on the type of drug consumed.

3.2 Methods

The study consisted of participants from three different data collection processes (Table 1). The drug groups were collected in a drug recognition training facility in Jacksonville, FL, and further categorized into three groups based on their urine sample tests: the cannabis group (CAN), the cocaine group (COC), and the cannabis and cocaine group (CAN/COC). The younger control group consisted of undergraduate university students, and the older control group was assessed as a part of a previous study (Bakhtiari et al., 2020). Each participant in the drug and control groups completed a cognitive test battery related to on-road driving portrayed in Table 2 (Bakhtiari et al., 2020).

3.3 Participants

The participants in the drug groups were chosen from a larger cohort that attended a drug recognition training facility. Most of these individuals were frequent drug users and completed a self-report questionnaire screening for past and current drug use, and medical conditions such as epileptic and cardiac conditions. After completing intake paperwork and consent within 2-4 hours after arrival, they completed a urine toxicology panel screening for substances present in the urine (MedTox EZ Screen Cup, Joldon Diagnostics BioCup Panel 12 and the Alcopro Gabapentin Urine Dip Drug Test). Based on the results of the urine test, the following three groups were identified and chosen for the current study: the cannabis group (CAN) included participants who only showed active cannabis compounds (THC) in their urine, the cocaine group (COC) included cocaine users only who were also screened for cocaine compounds in their urine, and the cannabis and cocaine group (CAN/COC) included participants who had active compounds of both cannabis and cocaine in their system. All participants had a valid driver's license and reported to have driven a car within the past six months. All participants completed consent forms approved by the University of Alberta Research Council and received a $10 USD reward and a hot meal after participating. No feedback on performance was provided, but participants were allowed to view the results of their urine test.

Table 1. Demographic Distribution

Group	n	Gender	Age (mean±SD)
CAN (Cannabis)	114	f=19, m=95, other=0	37.41±11.69
COC (Cocaine)	60	f=13, m=47, other=0	52.45±7.86
CAN/COC (Cannabis and Cocaine)	162	f=24, m=137, other=1	47.99±12.94
CtrlYounger (Control Younger)	278	f=186, m=90, other=2	19.89±5.36
CtrlOlder (Control Older)	47	f=22, m=25, other=0	66.06±6.85
Total	661	f=264, m=394, other=3	36.04

3.4 Cognitive Test Battery

3.4.1 Tablet-Based Cognitive Tasks (TBCT)

A set of tablet-based cognitive tasks (TBCT) was used to measure cognitive processes involved in driving. These tasks were designed and developed by a company, Impirica, to run as a continuous series and included: i) Reaction Speed: participants pressed a button as fast as possible after a visual cue (two stages, 15 trials in each stage). ii) Decision Making: participants pressed a 'Go' button after a visual cue while avoiding moving obstacles. A 'Stop' button was available as an additional control in obstacle avoidance (two stages; stage one had one set of obstacles and the second stage had two sets of obstacles, 20 trials in each stage). iii) Memory: participants drew a

previously presented geometric shape (four stages with four trials in each stage). The number of shapes to recall, shape complexity, and the mask duration increased over stages. The fourth and final task was a iv) Bi-manual Perceptual-motor: participants followed a target circle using the iPad in a steering wheel fashion while avoiding fixed and surprise moving obstacles (four stages with each stage increasing in speed). The TBCT were performed by a trained Impirica certified evaluator. Test scripts are standardized as are test prompts and feedback.

Table 2: Tasks and dependent measures from TBCT

Task	**Measure**	**Description**
Reaction Speed (available for stage 1 & 2)	Reaction time (RT)	Average reaction time to tap 'Stop' button after the visual cue
Decision Making (available for stage 1 & 2)	% Early collision	Percentage of hitting moving obstacles with the front side
	% Late collision	Percentage of hitting moving obstacles with a side other than front side
	Go count	Average number of times 'Go' button tapped
	Duration	Average duration between the visual cue and the end of trial
	Obstacle count	Average number of passed obstacles
Memory	% Correct shape	Percentage of shapes drawn correctly

Bi-manual Perceptual-motor	% Time inside target	Percentage of time inside the target

3.4.2 TBCT Dependent Measures

Fifty-eight measures were extracted for each participant from the TBCT. For the Memory and Bi-manual Perceptual-motor tasks, the measures were calculated by averaging the performance of each participant over all trials of all stages, and the Memory task scores were averaged over stage 1 and 2, and stage 3 and 4. During the Reaction Speed and Decision Making tasks, plotting participants' performances (e.g., reaction time or success rate) versus trial number showed there is a clear learning curve in their responses. To minimize response variations, the extracted measures in these two tasks were calculated by averaging scores from trial #6 in stage 1 and trial #8 in stage 2 to the last trial of each respective stage. Table 2 contains the list of dependent measures from each task used in this study.

3.4.3 Procedures for each Group

Both control groups (younger and older adults) performed all four tasks in the same order, and no counterbalancing or random task assignments were given. The order of the subtasks is outlined in Table 2: 1) Reaction Speed, 2) Decision Making, 3) Memory, 4) Bi-manual Perceptual-motor task. Participants in the drug groups were asked to complete the assessment no later than 45 minutes after providing the urine sample.

3.5 Statistical Analysis

To specify the driving-related cognitive characteristics of drug-impaired participants, their performance during the TBCT was compared with younger and older control adults. We expected worse (slower and less accurate) performances during cognitive tasks for the individuals that were under the influence of drugs. Moreover, we expected individuals in the COC group would perform slower and less accurately, and individuals in the CAN group and CAN/COC group would perform faster but less accurately compared to control groups on all four subtasks of the TBCT. It has been well established that cognitive abilities and driving skills deteriorate with chronological age (Anstey et al., 2012), so therefore, we expected the younger control group to perform better than the other groups. As the age distribution is not similar in the control and

drug-groups (Welch $t(86.55) = 7.11$, $p < .001$), a univariate analysis of covariance (ANCOVA) was used to examine differences in performance on cognitive tasks between the five groups.

3.6 Results

The results of this study were organized into the variables listed in Table 2. These nine variables were the most important ones for this study and were identified through a post hoc comparison of conditions. As we hypothesized, the performance of the younger control group (CtrlYounger) was significantly better (faster or more accurate) than the older control (CtrlOlder) and drug groups in all the cognitive tasks. This is in line with previous studies that show cognitive abilities decline with age, and with studies that show drugs of abuse impact various domains of cognition. The comparison between the cognitive abilities in these two groups would shed light on the specific pattern of cognitive decline in each of these populations.

