Investigation of Mobile Games for Cognitive Assessment and Screening with a Focus on Touch-based and Motion Features

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By

Jittrapol Intarasirisawat

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This thesis is dedicated to my family who have been a great source of encouragement and support

Abstract

Early detection of cognitive decline is important for timely intervention and treatment strategies to prevent further deterioration or development of more severe forms of cognitive dysfunction. Therefore, many tests have been developed for screening and monitoring changes in cognitive status. However, these existing assessment and screening tools are not designed for self-administration without a trained examiner. Moreover, the lack of multiple variations of these paper-based measures and repeated exposure to such tests could reduce their sensitivity to detect cognitive changes due to practice effects. These limitations pose clinical challenges to early identification of cognitive deficits and monitoring of longitudinal changes in cognitive function, especially in resource-limited settings. To this end, a number of studies have adopted mobile technology and gamification to facilitate remote and self-administered cognitive assessment and screening in a less effortful and engaging manner. Despite this, existing literature has so far only examined the feasibility of using gameplay performance as a means for cognitive assessment. There has not been any attempt to explore gameplay behaviours as revealed through patterns of touch interactions and device motions as indicative features for cognitive evaluation. Therefore the aim of this thesis is to investigate the use of touch and motions features in game-based cognitive assessment and screening. This is achieved through two studies.

The first study was carried out to examine the links between cognitive abilities and underlying patterns of user-game interaction with a focus on touch gestures and device motions. Twenty-two healthy participants took part in the two-session experiment where they were asked to take a series of standard cognitive assessments followed by playing three casual mobile games in which user-game interaction data were passively collected. The results from bivariate analysis indicated that increases in swipe length and swipe speed, in the game context, were significantly correlated with declines in response inhibition ability but increased performance on attention. However, it remained unclear whether the device motion features alone could be used to identify cognitive ability as the results provide only weak evidence for relationships between cognitive performance and the underlying device motion patterns while playing the games.

In the second study, we evaluated the potential use of these behavioural features and mobile games as a potential screening tool for clinical conditions with

cognitive impairment. Alcohol-related brain damage (ARBD) is often found to be associated with deficits in multiple cognitive functions in patients with alcohol dependence, which is the focus of this thesis. Based on findings from the preliminary study, the second experimental study was carried out to investigate the feasibility of using such user-game interaction patterns on mobile games to develop an automated screening tool for alcohol-dependent patients. The classification performance of various supervised learning algorithms was evaluated on data collected from 40 patients and 40 age-matched healthy adults. The results showed that patients with alcohol dependence could be automatically identified accurately using the ensemble of touch, device motion, and gameplay performance features on 3-minute samples (accuracy=0.95, sensitivity=0.95, and specificity=0.95).

The findings provide evidence suggesting the potential use of user-game interaction metrics on existing mobile games as discriminant features for developing an implicit measure to identify alcohol dependence conditions. In addition to supporting healthcare professionals in clinical decision-making, the game-based method could be used as a novel strategy to promote self-screening, especially outside of clinical settings. The findings from this thesis were also applied to guidelines to aid researchers in the game interaction design to capitalise on the use of touch and device motion features with regard to cognitive assessment and screening.

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List of Acronyms

ACE	Addenbrooke's cognitive examination
AD	Alcohol dependence
ADHD	Attention deficit hyperactivity disorder
ARBD	Alcohol-related brain damage
AUD	Alcohol use disorder
AUDIT	Alcohol use disorders identification test
CANTAB	Cambridge neuropsychological test automated battery
CBT	Cognitive-behavioural therapy
CFS	Correlation-based feature selection
DSM	Diagnostic and statistical manual of mental disorders
EEG	Electroencephalography
EF	Executive function
GPS	Global positioning system
ICD	Diagnostic and statistical manual of mental disorders
JSON	JavaScript object notation
LR	Logistic regression
LSVM	Linear support vector machine
MCI	Mild cognitive disorder
MMSE	Mini-mental state examination
MoCA	Montreal cognitive assessment
NCV	Number of direction changes of velocity
OCD	Obsessive-compulsive disorder
RF	Random forest
SAGE	Self-administered gerocognitive exam
TBI	Traumatic brain injury
TMT	Trail making test
VR	Virtual reality
WHO	World health organization

Chapter 1: Introduction

1.1. Background

Cognitive impairment is a condition that can significantly affect individuals' well-being in a variety of ways, including emotional imbalance, memory loss and dysfunctional motor coordination, impairing their abilities to carry out daily activities independently. Apart from neurodegenerative diseases such as Alzheimer's diseases and mild cognitive impairment, other common causes of cognitive disorders include developmental disabilities, brain injury and persistent abuse of alcohol and drugs (Sacktor et al., 2002, NHS, 2020, Collie, Darby & Maruff, 2001, Jauhar, Marshall & Smith, 2014, Deik, Saunders-Pullman & San Luciano, 2012). The high prevalence of multiple chronic conditions associated with cognitive impairment is placing increasing burdens on the healthcare system worldwide. The global estimate of the economic impact of dementia alone is projected to exceed US$ 2 trillion by 2030 (Wimo et al., 2017). Such a growing demand for healthcare resources poses a serious challenge in medical facilities with inadequate staffing and limited resources. Besides, coping with cognitive disorders can place physical and emotional burdens not only on patients but also on their family members, adversely affecting their mental well-being and quality of life. It is thus important to identify individuals with early signs of impairment to provide appropriate care and timely treatment. Frequent cognitive assessment and screening could reduce the risks of progression to more severe forms of impairment which require more intensive care and support.

Although widely used in clinical practice, current neuropsychological tests require qualified examiners to administer and lack alternative forms which could allow learning effects to take place. In that, where repetitive cognitive testing occurs, the test performance of an individual tends to improve due to prior test exposure. These practice effects may, in turn, undermine the ability of the test to early detect cognitive decline (Howieson, 2019). Similarly, aside from these limitations, the traditional screening instruments for alcohol-related cognitive impaired conditions known as alcohol use disorders mainly involve retrospective self-report which could be biased and thus may affect the accuracy of the results (Babor et al., 2001, Gilligan et al., 2019). Given such limitations, substantial research effort has been made to explore new technology-assisted screening methods, which can allow more frequent self-assessment with minimal assistance or supervision to monitor changes in cognitive functioning and detect early signs of impairment.

In the past decade, technological advancements, particularly the computerised cognitive assessments, have been investigated for their potential to allow self-administration and therefore reduce administrative burdens on healthcare providers. Furthermore, the increasing availability of Internet access provides a unique opportunity for large-scale implementation of cognitive screening using such computerised measures (Wild et al., 2008). Despite several advantages over traditional paper-based approaches, the use of mouse and keyboard in computer-based tests has been often criticised for posing particular difficulty for individuals with severe cognitive impairment (Zorluoglu et al., 2015). On the contrary, mobile devices offer a more intuitive interface through gesture-based interactions making them easy to use even for people with little or no computer experience. Besides, the inherently portable feature of mobile devices can facilitate remote cognitive assessment, allowing pro-active cognitive screening to early detect acute cognitive decline outside of clinical settings (Koo, Vizer, 2019). However, these neuropsychological tests are often considered as time-consuming, repetitive and boring, leading to individuals' disengagement and difficulty promoting in-home, self-directed cognitive assessment and screening (Lumsden et al., 2016, Flores et al., 2008).

In addressing this concern, a growing body of research explored the feasibility of using gamification to motivate individuals to adhere to continual cognitive assessment. It has been argued that by incorporating game design elements into cognitive measures such as challenges, audio-visual game effects and dynamic game environment can increase levels of interest and therefore potentially create long-term engagement in game-like cognitive assessment (Lumsden et al., 2016). The shift of game development from desktop to mobile platforms enables researchers to exploit the ubiquitous sensing capability to passively track user-behaviours during the gameplay. Previous studies investigated the use of these new data streams in cognitive assessment and screening, for example, gameplay performance (Tong et al., 2016), irregularities in speech (Konig et al., 2018) and finger dexterity (Suzumura et al., 2018).

Furthermore, studies have shown that several neurological disorders were found to exhibit cognitive deficits and irregular patterns, in fine motor movement, when interacting with a digitised tablet using a digitised pen (Tigges et al., 2000, Mavrogiorgou et al., 2001, Schroter et al., 2003). Thus it could be anticipated that touch and device motion patterns collected via user-game interactions can be used as indicative features to enhance the accuracy of cognitive assessments. Therefore, the present thesis aims to examine this unexplored area of research and to demonstrate the feasibility of using such features as implicit measures in game-based cognitive assessment and screening.

1.2. Aim and research questions

Based on the review of existing literature regarding gamification and cognitive assessment and screening, it was evident that most of the research in this field focuses on the gameplay activities (e.g. response time, number of moves and max scores) as evaluation metrics to measure cognitive abilities. Given that mobile games generally involve touch-based interactions through intuitive touch controls (e.g. virtual joysticks and buttons) to interact with the game elements, there is no previous research examining the use of the touch input and device movement which can be passively collected via motion sensors built in a mobile device. Furthermore, the most common challenge in using serious games in the cognitive research is that it involves an iterative design and development process, which requires expertise, financial resources and a significant amount of time to test and refine the game before it can finally be deployed in the experiment. Thus, the aim of this thesis is to investigate the feasibility of using off-the-shelf mobile games and user-game interaction patterns for cognitive assessment and detecting individuals with a clinical condition associated with cognitive impairment. The main focus is on identifying the patterns of touch gesture and device motion during gameplay that are associated with cognitive performance and examining whether such patterns can be used as discriminant features for developing an automated screening tool. The results of this research demonstrate the feasibility of using touch gesture and device motions in cognitive assessment and screening. This thesis will address the following research questions:

1. *Do implicit user-game interaction patterns, i.e. touch interaction and device motion, correlate with cognitive performance?*

   The first research question aims to identify existing relationships between cognitive performance and underlying patterns of user-game interaction through touch gesture and device movement. Examining the links between these features and cognitive performance would be the first step to determine the potential use of touch-based and device motion patterns in developing an automated cognitive screening instrument. This question is mainly addressed in Chapter 3, where a study was carried out. User-game interaction data were passively collected from playing off-the-shelf mobile games and analysed to identify associations that exist between such mobile gameplay behaviour and cognitive abilities.

2. *Do game mechanics and related cognitive demand influence gestural characteristics?*

   The second research question aims to investigate whether touch interaction patterns could be potentially influenced by game mechanics and cognitive demands associated with in-game tasks. Given that the primary objective of performing specific gestures on the screen is to accomplish the game missions by strategically interacting with visual elements within the game, it is anticipated that user gestural interaction is also likely to be triggered by such visual stimuli, rules and gameplay mechanics. Therefore, a broad set of mobile games with different gameplay and rules were employed in the study in Chapter 3 to examine the influence of game mechanics and respective cognitive demands on gestural characteristics. The findings of this study also provide suggestions on how the touch and device motion features can be used in mobile game-based cognitive assessment, taking into account the influence of game mechanics and associated cognitive demands.

3. *Can touch interaction and device motion patterns be used to identify individuals with a clinical condition associated with cognitive impairment?*

   Based on the findings from the study in Chapter 3, it was found that the proposed touch-based and device motion features were significantly related to performance on multiple measures of domain-specific cognitive function. The study in Chapter 4 aimed to explore further whether such features extracted from user-game interactions can be used in conjunction with machine learning algorithms to automatically identify individuals with a medical condition associated with impaired cognitive functioning. Given that the deficits in multiple cognitive abilities and impaired control over hand movement are closely linked to long-term excessive alcohol drinking behaviour, the controlled study carried out in Chapter 4 involved patients diagnosed with alcohol dependence and a control group of cognitively normal individuals. Extracted features from touch interaction and device motion patterns during gameplay were used to train classifiers for identification of patients with alcohol dependence. The results of this study are presented in Chapter 4. Moreover, the implications of the results are further discussed in Chapter 5.

4. *Which specific user-game interaction features are important features for developing a classification model?*

   The results of the controlled study in Chapter 4 demonstrated the feasibility of using user-game interaction patterns in a mobile game-based screening tool for alcohol dependence. The findings, in turn, led to this question which aims to identify key features that are most important for developing the game-based classifier. This research question is mainly addressed in Chapter 4.

1.3. Contribution

The key contribution of this PhD thesis provides insights into how touch interaction and device motion patterns can be used in game-based cognitive assessment and screening, a topic which is a relatively unexplored area of research in the field of gamification and cognitive psychology. The overall contributions of this thesis can be summarised as follows:

1. Demonstrate the feasibility of the proposed mobile game-based assessment with healthy young adults in a lab setting. The findings in Chapter 3 demonstrate potential correlations between user-game interaction features and cognitive performance in multiple domains.
2. Demonstrate the feasibility of using off-the-shelf mobile casual games and user-game interaction patterns with a focus on touch interaction and device motion to identify a clinical condition associated with cognitive impairment (alcohol dependence).
3. Identify and develop versions of off-the-shelf mobile casual games with sensing capabilities to track touch interaction and device motion patterns along with gameplay performance.
4. Generate a novel dataset of alcohol dependence and mobile game interaction patterns
5. Propose and demonstrate touch interaction and device motion features which can be used to improve the model classification performance to classify patients with alcohol dependence.
6. Provide an understanding of how game mechanics and related cognitive demands could influence gestural characteristics and statistical correlations between touch patterns and cognitive performance.

7. Provide some design recommendations on how the touch interaction and device motion can be used in mobile game-based cognitive assessment and screening.

1.4. List of publications

The findings derived from this thesis have been presented and published in peer-reviewed journals and conferences. The publications are summarised in Table 1.

Table 1: A list of publications arising directly from this PhD thesis

Chapter	Journal/Conference	Title	Citation
3	MobiUK, abstract presentation (2019)	Exploring the Touch and Motion Features in Game-Based Cognitive Assessments	Jittrapol Intarasirisawat*, Chee Siang Ang, Luke Dickens, Christos Efstratiou and Rupert Page
3	UbiComp: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, article paper (2019)	Exploring the Touch and Motion Features in Game-Based Cognitive Assessments	Jittrapol Intarasirisawat*, Chee Siang Ang, Luke Dickens, Christos Efstratiou and Rupert Page
4	UbiComp: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, article paper (2020)	An Automated Mobile Game-based Screening Tool for Patients with Alcohol Dependence	Jittrapol Intarasirisawat*, Chee Siang Ang, Christos Efstratiou, Luke Dickens, Burachai Asawathaweeboon, Naranchaya Sriburapar and Dinkar Sharma