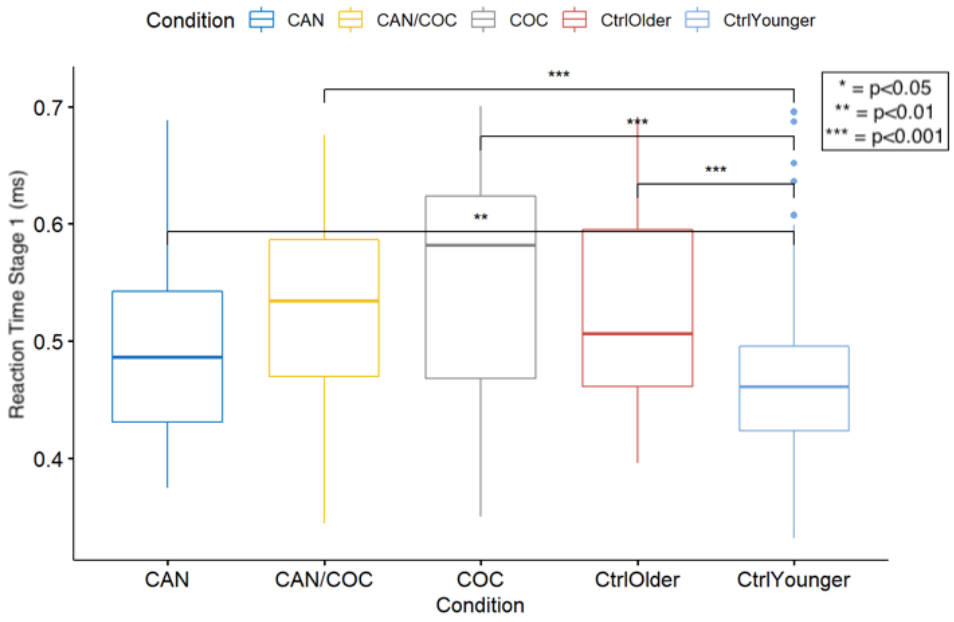

Fig. 1. Reaction Time means (ms) and group differences for Stage 1. It is clear that CtrlYounger outperformed the other groups. COC and CAN/COC performed the slowest and CAN showed a similar performance pattern to CtrlOlder. $F(4, 661) = 18.81$, $p < .001$.

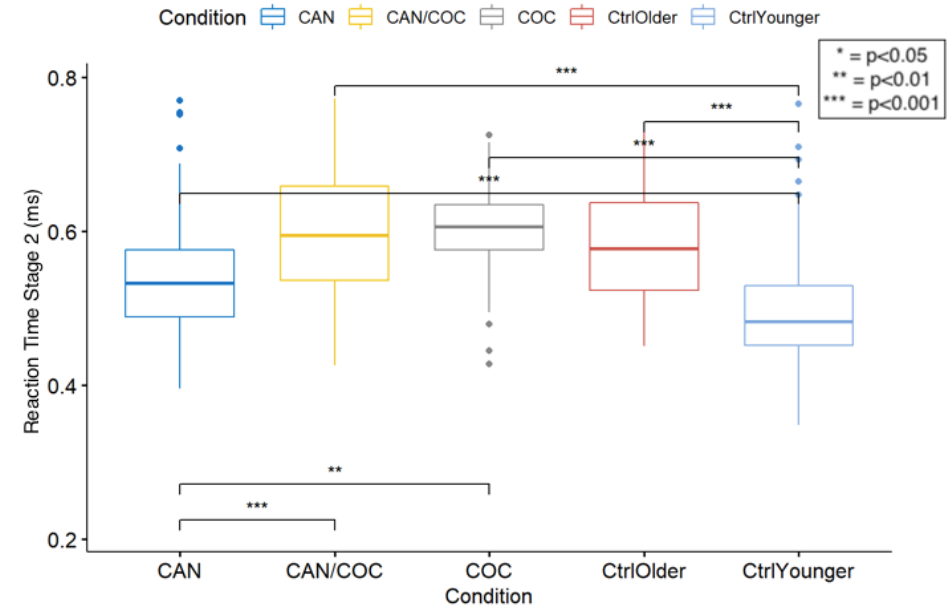

Fig. 2. Reaction Time means (ms) and group differences for Stage 2. A similar performance pattern as in Fig. 1 can be seen with CtrlYounger performing the fastest, followed by CAN and CtrlOlder. The COC and CAN/COC group performed slowest. $F(4, 661) = 48.91$, $p < .001$.

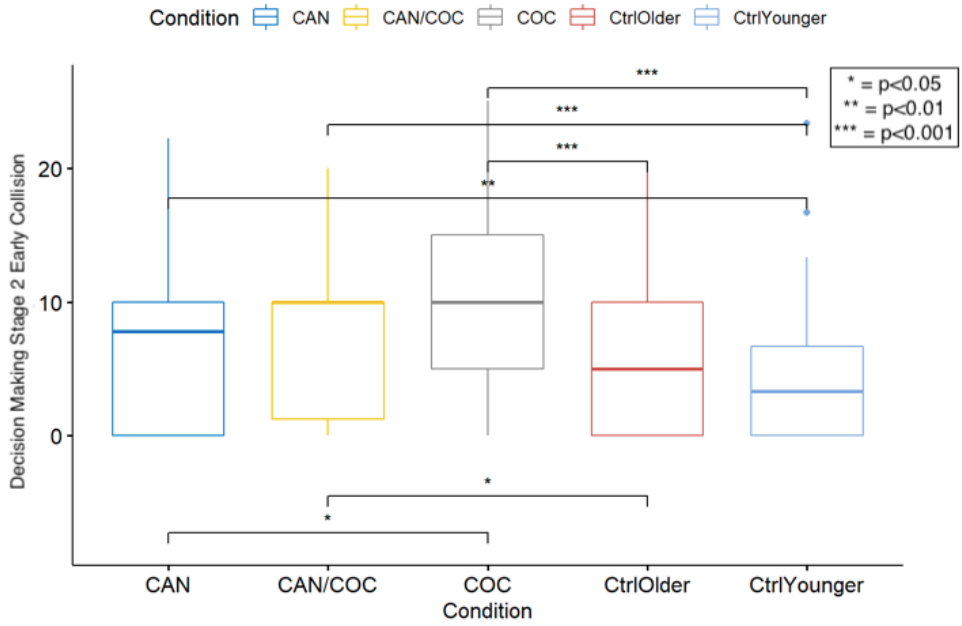

Fig. 3. Decision Making means and group differences for Stage 2 Early Collision Rates. CtrlYounger and CtrlOlder performed best, COC and CAN/COC performed worst, and CAN performed in the middle range. $F(4, 661) = 16.51$, $p < .001$.

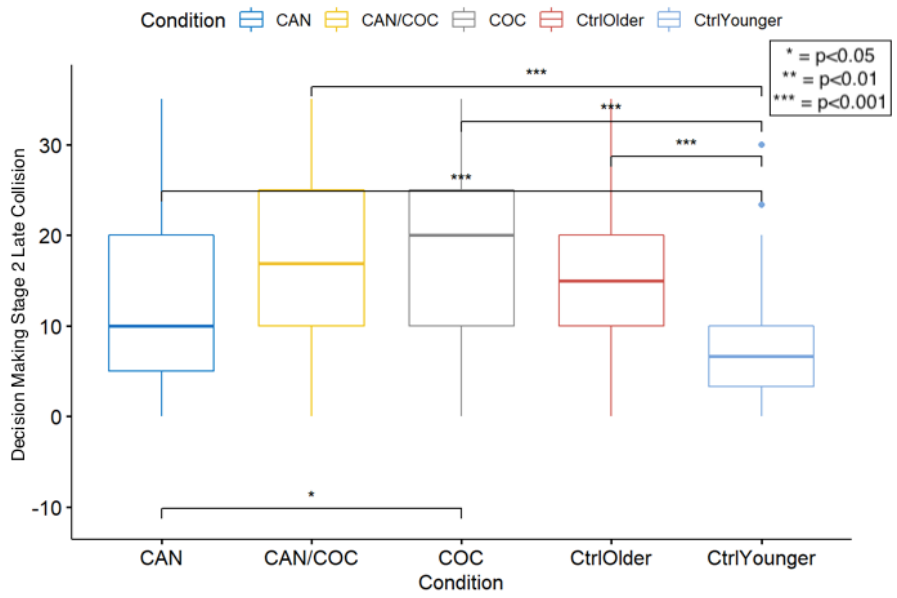

Fig. 4. Group means and differences for Decision Making Stage 2 Late Collision Rates for Stage 2. CtrlYounger and CAN seem to perform faster than the other drug groups and CtrlOlder. $F(4, 661) = 38.16$, $p < .001$ (Note: this measure shows speed only - no accuracy measures are shown here).