1.5. Scope

The overarching aim of this thesis is to explore the feasibility of using user-game interaction patterns passively collected via off-the-shelf mobile games to develop an automated screening tool for a medical condition closely associated with cognitive impairment. Examining the potential use of touch interactions and device motions to assess cognitive abilities and identify individuals with cognitively impaired conditions is the focus of this research. In particular, patients diagnosed with alcohol dependence are the target population, given that declines in cognitive abilities and motor deficits are commonly found in such a condition. Each year in the UK, there are over 7 million alcohol-related attendances in the emergency departments (ED) and more than 1 million hospital admissions attributable to unhealthy alcohol use (The Institute of Alcohol Studies, 2015, NHS England, 2021). Despite the high number of patients with alcohol-related presentations in primary care and emergency departments, as well as the national recommendations for early alcohol screening and intervention, the implementation of routine screening for alcohol use disorders in these settings remained sparse (Forsythe, Lee, 2012). The attitude of ED healthcare workers towards current alcohol screening and intervention practices was one of the primary barriers (Karlsson et al., 2005). Most nursing staff reported their concerns about the workflow disruption in stressful working conditions and the fear of offending patients when asked about their drinking habits (Karlsson et al., 2005, Anderson et al., 2001). Therefore, previous studies suggested that non-resource demanding self-screening activities could be used in the waiting area where patients spent time queuing for medical treatment and results (Karlsson et al., 2005, Bendtsen, Holmqvist & Johansson, 2007, Forsythe, Lee, 2012). Nevertheless, when informed of screening results, many people with alcohol addiction often do not have sufficient motivation to seek treatment. They may not see that their drinking habit is severe enough to be a problem (SAITZ, 2010, Glass et al., 2017, Edlund, Booth & Feldman, 2009). When identified as a person with alcoholism, seeking alcohol addiction treatment would induce more feelings of shame and low self-esteem as their unhealthy drinking behaviours are deemed to violate social norms (Glass et al., 2017). Such an attitude towards alcohol drinking and the stigma of alcohol use disorders are often seen as the main barriers to receiving appropriate alcohol intervention (Mojtabai, Crum, 2013, Glass et al., 2017, Grant, 1997, SAITZ, 2010).

For these reasons, self-screening alone may not be effective enough to influence changes in drinking behaviours. Indeed, clinical advice for further diagnosis and perhaps referrals to treatment should also be given by healthcare practitioners based upon screening results. This thesis was motivated by such a real-world clinical scenario, where a game-based measure could be used for alcohol self-screening while ED or primary care patients are spending a significant amount of time in a waiting area. Screening results could be sent to clinicians who would provide further discussions and recommendations when alcohol use disorders are identified.

Investigating the use of game-based cognitive assessment on age-related cognitive disorders, e.g. mild cognitive impairment and dementia in older people are not within the scope of this thesis. It should also be noted that this thesis does not aim to provide insight into a methodology of design and development of a new serious game for assessment of cognitive abilities. Instead, this research focuses on exploring the use of off-the-shelf mobile games as a novel screening measure for the particular cognitively impaired condition (i.e., alcohol dependence). An understanding of the links between the proposed features extracted from user-game interactions and cognitive performance is essential to identify key features for building the automated game-based cognitive measure. Thus, the first study (see Chapter 3) involved 22 healthy young adults (18-34 years old) with an aim to address such a research gap. The rationale for selecting this group of individuals as a target population in the first study is that they would likely be more familiar with interactions in mobile mode and game-like applications. However, these cognitively normal participants would likely exhibit scores in paper-based cognitive tests within a narrow range closer to maximum scores (Schroter et al., 2003). Therefore, a particular cognitive task was employed to stimulate mental fatigue for inducing a temporary cognitive decline to gain a greater variability in scores of standard cognitive measures for these participants. Individuals with excessive gaming behaviour were excluded to reduce the effects of prior game experience on research outcomes.

The second study (see Chapter 4) investigates the potential use of gameplay behaviour with a focus on gesture and device motion patterns to facilitate self-screening for early detection of potential alcohol dependence outside of clinical settings. Data samples were collected from 40 alcohol-dependent patients admitted into an inpatient rehab facility after being detoxified and 40 age-matched healthy adults (24-65 years old). The justification for using such criteria for recruiting participants in the patient group is that patients undergoing alcohol detoxification usually cannot maintain their focus and attention, thus having difficulties completing tasks at hand (Chris Elkins, 2020). In particular, this study aims to develop a classifier that can identify patients with alcohol dependence using combinations of user-game interaction features as input.

Although usability issues are essential points to consider in research exploring the use of mobile game technology, such issues are not the main focus and beyond the scope of this thesis. The main focus of this thesis is to examine the potential use of user-game interactions with a focus on touch-based and device motion for cognitive assessment and early detection of individuals who are at risk of developing the alcohol dependence condition.

1.6. Structure

The thesis is structured as follows:

- Chapter 2 presents a review of the literature and studies related to this thesis. The key topics related to cognitive impairment as well as the limitations of existing cognitive measures, are discussed. Next, the potential use of computer and mobile technology, including gamification for assessment, is reviewed. This is followed by a review of current standard measures for alcohol use disorder, current alcohol screening implementation and the use of technology to facilitate assessment and screening activities. At the end of the chapter, the association between health conditions and changes in fine motor abilities is discussed.

- Chapter 3 outlines the results of a preliminary study which examines the association between user-game interaction behaviours and performance on conventional cognitive tests. The results of the correlation analysis revealed significant correlations between several proposed features and cognitive scores. For instance, poorer performance on multiple cognitive domains was related to increased levels of device movement variability during the gameplay. The findings suggest that touch interaction and device motion patterns could be used as indicative features on mobile game-based cognitive assessment.

- Chapter 4 extends the findings of the study in the previous chapter by employing these user-game interaction metrics on off-the-shelf mobile games to develop an automated self-screening measure for alcohol dependence. The results demonstrate that mobile game-based measures could be a cost-effective and promising solution to promote home-based self-screening for early detection of alcohol dependence.

Chapter 5 provides an overall discussion and conclusion to the thesis where gameplay behavioural patterns with the focus on touch interaction and device movement were used as key features to develop an implicit measure to assess cognitive abilities and identify patients with alcohol dependence. Research contributions and implications drawn from the studies are presented to provide possible practical applications of mobile game-based measures and aid health professionals, game designers and researchers to optimise the use of touch and device motion patterns in mobile game-based cognitive assessment. Finally, this final chapter then discusses the limitations of the present thesis and suggests possible research areas for further work.

Chapter 2: Literature Review

This chapter presents a review of existing literature and research on a range of topics related to the key components of this thesis. The chapter first discusses the key terms and definitions with regard to basic cognitive functions (section 2.1), cognitive impairment (section 2.2.1) as well as the importance of early detection and timely intervention of such conditions (section 2.2.1). Then, the current standard measures, their limitations (section 2.2.2) and the potential use of technologies for assessment and intervention (section 2.2.3) are examined. This is followed by the definitions and current clinical assessment of alcohol user disorder (section 2.4), a clinical condition which adversely affects cognitive functioning. The limitations of these conventional assessment methods led us to the review of the potential use of digital technologies, especially mobile games, to support assessment and clinical intervention (section 2.3). Finally, the relationship between gesture and motor patterns and health conditions is explored (section 2.5).