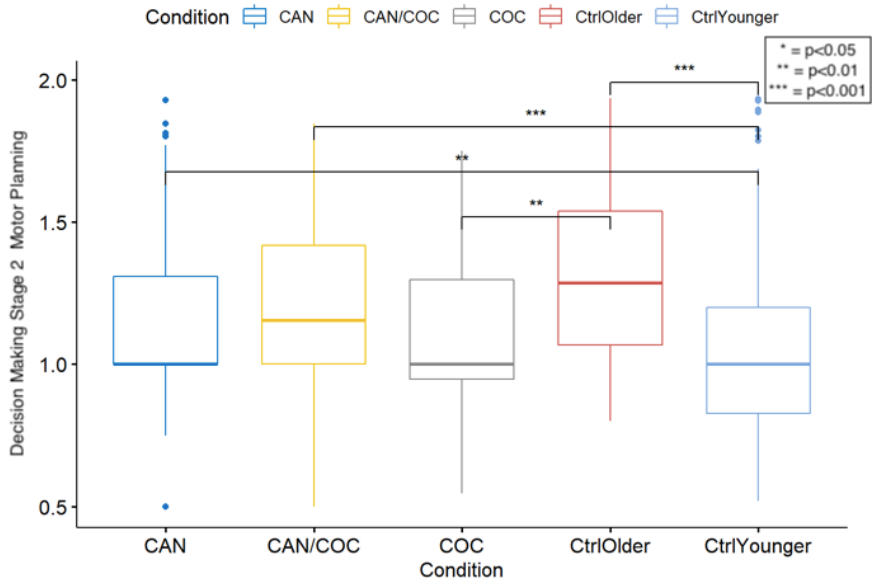

Fig. 5. Group means and differences for Decision Making Stage 2 Motor Planning (Line Numbers Passed). CtrlYounger performed fastest, followed by CAN and COC. CAN/COC and CtrlOlder performed the slowest. However, a speed response was measured here - not response accuracy. $F(4, 661) = 12.86$, $p < .001$.

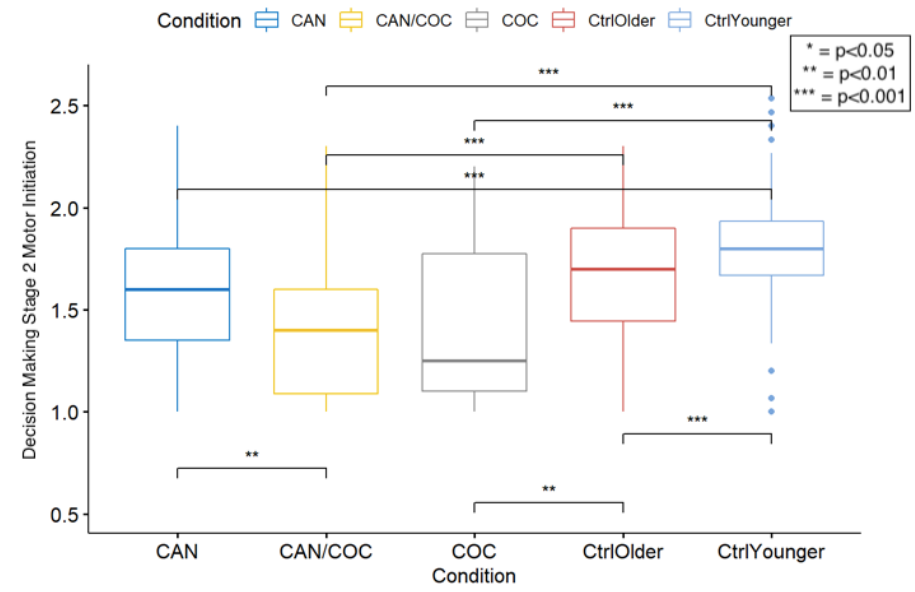

Fig. 6. Group means and differences for Decision Making Stage 2 Motor Initiation Measure (Go Count). CtrlYounger and CtrlOlder performed the fastest, followed by CAN. The CAN/COC and COC group performed the slowest. $F(4, 661) = 39.86$, $p < .001$.

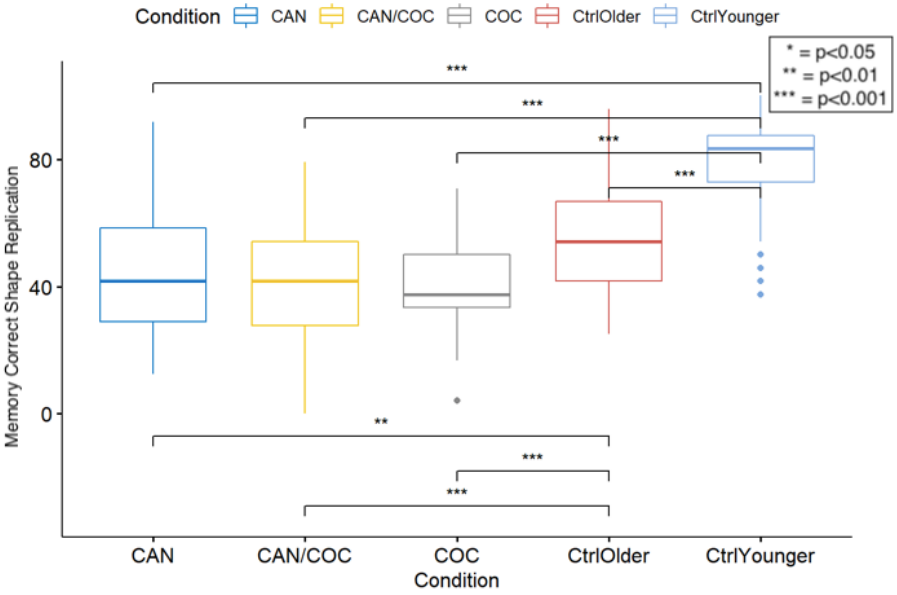

Fig. 7. Group means and differences for Memory task Shape Replication. CtrlYounger and Ctrl-Older outperformed all 3 drug groups in shape replication accuracy. $F(4, 661) = 28.98$, $p < .001$.