2.1. Cognitive Functions

Cognitive functioning refers to a range of mental abilities to acquire and process information in order to successfully carry out any tasks from the simplest to the most complex (Carroll, 1993). In other words, it can be described as an individual's capacity to learn, remember, pay attention, make decisions, and understand complex ideas. Cognitive functioning is, therefore, essential for autonomously performing daily activities and maintaining a person's general well-being (Cambridge Cognition Ltd., 2015). Cognitive functions can be categorised into multiple domains, including attention, memory, visuospatial ability, and executive functions (EF). These basic cognitive processes are described as follows:

a) *Attention*: A complex ability that allows an individual to focus on specific stimuli among a range of stimuli from the environment simultaneously received by our sensory organs (Hodges, 2007). It can be further divided into several types, e.g., sustained attention, selective attention, and divided attention.
b) *Memory*: A process of maintaining information over time, involved in encoding, storage, and subsequent retrieval of information (M., 2012). Memory is broadly divided into two major categories: long-term memory and short-term memory or so-called working memory.

c) *Visuospatial Ability*: It is an ability to visually determine the spatial relationship among objects. It is required for movement and navigation in relation to the surrounding environment (Luursema, Verwey & Burie, 2012).

d) *Executive Functions (EF):* A set of mental processes that allow an individual to control behaviour to resist acting on impulse, maintain focus, and flexibly respond to unexpected situations in order to achieve their goals. Core executive functions include inhibition control, selective attention, working memory, and cognitive flexibility. In addition, reasoning, problem-solving, and planning abilities are built based on these core executive functions (Diamond, 2013).

Considering the importance of cognition in our daily functioning, it is crucial to maintain cognitive health and prevent cognitive decline. A severe deterioration in cognitive functions can adversely affect a person, resulting in difficulties in accomplishing day-to-day tasks independently. This particular condition is termed "cognitive impairment".

2.2. Cognitive Impairment

2.2.1. What is cognitive impairment

Cognitive impairment occurs in a wide range of clinical conditions which adversely impact higher brain function. Causes of cognitive deficits include stroke, dementia, traumatic brain injury, and alcohol and drug use as well as less common causes such as developmental disorders and encephalitis (Sacktor et al., 2002, Jauhar, Marshall & Smith, 2014, Barkley, 1997). Mild cognitive impairment (MCI) is a diagnostic term referring to a stage of cognitive decline beyond normal cognitive ageing but not as severe as dementia. People with MCI display early symptoms of cognitive deficits, for instance, rapid mood changes, being easily distracted, struggling with reasoning and making decisions, or forgetting things more often than usual. However, this slight but noticeable change in cognition is not severe enough to cause major problems in daily activities (Alzheimer's Society, 2020, National Institute on Aging, 2020). Often people with MCI are at higher risk of progressing to a more severe form of cognitive impairment such as dementia that can interfere significantly with individuals' daily life (Petersen et al., 2001). Symptoms of dementia are progressive over time. This means the cognitive functioning will continue to decline throughout the patient's life. Severe levels of dementia can lead to losing abilities to do simple daily tasks independently, e.g. taking a shower or getting dressed (NHS, 2020).

A traumatic brain injury (TBI) is another risk factor for cognitive dysfunction. Athletes with exposure to accumulative traumatic brain injuries in sports, e.g. boxing, football, or rugby, often exhibit symptoms of cognitive deficits. In severe cases, patients with TBI may experience persistent cognitive disabilities, such as disturbance of attention, memory and executive functioning. To reduce the risk of progressing to the long-lasting stage of cognitive impairment, regular monitoring of cognitive changes is required to determine whether they can safely resume their participation in the game (Collie, Darby & Maruff, 2001).

Long-term excessive alcohol use can also cause significant brain damage resulting in cognitive deficits and impaired physical functioning. The term alcohol-related brain damage (ARBD) is used by therapists to describe a spectrum of alcohol-related cognitive impairment (Jauhar, Marshall & Smith, 2014, Chris Emmerson and Josie Smith, 2015). In addition to malnutrition (vitamin B1 deficiency), chronic excessive alcohol consumption can cause cumulative damage to brain function. A person with ARBD is likely to exhibit memory problems, poor judgment, impaired visuospatial abilities, and reduced motor control, including uncontrollable shaking of hands and poor physical coordination and balance (Bernardin, Maheut-Bosser & Paille, 2014, Jauhar, Marshall & Smith, 2014, Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998).

In general, cognitive impairment, especially with mild symptoms, often remains unnoticed and, therefore, untreated even in patients during their hospital admission (Torisson et al., 2012). This could lead to further functional decline, exacerbating the condition and other health problems.

According to the World Health Organization (WHO), approximately 50 million people worldwide have dementia. With about 10 million new cases each year, the global number of people with dementia is forecast to triple by 2050 (World Health Organization, 2020). In the UK alone, around 850,000 people are living with dementia. This figure is projected to double by 2040 (Alzheimer's Society, 2020a). With regard to the financial impact, the estimated global cost of dementia is approximately US$ 820 billion a year (World Health Organization, 2015). Moreover, each year an estimated 200,000 people in England and Wales are hospitalised with head injuries. About 20% of admitted patients are diagnosed with traumatic brain injuries. In severe cases, detrimental effects of the injury may result in long-term disability which could potentially be avoided with the early intervention (National Clinical Guideline Centre, (UK), 2014). With respect to alcohol-related cognitive impairment, research evidence has shown that the prevalence of ARBD in the UK was around 0.5% in the general population and 30% in heavy drinkers as a result of excessive alcohol misuse (Cook, Hallwood & Thomson, 1998). Evidence from several countries suggested that ARBD may account for 10-24% of all cases of dementia among care home residents (Chris Emmerson and Josie Smith, 2015). Despite the prevalence of ARBD, the condition is likely to be underdiagnosed. Many people with ARBD yet are unrecognised and often remain untreated (Alzheimer's Society, 2020). These statistics pose an adverse impact and a critical challenge to health care systems and patients' well-being.

Hence, early detection of subtle signs of cognitive decline provides a greater opportunity for timely intervention (Dubois et al., 2016). Studies have shown that 75% of people with ARBD show improvement in their cognitive abilities with timely and appropriate treatment (Wilson, 2014). Although for people with severe cognitive impairment, e.g., dementia, the symptoms worsen over time and in some cases are irreversible, early diagnosis and timely treatment can still slow down its progression as well as allow family members and caring partners to prepare a care plan to cope with patients' condition in the future (Boise et al., 1999).

2.2.2. Standard measures and limitations

The previous section highlighted the importance of timely diagnosis of early symptoms of cognitive impairment to prevent and better manage further decline. In some cases, such cognitive changes are relatively subtle and often overlooked. Therefore, cognitive testing is crucial to assess individuals' cognitive functioning and recognise early warning signs of more severe cognitive deficits, allowing the individuals to seek support from health care professionals and receive timely appropriate treatment.

In this regard, a multitude of neuropsychological tests has been developed and used as screening measures for cognitive impairment and monitoring of cognitive changes. This section will describe some of the key standard assessments. These include Mini-Mental State Examination (MMSE) (Tombaugh, McIntyre, 1992), Addenbrooke's Cognitive Examination-III (ACE-III) (Hodges, 2007), Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005), the Stroop Color-Word Test (Homack, Riccio, 2004), Go/No-Go discrimination task (Yechiam et al., 2006), and Trail Making Test (TMT) (Tombaugh, 2004).

2.2.2.1. Mini-Mental State Examination (MMSE)

It is a 30-point questionnaire that is widely used to measure cognitive impairment in both clinical and research settings (Pangman, Sloan & Guse, 2000). It was purposely developed to examine the cognitive decline in older people with dementia and delirium in a number of different areas of cognitive abilities such as attention/concentration, memory, language and visuospatial abilities. A score of less than 24 was suggested to indicate significant cognitive impairment (Hodges, 2007, Tombaugh, McIntyre, 1992).