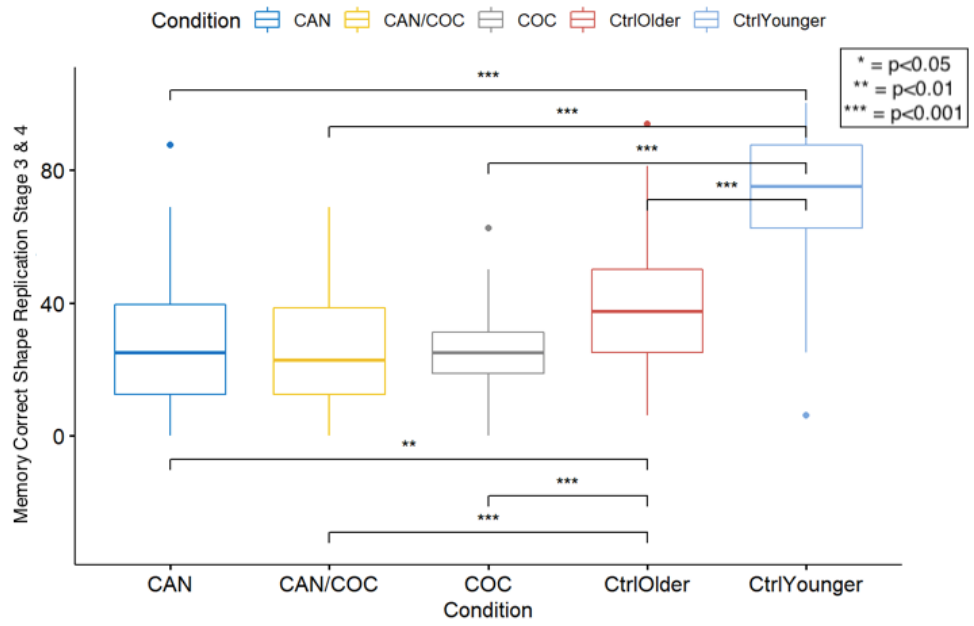

Fig. 8. Group means and differences for Memory task Correct Shape Replication for Stages 3 & 4 with CtrlYounger performing better than CtrlOlder and both Ctrl groups outperforming all drug groups. $F(4, 661) = 181.79$, $p < .001$.

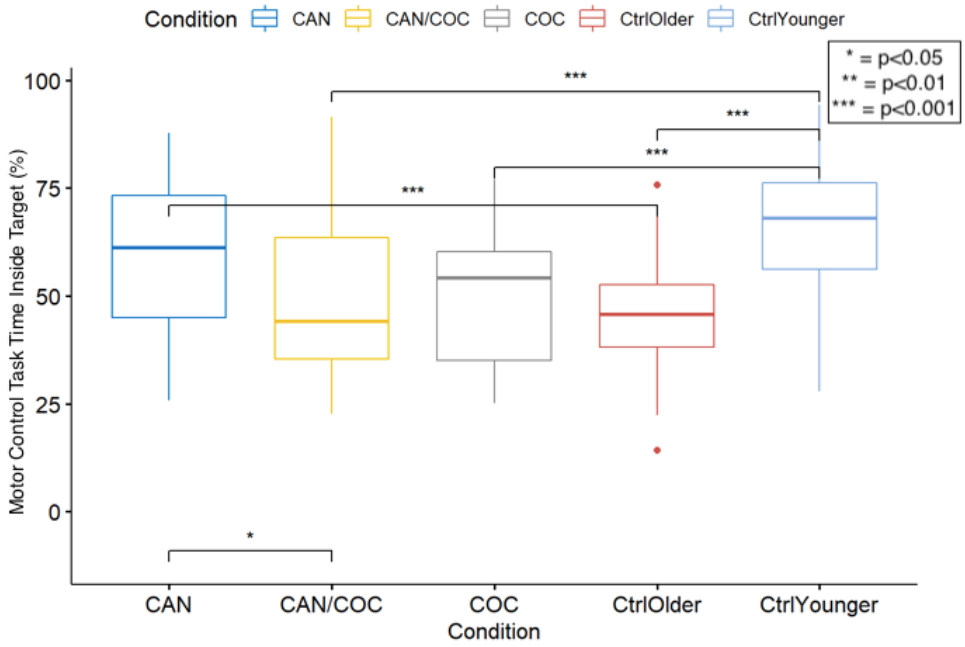

Fig. 9. Group means and differences for Motor Control task Time Inside Target (%). CtrlYounger and CAN performed better than CAN/COC, COC, and CtrlOlder. $F(4, 661) = 40.01$, $p < .001$.

In summary, the CtrlYounger and CtrlOlder groups performed better on most tasks of the TBCT than all three drug groups. However, the CtrlOlder group performed worse than the CtrlYounger group. For the Decision Making task Stage 1 & 2 and for the Memory task this exact performance pattern was observed. For the Decision Making task, CtrlYounger and CtrlOlder outperformed the COC and CAN/COC groups; the CAN group performed in the middle range portraying an overall better performance than the CtrlOlder group. For the Motor Control task, a somewhat similar performance pattern to the Memory task can be seen as the CtrlYounger group performed best, followed by the CAN group. The COC, CAN/COC, and CtrlOlder groups performed the worst.

3.7 Discussion

The main goal of this study was to identify differences in a wide range of cognitive performance based on different performance measures on a set of tablet based cognitive tasks. We used a cognitive test battery that we previously used to predict on-road driving in older adults (Bakhtiari et al., 2020) to compare the performance of participants under the influence of cocaine and/or cannabis with younger and older adult controls. Understanding drug impairment is crucial as drug legislation has recently changed in many jurisdictions and it is well known that drug-induced cognitive impairment can adversely affect driving performance (Sewell et al., 2009; Ramaekers et al., 2006). This study also investigated performance differences between drug-imapired participants classified into three groups; 1) Cannabis (CAN), 2) Cocaine (COC), and 3) Cannabis and Cocaine (CAN/COC) compared to two control groups 1) Control Older (CtrlOlder) and 2) Control Younger (CtrlYounger). The results suggest there are significant differences in performance of the two control groups as well as further differences related to different combinations of drug impairment. Overall, both control groups performed significantly better than all drug groups in most tasks. Additional analyses compared all drug groups with both control groups and the results showed significant differences among most of the variables.

Driving is a task that requires numerous and varied cognitive, perceptual, and motor abilities. Cognitive abilities are a crucial part of driving performance and include executive functions (attentional control, cognitive inhibition, inhibitory control, working memory, cognitive flexibility, and planning (Theunissen et al., 2021; Diamond, 2013), episodic memory (memory

for personal events), semantic memory (knowledge about the world), and procedural memory (ability to use a learned skill in an automatic way such as gear shifting or steering) (Wagner et al., 2011). Perceptual abilities include visual information selection, visual perception, and audition (Wagner et al., 2011; Edwards et al., 2017; Devos et al., 2015). Motor abilities include fine hand, arm, foot, leg, and neck movements (Devos et al., 2015; Wagner et al., 2011). A large degree of integration is needed among these processes (Devos et al., 2015). All the above-mentioned abilities that are crucial for accurate driving performance are measured with the TBCT in this study as has been explained thoroughly in Bakhtiari et al. (2020). The four tasks of the TBCT showed the following between and within group differences.

Control groups vs Drug groups

Both control groups, CtrlYounger and CtrlOlder, were grouped together and overall performance was compared with the performance of all three drug groups that were also grouped together. Cannabis and cocaine target different neuroreceptors and impact the brain differently, both in the scope of cognitive abilities impacted (either positively or negatively), and the pharmacokinetics and pharmacodynamics of the drug action. Therefore, we compared the performance of groups of different drug users to investigate patterns of cognitive deficits for each group. In all cases, the combined control group performed equally well or better than the experimental groups.

Within Drug group Comparison

There were notable performance differences between drug groups. There is a significant gap in the literature looking at both cannabis and cocaine combined and how the interaction of both drugs in the body affects driving performance. While polysubstance use (PSU) (using more than one drug at a time, such as cocaine and alcohol or cocaine and cannabis) has been well-documented in relation to personal and public health (Crummy et al., 2020), the neurobiological, cognitive, and behavioural effects of PSU (especially for cocaine) are relatively unknown (Liu et al., 2018). As previously explained, a cocaine high seems to be rather short-lived compared to other drug induced highs and only lasts 30-40 minutes and is characterized by an abrupt fading post-consumption (Gold et al., 1985; Snyder, 1996). The inhibited reuptake of nor-

epinephrine (NE) causes of a very acute elevation of NE within the first 10 minutes after cocaine is consumed that is followed by an overall reduction of NE below normal levels leaving the user feeling a "comedown" effect only 20-30 minutes after consumption of cocaine (Gold et al., 1985; Langer et al., 1980). The participants in this study belonging to either the COC group or CAN/COC group were all past the initial 30-40 minutes onset of a cocaine high.

The CAN group performed better than the CAN/COC group: Overall, the CAN group performed better than the CAN/COC group for reaction time (Stage 1 and Stage 2), Decision Making, replicating the correct shape in the Memory task, and time spent within the target circle during the Bi-Manual Perceptual-motor task. The CAN group showed a faster reaction time compared to the CAN/COC group, had a higher Go count for the Decision Making task, and more time spent within the target circle during the motor control task indicating higher levels of control in these tasks. These performance differences could suggest a different form of impairment where the combination of cannabis and cocaine in the body might create a more severe form of impairment. It may also reflect the deteriorating impact of cannabis when combined with other drugs.

The CAN group performed better than the COC group: There were significant performance differences between the CAN group and COC group, with the CAN group performing better than the COC group for reaction time and several variables in the Decision making task. For instance, the CAN group performed better for reaction time in Stage 2. For Decision making, early collision, and late collision, the CAN group performed better than the COC group, as well as for Decision Making Stage 2. These performance differences could suggest a different, possibly lesser degree of cognitive impairment when comparing cannabis to cocaine.

A study by van Wel et al. (2013) showed that a single dose of cannabis impaired psychomotor function but increased response errors during impulsivity tasks, whereas single doses of cocaine improved psychomotor function while decreasing response time in impulsivity tasks, simultaneously increasing errors. Similar results can be seen in the performance of the CAN group where performance was faster but less accurate than the CtrlOlder Group. However, the COC group did not show a decreased response time in impulsivity tasks, likely because most participants were in the "wearing off" phase post cocaine consumption.

Similar COC and the CAN/COC group performances: No significant differences in performance were found between the COC and CAN/COC groups. This could be due to binary measures being picked up in urine samples through metabolites, or cannabis possibly being consumed to counterbalance a cocaine high. Another explanation could be the bolder impact of cocaine compared to cannabis (i.e., the effects of cocaine "overwrite" the effects of cannabis). Due to observational reasons, no exact time frames of participants' drug consumption can be given and participants might have been unsure about their exact time of consumption and participants possibly coming off a cocaine high. This likely influenced the accuracy of their self-report. More data is needed within the CAN/COC group to further investigate possible differences.

Overall, the CAN/COC group is a very new population to current driving literature and has not been extensively studied yet. There is a significant gap in the literature looking at both cannabis and cocaine combined and how the interaction of both drugs in the body affects driving performance. While polysubstance use (PSU) (using more than one drug at a time, such as cocaine and alcohol or cocaine and cannabis) has been well-documented in relation to personal and public health (Crummy et al., 2020), the neurobiological, cognitive, and behavioural effects of PSU (especially for cocaine) are relatively unknown (Liu et al., 2018).

CtrlOlder vs Drug group

Aging is accompanied by various changes in the brain including enlargement of cerebral ventricles, decreased brain volume, shrinkage of neurons, and myelin loss (Lyman et al., 2001). These cortical changes often result in deterioration of cognitive abilities demonstrated by increased reaction time, decreased performance in spatial attention and memory, decreased visual acuity, and decreased head and neck flexibility. Due to its complexity, driving a vehicle is often adversely affected in healthy aging older adults (Wang et al., 2021). Although both aging and drugs impact cognitive abilities, it is not clear whether their patterns of cognitive decline are similar or not; there is a dearth of research addressing this important question. Therefore, in the following sections, we organized the results of comparing each drug group with the CtrlOlder group first.

Overall, it seemed as if older adults were more accurate than both drug groups, COC & CAN/COC groups. Older adults were more accurate and more able to press the stop button than

both COC & CAN/COC groups. It seemed as if the COC group were rushing more into starting the task.

CAN, CAN/COC, and COC group seem less accurate than CtrlOlder: We found that the COC group performed less accurately during the Decision Making task (decreased success rate and increased early collision rate in Stage 2, decreased number of correct shapes and matching lines in Memory tasks replicated) and slower (increased motor planning and initiation duration during Decision Making task, Stage 2) than the CtrlOlder group. Interestingly, during the Memory task, the COC group performed less accurately (decreased rate of correct shape, and matching line). Due to the euphoric states experienced during a cocaine high, cocaine impairment may lead to speeding behaviour, increased risk taking, short-term memory impairment, and increased reaction time (Marillier &, Verstraete 2019; MacDonald et al., 2008). Some of the signs of driving impairment related to cocaine consumption are speeding, collisions, losing control of the vehicle, high-risk behavior, turning in front of other vehicles, inattentive driving, and poor impulse control. Once the effects of cocaine wear off after 30-40 minutes post-administration, fatigue, depression, and shivering may also lead to impaired driving (MacDonald et al., 2008; Efflein, 2018; Marillier & Verstraete, 2019).

More importantly, adverse reactions have been reported after long-term cocaine use even when no measurable drug levels were found in the blood (Jedema et al. 2021). This could explain the significant difference between the CtrlOlder and COC group where the COC group seemed to impulsively rush into tasks resulting in worse performance.

Older adults were slower but more accurate than both CAN and CAN/COC groups, in the Memory task: During the Memory task, the CtrOlder group performed more slowly than the CAN group (overall duration in seconds for Stage 3 and Stage 4) and the CAN/COC group (overall duration Stage 3 and Stage 4). However, the CtrlOlder group performed more accurately than the CAN group (correct shape total, and correct shape replication for Stage 3 and Stage 4) and CAN/COC group (correct shape total, and correct shape for Stage 3 and Stage 4, and matching line total).

These findings can be better understood by the speed-accuracy tradeoff (SAT) concept. The SAT is the phenomenon of individuals performing tasks with higher error rates when they

move or react fast, and with more accuracy when doing it more slowly (Wickelgren, 1977; Rabbitt, 1979). Age-related slowing and SAT is apparent during perceptual decision-making tasks, in which older adults respond slower but more accurately than younger adults (Forstmann et al., 2011). The SAT also occurs during recognition memory tasks, with older adults showing a lower maximum discriminability of target shapes, and a slower rate of information processing than younger adults (Kumar et al., 2008). This points to a lower working memory capacity and efficiency in older adults. Although the SAT is a well-known phenomenon, many factors contribute to choosing speed over accuracy or vice versa, including the task requirements and individual differences. In both the Decision Making and Memory tasks, participants were instructed to perform the task as accurately as possible, which means prioritizing accuracy over speed. The reasoning behind choosing accuracy over speed in the CtrlOlder group and speed over accuracy in the CAN and COC/CAN groups may be that either the older adult group paid more attention to the instructions, or that was a more favourable choice given their age. Additionally, in the Decision Making task, the CAN/COC group was less able to control the moving box by pressing the stop and go buttons (less Go count in Stage 2) and therefore performed worse (higher early collision rate in Stage 2) than the CtrlOlder group indicating an overall slow response time.