Although the test is quick and easy to administer covering multiple cognitive domains, the use of the MMSE is restricted by copyright and requires a license to be purchased for administration (Newman, Feldman, 2011). The test is also less effective in detecting mild cognitive impairment but more useful for screening patients with advanced degrees of dementia. Moreover, the assessment score is subject to the effects of age, education and ethnicity (Hodges, 2007).

2.2.2.2. Addenbrooke's Cognitive Examination (ACE-III)

The Addenbrooke's Cognitive Examination (ACE-R) was developed in the 1990s with the aim to introduce an assessment with more sensitivity to mild cognitive impairment and provide clearer cognitive subset scores than MMSE. Participants are asked to follow the instructions to perform various tasks to assess cognitive abilities in attention/orientation, memory, verbal fluency, language and visuospatial domains. The scoring is carried out at the end of the session to avoid the anxiety that may disturb the participants' performance on the test (Hodges, 2007) .

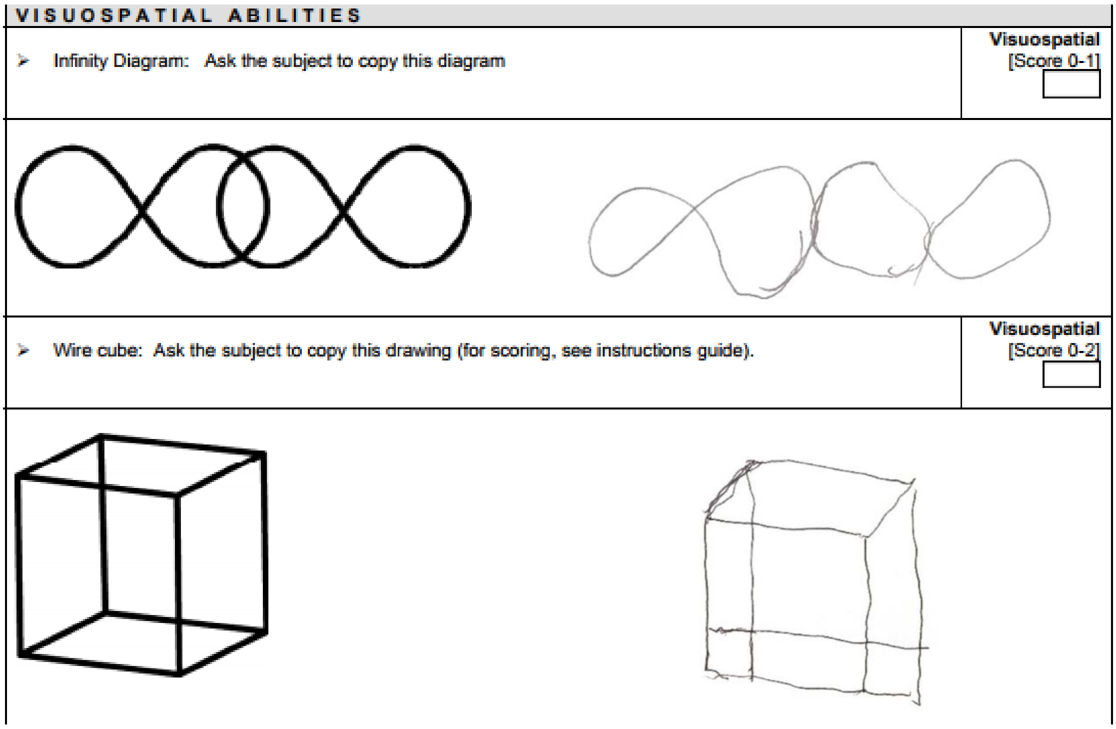


Figure 1: Examples of drawing tests available in ACE-III assessing visuospatial abilities

The author of this test had to withdraw ACE-R due to the copyright violation with MMSE. The subsequent ACE-III was developed by removing MMSE-items and has been made freely available. The main changes are in the language and visuospatial domains (Figure 1). The score is highly correlated to its predecessor (Hodges, Larner 2017).

Generally, the administration takes approximately 15 minutes. The test is assessed in a total score of 100. A score of 82 or lower suggests cognitive impairment (Hodges, 2007).

2.2.2.3. Montreal Cognitive Assessment (MoCA)

The test was specifically developed for detecting mild cognitive impairment by assessing attention and concentration, executive functions, memory, language, visuospatial abilities, calculations, orientation and conceptual thinking. The administration of the MoCA takes 10 minutes on average. Out of 30 points, a score of 25 or lower indicates that participants are cognitively impaired (Nasreddine et al., 2005). The MoCA has been considered to be a better screening tool for the early stages of cognitive decline (Hobson, 2015). Given its high sensitivity and specificity in detecting mild cognitive impairment, the MoCA is commonly used as a brief screening instrument to identify alcohol-related cognitive deficits in patients with alcohol use disorders (Alarcon et al., 2015, Pelletier et al., 2016, Bernardin, Maheut-Bosser & Paille, 2014).

2.2.2.4. The Stroop Color-Word Test

The Stroop Color-Word test provides a measure of selective attention and executive functions, mainly in inhibition controls. Within a time limit, a person is required to name the ink colours rather than to read words which sometimes printed in conflicting ink colours (e.g. the word ‘red’ printed in blue ink) (Homack, Riccio, 2004). When the ink colour and the meaning of the word are incongruent, it creates a conflict in the brain and requires longer processing time to name the ink colour correctly. For instance, if a yellow ink is used on a printed word “yellow”, the response time is shorter than when the word “yellow” is printed in a different ink colour, e.g. “red” or “blue” (Hodges, 2007). More response time (RT) is required in case of individuals with impaired cognitive abilities. In general, weaker performance is exhibited in cognitively impaired individuals, as they also tend to make more errors than normal adults (dos Santos Assef, Ellen Carolina, Capovilla & Capovilla, 2007).

2.2.2.5. Go/No-Go Discrimination Task

The task was designed to assess behavioural inhibition in individuals. In the task, two types of stimuli are continuously presented to participants while they have to learn to respond to positive cues and withhold their response to negative cues. Upon correct responses, participants receive a reward (e.g. financial incentive or gaining points) for the positive feedback. Punishment or negative feedback (e.g. monetary loss or point penalty) is given to incorrect responses. The task examines the failure to inhibit a response to negative stimuli (commission errors) and the failure to respond to positive stimuli (omission errors) (Yechiam et al., 2006).

More commission errors caused by ignoring negative cues tend to occur with individuals who pay more attention to reward rather than punishment. In contrast, individuals who have more attention to punishment rather than reward tend to miss more positive cues; as a result, have more omission errors (Yechiam et al., 2006).

2.2.2.6. Trailing Making Test (TMT)

TMT is commonly used as a neuropsychological test and is bundled in many test batteries. The TMT provides measures of visual search, scanning, speed of processing, mental flexibility and executive function. The test consists of two parts. Both parts of TMT consist of 25 circles scattered on a sheet of paper. In Part A, the circles are labelled with numbers from 1 to 25. Participants are required to draw a line to connect all circles in ascending order as quickly as possible without lifting a pen or pencil from the paper. In Part B, the circle includes both numbers and letters. Similar to Part A, participants are asked to draw a line connecting all circles in ascending pattern in which they must alternate between numbers and letters, e.g., “1-A-2-B-3-C”) (Tombaugh, 2004).

Performance on the TMT is sensitive to age, and individuals with impaired executive functions usually perform poorly on Part B (Hodges, 2007).