Moreover, the CtrlOlder group performed less accurately than the CAN group during the Bi-manual Perceptual-motor task (less amount of time inside the target). To excel in this task, a high degree of integration and coordination among sensory, decision making, and motor areas is necessary. As previously mentioned, older adults were slower than the CAN group. This, in addition to the fact that they are generally less familiar with tablet technology, may explain their worse performance in the Bi-manual Perceptual-motor task. Although, Boggs et al. (2018) suggest after THC consumption there are dose dependent impairments in fine motor control and motor timing, the extent of such impairment might be more highly correlated to age than to cannabis impairment. Most mentioned studies are in line with our findings that aging is a more influencing factor for this task.

3.8 Conclusion

In conclusion, the drug groups seemed to perform worse than the control groups. There are different performance patterns indicating specific blueprints for impairment for each drug group. While the cocaine group (COC) seemed to perform the worst, the other drug groups, cannabis (CAN) and cannabis plus cocaine (CAN/COC), show clear impairment patterns as well compared to both control groups. These different impairment patterns need to be further investigated while proper drug screening technology should be utilized to help accurately differentiate blood/urine metabolites and associated cognitive performance differences.

3.9 Limitations

There are some limitations to this study. First, the threshold for urine screens was not shared with the researchers post data collection. Further, no alcohol screening was conducted. Testing blood alcohol content is crucial to rule out any possible drug-alcohol interactions that could appear in the form of synergistic and adaptive effects. Second, younger adults are generally more familiar with technology, including gaming technology on touch screen devices. Therefore, the younger control group as well as younger participants in the drug groups may have had an advantage over the older adults and control group in this study. Third, in a follow-up study, a control group within the 30-45 years of age range (middle-aged) should be included in addition to the younger and older control groups to compare drug impaired participants with another healthy control group that are not young adults or seniors. Lastly, the cocaine (COC) group showed urine metabolites associated with cocaine consumption, however, participants were coming off a very short-lived cocaine high that, by the time of assessment, did not properly show impairment associated with a new cocaine high. These two phases of cocaine consumption (drug high phase and wear-off phase) may present different performance patterns and should be controlled for.

3.10 Future Directions

The next step for this project is to replicate these findings with larger sample sizes for each group and to report the exact urine toxicology protocol for each participant. Increasing the number of participants would mean that a more concrete blueprint for impairment could be created, especially for the COC and CAN/COC groups where there is a clear lack of research looking at cognitive performances within these populations. Lastly, we did not account for possible personality traits commonly associated with substance use disorder (SUD). A future study could include the AUDIT or DAST-10 to identify possible alcohol and/or drug use disorders (Maisto et al., 2000) associated with severe mental illness, or the MMPI to identify personality patterns associated with SUD (Weybrew, 1996).

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Conflict of Interest

A.G. and F.V. are employees of Imperica/DriveABLE Inc. and A.G. has ownership interest in Impirica/DriveABLE Inc.

Chapter 4: Thesis Discussion

Cognitive impairment in relation to on-road driving can appear in many different forms. As chapter two and three of this thesis have shown, age related cognitive decline and cognitive impairment in relation to recreational drug use are commonly associated with increased accident risk when operating a vehicle. Cognitive impairment can be characterized by different performance patterns caused by either short term or long term impairment. This thesis is contributing to a very popular and current way of understanding cognitive impairment in relation to on-road driving; it portrays two different projects looking at different patterns of impairment related to cognitive performance using computerized tasks that have shown in a previous study to be predictive for on-road driving behaviour (Bakhtiari et al., 2020). Both studies presented in this thesis have used a computerized task (TBCT) studying cognitive performance differences associated with on-road driving. These performance differences are dependent on a) age and age related cognitive decline, as well as b) drug impairment associated with different drugs and even potential permanent cortical changes or premature cognitive decline due to substance use disorder (SUD). The central questions and theme of this thesis therefore aims to identify common and/or unique performance patterns of cognitive impairment related to driving.

It is crucial to mention that old age alone is not a reliable predictor for poor driving performance and many other variables need to be taken into account when determining an adversely affected driving performance due to aging. However, an increasing number of older adults seem to be involved in an increased number of vehicle accidents that may be associated with the Canadian aging crisis. Furthermore, polysubstance use (PSU) affects the majority of the substance-using population as one drug dependence often leads to further dependences and ad-

diction (Crummy et al., 2020; Ignaszewski, 2021). As previously mentioned, polysubstance use (PSU) (using more than one drug at a time, such as cocaine and alcohol or cocaine and cannabis) has been well-documented in relation to personal and public health (Crummy et al., 2020), as well as its neurobiological, cognitive, and behavioural effects (Liu et al., 2018). Due to a possible polysubstance use crisis, the second study of this thesis (Chapter 3) seems of utmost importance as unique performance patterns could be identified when it comes to PSU compared to single drug usage.

4.1 Chapter 2 continued: Age Related Cognitive Decline & Clinical Populations

When it comes to aging and age related cognitive decline Chapter 2 has shown that driving skills seem to be adversely affected. Due to Alberta's routine driving assessments of older adults at the age of 75, 80 and every two years after, driving assessments are of high demand. Not simply the process of healthy aging needs to be considered when assessing older drivers but particularly the onset of chronic disease that result in cognitive impairment such as Alzheimer's, dementia, or increasing visual and mobility issues (Álvarez and Javier Álvarez 2016). Diabetes-related neuroglycopenia causes increased risk of neurocognitive dysfunction leading to visuospatial impairment and impaired driving behaviour. Also, pain relieving medications and antidepressants may lead to cognitive dysfunction and should be carefully reviewed before driving a vehicle (Ghosh et al. 2017). Further, medication use that might be potentially driver-impairing (PDI) seems to adversely affect driving performance in adults adding another hurdle to the urgency and assessment process of older adults that actively drive (Ghosh et al. 2017; Hetland et al. 2014).

Clinical populations that are at-risk for impaired driving performance are becoming a vastly growing area of interest. Resuming on-road driving after a stroke or during the on-set of

Parkinson's disease are current areas that need further investigation. Research by (Lodha et al. 2021) showed that driving rehabilitation post stroke seemed to be beneficial while focusing mainly on attentional and motor skills to improve braking behaviour during a simulator driving performance. Other than older or medicated adults, commercial drivers and individuals with specific health conditions (e.g neurological conditions, mild cognitive impairment) are also required to complete a driver's medical examination periodically depending on their health conditions and overall diagnosis (CCMTA, 2018).

Considering the high demand of commonly used on-road driving assessments for adults at any age, there are high costs, waiting times, and stressors associated for individuals and families when these driving assessments have to be completed, periodically or one-time only. Therefore, there is an urgent need for fast, efficient and low cost driving assessments that are reliable and able to distinguish between at risk and not at risk drivers. The tablet based cognitive assessment tool (TBCT) used in both studies of Chapter 2 and Chapter 3 of this thesis is a well developed computerized cognitive assessment tool that has shown to be predictive for on-road driving. Potential future directions in association with the TBCT could be looking at combining clinical cognitive and neuropsychological assessments that have also been shown to be predictive of on-road driving such as outlined in Chapter 1 in order to validate screening tools further, and mainly to combine commonly used clinical assessment tools used for older adults, medicated and cognitively impaired adults.

4.2 Chapter 3 continued: Drugs and Permanent Brain Changes resulting in Premature Cognitive Decline

What we have seen in Chapter 2 and 3 of this thesis shows different forms of impairment and different cognitive performances based on such. When it comes to Chapter 3, cognitive impairment in relation to drug use, an important question arises; is there a difference in overall cognitive decline depending on the frequency of substance abuse? Individuals that consume drugs less than two times per month are considered "occasional" users whereas individuals that have the urge to consume on a weekly or daily basis are considered "frequent" or "habitual" users that might suffer from substance use disorder (SUD). Participants impaired due to drug consumption in Chapter 3 were not screened for long-term substance abuse or occasional use. Individuals that collected the data reported most of the participants were long term users but no self-report or toxicology history questionnaires were administered at the time of data collection.