2.2.2.7. Limitations of Existing Clinical Measures

In summary, the broad cognitive domains assessed by the standard tests such as those described in section 2.1 are attention, orientation, memory, language, visuospatial, and executive functions. Examples of these assessments can be found in the Appendix. Clinicians assess performance across these domains according to either established statistical population data or practice-based heuristics (Hodges, 2007). These measures can provide a diagnostic snapshot of cognitive functions allowing differentiation between normal and disease states. However, these cognitive tests are typically paper-based and not designed for self-administration or for use by non-healthcare providers. As a result, the assessment is commonly performed within medical facilities during face-to-face clinical visits.

Although widely used in research and clinical practice, these brief cognitive tests have been criticised for being sensitive to practice effects (Chapman et al., 2016, Cooley et al., 2015, Khaligh-Razavi et al., 2019). These learning biases are likely to inflate scores on the tests and thus could significantly undermine diagnostic reliability (Cooley et al., 2015, Khaligh-Razavi et al., 2019). Hence, repeated exposure to the same cognitive tests over a short interval could limit their sensitivity to detect longitudinal changes in cognitive function (Cooley et al., 2015). This poses a barrier for using these existing assessment tools in clinical evaluation for people with early cognitive impairment but at high-risk of developing more severe cognitive disorders. Similarly, in many sport settings, assessments typically need to be conducted frequently to monitor the cognitive status of the athletes to determine their readiness to return to sport after injury. Practice effects are likely to substantially influence their performance on serial cognitive assessments (Cooley et al., 2015).

Owing to the lack of multiple variations of the tests and the inability to self-administer, it is infeasible to run the traditional cognitive measures frequently to monitor changes in cognitive functions over time due to learning effects, costs and resource requirements around the availability of qualified clinical staff to administer them. These can adversely affect the ability of clinicians to detect the early signs of decline in cognitive functions, potentially delaying diagnosis and treatment as well as undermining the effectiveness of medication or other interventions (Schweiger et al., 2003). These indicate an underlying need for alternative cognitive measures that allow frequent repetitive testing. The next section will review past and current studies that explored the use of computerised technologies for early detection of cognitive changes and facilitating continuous cognitive assessment.

2.2.3. The use of computerised technologies in cognitive assessment

To address the limitations of traditional paper-based measures in early recognition of cognitive changes, a growing body of research has examined the feasibility of assessing cognitive functions on digital platforms. Previous studies have recognised the potential use of computerised (Wild et al., 2008) assessment instruments for large scale screening and monitoring of cognitive decline , citing the capacity to generate random stimuli, provide highly accurate measurement of task performance, and allow immediate access to results as key advantages (Collie, Darby & Maruff, 2001, Wild et al., 2008, Lenehan et al., 2016, Onoda et al., 2013, Soares et al., 2014). Another frequently cited advantage of using computer technology in psychological assessment is that it could reduce administrative burdens on medical staff and materials, thus saving administration time and costs (Wild et al., 2008) .

In this literature review, computerised cognitive measures were further categorised into two groups: PC-based and mobile-based platforms.

2.2.3.1. PC-based cognitive measures

In the early development of computerised cognitive assessments, desktop computers with a mouse and keyboard are commonly used.

For instance, the Stroop Word Colour test is one of the existing traditional cognitive tests that have been translated to a computer platform. Its computerised version was developed based on the Victoria Stroop test and was validated its use in many research studies (Khaligh-Razavi et al., 2019, Coelli et al., 2016). In this test, visual stimuli are presented on the screen, while responses are made via a computer keyboard using a restricted set of keys. It has been demonstrated that the computer-based version can provide a more reliable evaluation with more accurate response time and the number of errors that are made during the test.

Other studies have investigated the efficacy of newly developed computerised cognitive tests. Both MCI Screen[1] (Trenkle, Shankle & Azen, 2007) and CANS-MCI[2] (Tornatore et al., 2005) are computer-administered neuropsychological tests developed as a screening tool for mild cognitive impairment. The tests focus on a limited range of cognitive domains including language, memory and executive functions. Therefore, the tests are rather short and take about 10 – 30 minutes to complete. MCI Screen, a word-list recall test, was claimed to be more sensitive in detecting cognitive impairment as compared to the paper-based MMSE. Nevertheless, the test must be fully administered by clinical staff rather than self-screening (Trenkle, Shankle & Azen, 2007). Similarly, although claimed to be fully self-administered, the administration of CANS-MCI has to be set up by a moderator and was designed for use only within clinical premises. CANS-MCI was argued to demonstrate significant correlations with conventional paper-based tests, showing promise as a short, reliable and valid cognitive screening instrument (Trenkle, Shankle & Azen, 2007, Tornatore et al., 2005).

Some of the tests offer a more comprehensive evaluation of cognitive functioning, i.e., cognitive test batteries, which typically comprise multiple subtests for various cognitive domains. One of the most widely used comprehensive test batteries for cognitive measurements in clinical research is the Cambridge Neuropsychological Test Automated Battery (CANTAB)[3]. The test battery includes various tests measuring a range of cognitive functions, e.g. executive function, attention, memory and decision making (Zygouris, Tsolaki, 2015). It has been used extensively to measure cognitive functions in older people (Robbins et al., 1994), athletes with exposure to repeated brain injuries (Collie, Darby & Maruff, 2001), for paediatric neuropsychological assessment (Luciana, 2003), HIV dementia patients (Sacktor et al., 2002) and alcohol drinkers (Hermens et al., 2013). However, the test battery requires a trained examiner for cognitive evaluation (Wild et al., 2008). MicroCog is another fully self-administered test battery on a multiple-choice format covering six domains: attention, memory, reasoning, calculation, mental control and spatial processing. The test was reportedly able to identify cognitively healthy adults from MCI patients (Green et al., 1994). CogState[4] is a battery of card-based tasks targeting continuous assessment of cognitive functions associated with reaction time, working memory and matching ability. No

[1] http://www.mciscreen.com/
[2] https://screen-inc.com/
[3] https://www.cambridgecognition.com/cantab/
[4] https://www.cogstate.com/

practice effects were found on repeated administration at two-time points with one month apart (Falleti et al., 2006). Furthermore, with the widespread use of the Internet, the Cognitive Stability Index (CSI), an internet-based cognitive screening tool provides an opportunity for self-assessment outside of clinical facilities, giving health professionals immediate access to current and past records of patients' cognitive status. The authors argued that CSI could be potentially used for monitoring cognitive changes at home with minimal clinical supervision (Erlanger et al., 2002).

In summary, current tests and relevant studies have identified benefits of cognitive evaluation on digital platforms over the traditional test batteries in many aspects including automated scoring, immediate report generation and access to previous records for comparison. However, other than the web-based approach (Falleti et al., 2006, Erlanger et al., 2002), most of these computerised tests were designed for use in clinical settings. With regard to administration time, the test batteries often take a longer time to complete the entire test but allow a comprehensive evaluation of cognitive functions. Some of these tests still require clinical examiners to provide instructions and administer the tests, for example, MCI Screen (Trenkle, Shankle & Azen, 2007) and CANTAB (Wild et al., 2008) while others, like CSI (Erlanger et al., 2002), CogState (Falleti et al., 2006), and MicroCog (Green et al., 1994) can be fully self-administered.

Despite just using a limited set of response keys and a mouse for the test, some users who are unfamiliar with computers, especially in the older population, were reported to experience difficulties in using such an interface for navigation through the tests, causing anxiety and frustration (Wild et al., 2008, Zorluoglu et al., 2015, Green et al., 1994). As opposed to the keyboard and mouse, interaction with smartphone touchscreen has been argued to be more intuitive and much easier to use for populations at all ages (Zorluoglu et al., 2015). The next section will provide further discussion on advanced computer-based tests and related studies which have adopted mobile technology for cognitive assessment.