Further, Chapter 3 indicated that different drugs and their combinations have different effects on cognitive skills related to driving based on overall performances on the tablet based cognitive screening tool. Polysubstance abuse is a crucial issue when it comes to drug related research and on-road driving. When it comes to cannabis and driving, increasing amounts of research have been done since the legalization of cannabis in countries such as Canada or some parts of the US. Studies clearly show that cognition and cross motor function are impaired when THC is consumed. Depending on the tolerance, doses and compounds that are consumed, impairment can come in different forms.

When it comes to cocaine, there is a lack of research investigating the direct link between cocaine highs and overall driving performance (Asbridge et al., 2012; Downey et al.,

2012). Nevertheless, literature that investigated the mere effects of cocaine on overall cognition, attention, and gross motor skills suggests that a cocaine high may increase overall reaction time and responsiveness to stimuli, however, performance accuracy decreases (Marillier & Verstraete, 2019). This may indicate that individuals consuming cocaine can be considered risky drivers due to impulsiveness and potential reckless driving. On the other hand, once the fast onset cocaine high wears off (roughly 30-40 min post consumption), individuals may perform slower and less accurately overall (Marillier, & Verstraete, 2018; MacDonald et al., 2008). Both drugs combined, cannabis and cocaine, do not have a vast amount of research indicating possible cognitive deficits of impairments and further research is needed.

Overall, existing literature suggests that there are different forms of impairment related to drug consumption merely depending on the drug of choice, physical tolerance to the drug, and the amount of drug consumed (Efflein, 2018). Also, healthy aging, medical conditions and substance use disorder (SUD) affect cognition as well. As previously mentioned, the combination of different drugs in one person's bloodstream can also severely impaired performance outcomes.

Therefore, an important point to consider is the potential performance difference between occasional and long term users. Substance use disorders (SUDs) are defined by a compulsion to seek and consume one or more substances of abuse, with a perceived loss of control and a negative emotional state (Pando-Naude et al. 2021). Long-term substance use seems to be associated with morphological changes of multiple neural circuits such as the frontal–striatal but also the limbic pathways. Pando-Naude et al. (2021) completed a meta analysis suggesting that neuro-adaptations and cortical changes are evident across different substance disorders but these adaptations can vary depending on the type of drug, how much is consumed and possible other

factors. A study by Manza et al. (2020) suggests that chronic cannabis use is associated with structural differences in both, white and gray matter and supports the notion of domain-specific cognitive impairment in individuals with heavy cannabis use (HCU). Research suggests that there were abnormal CT scans in brain areas associated with long-term memory and attention (Manza et al. 2020) (Mason et al. 2019).

When it comes to cocaine use, a critical question from cross-sectional and clinical studies prompts to investigate, whether the cortical and functional differences between cocaine users and healthy control groups result from SUD or rather reflect already existing differences (Wang 2021; Wallis et al., 2020). Cocaine research with male rhesus macaques indicates that cocaine use is causal in producing regional brain changes that appear to result in cognitive impairment (Jedema et al. 2021) (Wang 2021).

Increasingly, more studies suggest that cannabis consumption, especially habitual cannabis use is associated with long term cortical changes adversely affecting cognitive performance. Cognitive performance is crucial for safe on-road driving and therefore future research is needed in order to investigate how these potential neuro-adaptive changes could affect the overall driving performance of chronic cannabis users while under the influence and during abstinent phases. Cocaine research seems to be suggesting similar cortical alterations when the substance is frequently consumed, however, further studies are needed to replicate these results with human participants. Overall, evidence suggests that frequent drug consumption may alter brain structures related to cognitive performance. This decline in cognition in otherwise healthy adults may be equivalent to premature cognitive decline that is often associated with aging.

4.3 Options for Future Cognitive Assessments

Cognitive testing has been vastly used to evaluate the cognitive and psychomotor abilities needed for driving. Clinical cognitive assessments are frequently used to identify at-risk drivers, or to screen for driving related cognitive impairment (Stav, 2008). The Mini Mental State Exam (MMSE) (Folstein et al., 1975); Wood et al., 2013) and the Montreal Cognitive Assessment (MoCA) (Nasreddine et al. 2005) are commonly used when assessing cognitive impairment in relation to on road driving and are measures of global cognition (Ott et al., 2013; Wood et al. 2013). This test is a quick screening tool to assess a quantitative evaluation of cognitive impairment. The MoCA (Nasreddine et al. 2005) is also used as a screening tool for mild cognitive impairment (MCI) and early Alzheimer's disease. Furthermore, the MoCA is frequently used in driving research to pre-screen participants for cognitive decline or dementia, especially older adults. Although failure results on these tests are used as indication of driving incompetency, passing these tests does not guarantee safe driving, and additional on-road test evaluations are required. There is a great need for evidence-based tools to identify unsafe drivers in a fast but accurate manner (Wang et al., 2021). Findings by Anstey et al. (2020) suggest that off-road screening assessments and test kits seem to reliably identify older drivers with a strong probability of failing an on-road driving test. This study successfully used various cognitive assessments in the field such as the Useful Field of View, DriveSafe/DriveAware, Multi-D battery, Trails B, Maze test, Hazard Perception Test, DriveSafe Intersection test, and 14-item Road Law test.

Challenges

As previously mentioned, individuals facing cognitive decline often portray challenged attention, memory, judgment, and motor skills meaning a fast variety of skills are adversely af-

fected and should be assessed independently (Groeger 2000) (Lee et al. 2003). Due to the complexity of on-road driving tests and in-office assessments, challenges and limitations often arise. Overall, specificity and sensitivity (determining false positives and false negatives) are most crucial when it comes to driving assessments as the main goal is to increase a patient's quality of life as well as their overall safety. Specificity and sensitivity of assessment tools are crucial to avoid suspending someone's license who is actually a good driver and for not taking away the license of a risky driver (Bernstein et al. 2019). The reliable consistency of an assessment tool is another crucial characteristic in order to identify consistent driving behaviour during a driving assessment.

Furthermore, a lack of precise literature outlining recommended clinical and neuropsychological recommendations has led to an increase in non-standardized assessments and guidelines. Non-standardized assessments are valid to explore, however, they often lack validity and credibility resulting in poor driving evaluations. Another challenge when it comes to assessing driving skills is the presentation of many different (clinical) populations that are commonly identified as at-risk drivers. For instance, individuals with TBI, dementia, epilepsy, or healthy aging seniors often require modified assessments tailored to their diagnosis or cognitive abilities. This means assessment times are often cut short or divided into blocks which can lead to confounding results (Saviola et al. 2018).

When it comes to clinical settings, acute care rarely allows the possibility of conducting hour-long assessments, whereas in a rehabilitation centre or specialized driving evaluation centre, it is more common to have the equipment and time necessary for extensive driving assessments (Asimakopulos et al. 2012). Additionally, older drivers with impaired driving skills are

likely to present multiple deficits. Due to the dynamic nature of the driving task, it is not likely that a single assessment tool will adequately identify at-risk drivers (Saviola et al. 2018). Across the literature, many assessments claim to be useful to assess driving properly, however, a proper combination of different assessment tools has still to be identified. Many researchers and clinicians have realized that a proper combination of different assessments need to be standardized to properly assess driving meaning there is not one single test that can assess an individual's driving performance correctly.