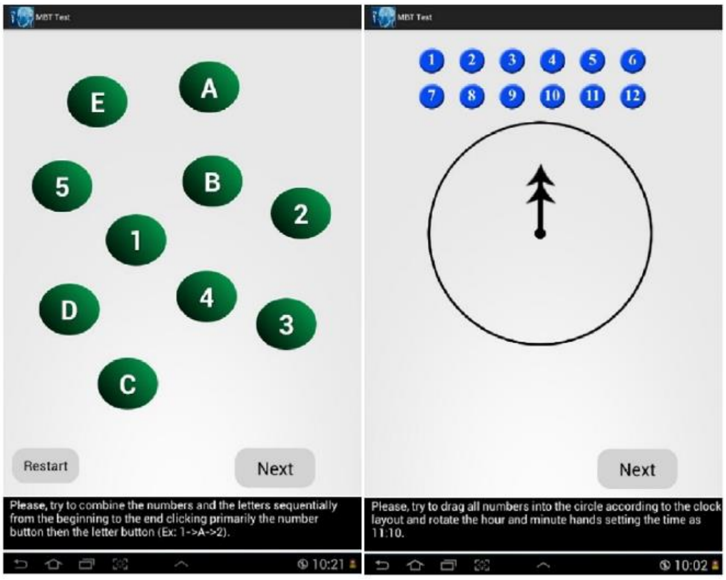
2.2.3.2. Mobile-based cognitive measures

In recent years, there has been a growing interest in developing mobile applications for cognitive assessment and diagnosis of cognitive impairment. Touch-based devices are now relatively inexpensive and easily accessible. Unlike the use of a keyboard and mouse, indicated as a barrier to use for some older adults (Taveira, Choi, 2009), intuitive touch controls reportedly enhance user-application interaction and ease of use (Caprani, O'Connor & Gurrin, 2012).

As such, by digitally converting questions and tasks from the original tests, several existing paper-based and PC-based test batteries have been translated to mobile platforms, for instance, eSAGE (Scharre et al., 2017), e-CT (Wu et al., 2015), eMOCA (Berg et al., 2018), CANTAB (Lenehan et al., 2016) and CogState (Mielke et al., 2015). In such mobile-based tests, instructions and tasks are automatically presented on the screen. Besides directly typing answers via the screen keyboard, mobile technology facilitates touch interaction on the screen display, allowing responses to be made via finger taps or swipes (Scharre et al., 2017, Wu et al., 2015). Task responses are recorded and automatically scored by the software. In some cases, a trained examiner is still required to assess specific tests, e.g. in a drawing task (Scharre et al., 2017). Researchers also examined the validity of these mobile-based measures in comparison with the tradition neuropsychological tests. Scharre et al. compared performance on the eSAGE and paper-based assessments. Results demonstrated that the eSAGE scores were significantly associated with scores on the original SAGE and other cognitive test batteries (Scharre et al., 2017). Similarly, in a study with cognitively impaired patients, no statistically significant difference in test performance was found between eMOCA and its original paper-based test (Berg et al., 2018). As opposed to the PC mode, the iPad versions of CogState battery (Figure 2) allows interaction and responses to be made via finger touch and stylus. Despite such a difference in interaction modes, the same set of questions and cognitive tasks were translated into a mobile platform. Results showed that participants performed better on the PC in terms of speed and accuracy comparing to the mobile counterpart. Nevertheless, the older adults reportedly preferred the iPad version over the PC (Mielke et al., 2015).

Figure 2: The iPad version of CogState

Others have developed new assessment instruments by adapting common tasks in standardised paper-based measures and incorporating them into the tests in a visually interactive way (Zorluoglu et al., 2015, Onoda et al., 2013, Barnett et al., 2015). A mobile cognitive screening application (MCS) (Zorluoglu et al., 2015) employed a battery of tests measuring a number of cognitive functions, e.g. arithmetic, attention and executive functions on a tablet device (See Figure 3 for a screenshot). Their analysis demonstrates strong correlations between MCS test results and MoCA in older adults and its feasibility for cognitive screening of dementia.



(a) (b)

Figure 3: Examples of subtests available in MCS (a) a trail making test and (b) a clock drawing test

A more recent study by Freedman et al. examined the feasibility of using mobile-based cognitive screening tools for detecting early cognitive impairment. The Toronto Cognitive Assessment (TorCA) consisted of multiple subtests covering a broad spectrum of cognitive functions for detection of MCI. Statistical analysis demonstrated that scores on subtests of the TorCA could correctly identify MCI patients from cognitively-normal adults with relatively high sensitivity and specificity (Freedman et al., 2018). In a similar study, the User eXperience-Trail Making Test (UX-TMT) demonstrated significant correlations with several traditional screening tests, including MMSE, MoCA and TMT. The relatively high sensitivity and specificity have verified the discriminating ability of the UX-TMT for classifying between people with cognitive impairment and healthy controls (Kokubo et al., 2018). In a more extensive study, test results from the proposed cognitive screening tool CADi (Onoda et al., 2013) were strongly correlated with MMSE scores. CADi also showed high sensitivity and specificity in differentiating people with dementia from healthy controls. Collectively, these studies showed evidence that mobile applications can discriminate healthy individuals from cognitively impaired patients.

Performance on the Color-Shape Test (CST) was another mobile-based cognitive screening instrument developed to assess cognitive and motor functions in older adults. The test was found to be significantly correlated with scores on multiple standard assessments of cognitive functions, including MMSE and TMT (Brouillette et al., 2013). In a similar study, scores on the computerised cognitive screening (CSS), a matching task-based cognitive test, were significantly associated with MoCA scores. No effect of computer experience on test performance was found (Scanlon et al., 2016). With regard to the feasibility of using computerised cognitive tests in home settings, Rentz et al. compared performance on the iPad version of their Computerised Cognitive Composite for Preclinical Alzheimer's Disease (C3-PAD) between in-clinic and at-home assessments. Results showed a significant correlation in performance between both settings. At-home performance on C3-PAD was also significantly associated with standardised paper-based tests, suggesting that mobile-based cognitive tests can be used for assessing cognitive functions in the home environment (Rentz et al., 2016).

In summary, previous studies have shown that computerised cognitive measures on mobile platforms provided comparable results to a number of existing clinical cognitive tests. Apart from automatic scoring and reduced dependency on clinical staff, the portability of mobile devices allows remote assessment and frequent monitoring of cognitive changes. In conjunction with the internet, mobile-based screening modality has enabled cognitive assessment outside of clinical facilities with access to evaluation results allowing comparison with individuals' prior cognitive status. Furthermore, intuitive interactions through the touch-based interface are perceived to be more user-friendly and easier to use for people with low technology literacy, especially in older adults. Such touch-based inputs on mobile platforms have addressed the barriers of the use of keyboard and mouse to computerised tests. Interestingly, among the reviewed articles, most studies chose tablets as a platform for cognitive measures within clinical settings, while mobile devices seemed to be a preferred option for research in home settings. It was anecdotally speculated that it was due to the difference in size and portability of the devices. In particular, with smaller screen size, mobile phones are more portable allowing more ubiquitous self-assessment outside of clinical settings. On the contrary, tablets with a larger screen are more beneficial to users and examiners administrating the trials within medical facilities (Koo, Vizer, 2019).