For instance, a cross-sectional study by Doroudgar et al. 2018 administered a variety of screening tools in conjunction with a simulator to assess driving performance in cannabis users. The Rapid Detect Saliva Drug Screen 10-panel was administered, a simple visual reaction time test (SVRT) and SFST consisting of the horizontal gaze nystagmus (HGN), the one leg stand (OLS), and the walk and turn (WAT) tests were administered. Overall, this study reported cannabis users were more likely to fail the SFST and the WAT and HGN components. Further, impaired users reported slower reaction times, deviated less in speed, and had difficulty matching a lead vehicle's speed compared to nonusers (Doroudgar et al. 2018). Furthermore, the data supports the notion of domain-specific cognitive impairment in individuals with HCU and provides a neuro-mechanical understanding of such deficits, particularly with respect to abnormal CT in brain areas associated with long-term memory processing (Wittemann et al. 2020). More studies like the ones by Doroudgar et al. 2018 and Wittemann et al. 2020 have to be done to further identify correlations between newly identified screening tools and already standardized clinical assessments.

Lastly, the availability of assessment tests in rehabilitation centers may present challenges for the consistency and availability of screening procedures as remote locations may not facilitate some of the required assessments due to a shortage in staff or assessment availability.

4.4 Future Outlook: Simulator Driving and Brain Oscillations

In order to further investigate impaired driving and cognition, simulator driving performance in conjunction to measuring brain oscillations could raise further insight into impaired driving research. When it comes to assessing oscillations and driving performance, it is critical to understand the different oscillation patterns of the human brain measured in cycles per second (Hz) (Buzsaki, 2006). Brain oscillations are often called “brain waves" and are correlated with mental states and states of consciousness. Different brain regions display different electrical forces and the interplay of such, as well as stimulation and inhibition, are described as brain waves (Buzsaki, 2006). Neurones can generate firing, either individually or in groups affecting oscillation patterns and the electromagnetic field associated with neurons. The different brain waves that have been identified and named by researchers are the following; gamma waves (>30 Hz) that are often described as active or “flow” brain waves. Theta brain waves (4-8 Hz) commonly known as deep relaxation waves. Alpha oscillations (8-12Hz) that are described as light relaxation waves. Beta waves (12-30 Hz) are active during day to day activities and when individuals are actively problem solving and engaged. Lastly, delta oscillations (1-4 Hz) are often associated with sleep and deep restful relaxation (Buzsaki, 2006).

Assessing the mentioned brain oscillations while individuals perform driving simulations has been done in a number of instances. A study by Hernandez and colleagues (2015) showed that response time to emergency braking situations can be affected by driver's cognitive states

(stress, fatigue, and extra workload). Beta waves seem to increase when a driver faces sudden lane change in the front vehicle in connection to breaking. Further, regression models revealed that significant predictors of worse steering deviation showed increased beta and delta power (Vakulin et al., 2016). A study from 2011 by Haufe and colleagues looked at EEG potentials predicting upcoming emergency braking during simulated driving. In this study, it was demonstrated that the viability of a neuroergonomic approach to driving assistance allows individuals to reduce response times by detecting a driver's intention to brake before any actions become observable.

4.5 Conclusion & Future Directions

The two studies outlined in this thesis are paving the way for future projects aiming to identify a blueprint for different forms of impairment. Within the next three years, the first study of my PhD research will compare drug users and risky drivers to investigate how these two populations differ in regards to cognitive performance and how different a drug impaired performance is to a clinically impaired cognitive performance. Both studies (Chapter 2 and 3) investigated impairment markers aiming to identify parts of a blueprint that could potentially define impairment based on the population being studied. Another area to be explored through my PhD research is the monitoring of biomarkers while driving. There is a balanced amount of research combining cannabis and simulator driving, cannabis and oscillation measures as well as cannabis and cognitive assessments. However, no research has been done combining all mentioned areas of interest and no study has investigated brain oscillations in regards to on-road driving performance and THC consumption, particularly in acute users. Therefore, it is of great importance to fill this gap in the literature and propose a study where individuals will consume THC and perform a simulator driving test while observing brain oscillations. The same participants will also

complete a cognitive assessment task that predicts on road driving performance and these results will also be compared to simulator performances.

In summary, cognitive impairment and on-road driving is not a safe combination. However, when it comes to different forms of cognitive impairment, there is still a vast unknown area of adversely affected human performance that we do not fully understand. Possible long-term effects related to medication use, long rehabilitation times after brain injuries, or even long-term brain changes associated with acute cannabis consumption are all examples that may contribute to unsafe driving performances putting not only the driver, but also others at risk. This thesis is a step into further exploring possible patterns and blueprints of impairment related to age-related and drug induced cognitive impairment. After completing the study outlined in Chapter 3, it seems of utmost importance to further investigate poly substance abuse (including combined alcohol and drug consumption) and cognitive impairment in relation to on-road driving. My goal is to raise more awareness about the dangers of drug consumption and cognitive impairment, thereby contributing to increased on-road safety within our province and country.

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APPENDIX A

Table A: Tasks and dependent measures from TBCT

Task	Measure	Description
Reaction Speed (available for stage 1 & 2)	% Premature go	Percentage of releasing 'Start' button before the visual cue
	% Lack of response	Percentage of timeout trials
	Reaction time (RT)	Average reaction time to tap 'Stop' button after the visual cue
	RT Congruent Correct	Average reaction time for trials where visual cue and box direction are congruent and were correctly responded to
	RT Incongruent Correct	Average reaction time for trials where visual cue and box direction are incongruent and were correctly responded to
	RT Incongruent Incorrect	Average reaction time for trials where visual cue and box direction are incongruent and were incorrectly responded to
	% Congruent Correct	Percentage of trials where visual cue and box direction are congruent and were correctly responded to
Decision making (available for	% Premature go	Percentage of releasing 'Start' button before the visual cue

stage 1 & 2)	% Success	Percentage of successfully navigating through the moving obstacles
	% Early collision	Percentage of hitting moving obstacles with the front side
	% Late collision	Percentage of hitting moving obstacles with a side other than front side
	Reaction time	Average time to tap ‘Go’ button after the visual cue
	Go count	Average number of times ‘Go’ button tapped
	Duration	Average duration between the visual cue and the end of trial
	Obstacle count	Average number of passed obstacles
	Missed opportunity count Close back Close front	Average number of missed opportunities Average number of close collisions on back end Average number of close collisions on front end
Memory	Duration	Average time to complete task

	% Correct shape	Percentage of shapes drawn correctly
	Matching Lines	Average number of matching lines
	Touch Count	Average number of recorded touches
	Duration Subtask 3&4	Average time to complete subtask 3&4
	Replication Subtask 1&2	Average number of replicated shapes task 1&2
	Replication Subtask 3&4	Average number of replicated shapes task 3&4
Bi-manual perceptual motor	% Time inside target	Percentage of time inside the target
	% Fixed obstacles avoided	Percentage of fixed obstacles avoided
	% Surprise obstacles avoided	Percentage of surprise obstacles avoided
	Time on Right Edge	Average time spend on right screen cut off edge
	Time on Left Edge	Average time spend on left screen cut off edge

APPENDIX B:

Figure B: Visual Clarification of Tasks 1 - 4 of Tablet-Based Cognitive Task