Despite showing great promise for assessment and screening of cognitive impairment, most of these well-validated mobile-based measures, for instance, CANTAB (Soares et al., 2014) and CogState (Mielke et al., 2015), are proprietary and still dependent on software and hardware which often require subscription fees. This limitation may hinder the widespread use of such a mobile-based modality for cognitive assessment and screening in clinical practice. More importantly, even though remote assessment using mobile technology can enable users to perform self-evaluation at their preferred time of a day, it is still challenging to motivate users to engage in frequent administrations to monitor cognitive changes over time. In particular, boring and repetitive tasks inherent in mobile cognitive measures could discourage users from taking frequent assessments as needed to monitor their condition continuously (Flores et al., 2008). This is in line with the findings of Koo et al., who argued that increased test completion rates were associated with shorter and more engaging tasks integrated into mobile cognitive assessment instruments (Koo, Vizer, 2019). In response to this concern, there has been increasing interest in the use of game technology for cognitive assessment. Given the entertaining nature of games, integrating gamified tasks into the cognitive measures could potentially encourage and motivate users to maintain interest during the test and promote engagement with frequent assessments over time (Tong et al., 2016). The next section will examine how game technology has been used in clinical applications with a focus on cognitive assessment and screening.

2.3. Games for Cognitive Assessments and Screening

Over the past decades, computer game technology has received substantial research interest due to its potential to enhance users' experience through visual, auditory and haptic stimuli and feedbacks. Gamification has been explored and applied in a variety of domains including, military training, safety training, advertising, education and health care. These games were specifically designed and served for serious purposes and not intended to be played primarily for entertainment. These games are often known collectively as "Serious Games". Serious games are often displayed in an immersive and attractive graphical environment either 2D or 3D with game mechanics designed to challenge and motivate players to complete given tasks or missions which relate to specific application domains (Laamarti, Eid & El Saddik, 2014).

More recently, serious games have received increasing attention for its application in healthcare, especially in longitudinal clinical assessment and intervention where participant engagement and motivation is essential. Prior studies have investigated the gamification of traditional clinical tasks with the aims to increase participant motivation for long-term engagement as well as to increase usability for the target populations, e.g., children (Tenorio Delgado et al., 2016), elderly (Siraly et al., 2015) and individuals with medical conditions (Tong et al., 2016, Dovis et al., 2012). Multimodal interactions, in conjunction with in-game challenges and intuitive rules, have been used to transform tedious tasks inherent in traditional forms of clinical assessment and therapy into more interactive and engaging activities (Lumsden et al., 2016). In particular, the element of fun, as well as the interactive environment, could potentially ease test anxiety and reduce drop-out rates in continuous assessments and intervention (Tong et al. 2016, Siraly et al., 2015, McPherson, Burns, 2007, McPherson, Burns, 2008).

2.3.1. Computer game-based assessment and screening

Familiar recreational activities such as card games have been employed as game-based measures for cognitive assessment and screening in a less effortful and enjoyable manner comparing to traditional forms of assessment. For instance, Jimison et al. conducted a study with a computer card game called “FreeCell” for monitoring cognitive changes in older adults (Jimison et al., 2004). It required participants’ strategic planning to make appropriate moves in order to win each level. Game performance determined by the number of moves, the smoothness and the speed of mouse trajectories was reported in the findings as strong indicators to discriminate people with MCI from cognitively normal individuals. In a similar study, a flipping card game was included in a game-based platform called “Ryokansan” to assess early signs of dementia (Kurata et al., 2012). Their results revealed signification correlations between game performance and existing paper-based cognitive test batteries in patients with dementia.

Studies have shown that even minimal gamification with a few game-like features was sufficient to enhance motivation and sustain participants’ engagement (Lumsden et al., 2016). For example, Space Code (see Figure 4 for a screenshot) has incorporated minimal game-like elements including simple black and white graphics, sound effects, real-time feedbacks and a scoring system into computerised cognitive tests. Participants were asked to fire laser blasts on an enemy spaceship by clicking the correct number on the numeric keypad which corresponds to the cell number where a spaceship appears at the bottom of the screen. Significant correlations were found between game performance and existing cognitive tasks measuring working memory and processing speed (McPherson, Burns, 2007, McPherson, Burns, 2008).

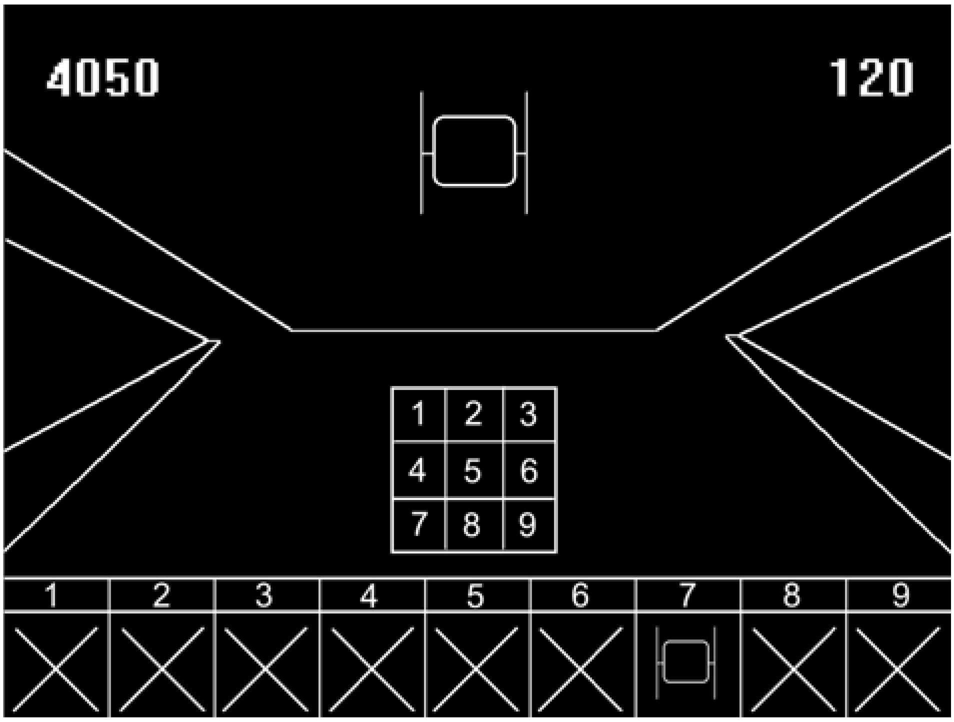


Figure 4: A screenshot of the Space Code

Apart from dementia assessment, there is a growing interest in adopting game-like elements to assess cognition in children with attention deficit hyperactivity disorder (ADHD). While being easily distracted and becoming bored, children with ADHD are drawn to computer games as they prefer sequences of rapidly changing visual stimuli and spontaneous rewards (Caroline Miller, 2020). As a result, prior research on cognitive assessment engaged children with ADHD through a game-like environment with interactive and appealing graphics, sounds and challenges to motivate and retain their attention (Lumsden et al., 2016, Heller et al., 2013). In a recent study (Heller et al., 2013), Groundskeeper (Figure 5) was developed to assess attention deficits in children with ADHD in a fun and engaging way. A tangible user interface in a cube block was employed to engage children and capture behavioural data during the gameplay through physical interaction with the device, which was wirelessly synchronised with a computer running the game. Gaming features, including measures of movement, responses and actions were used as input to build classification models. Results showed that such game performance could be used as indicative features to detect ADHD in children.

Figure 5: Groundskeeper is being played on a tangible gaming platform

2.3.2. Virtual reality game-based assessment and screening

Virtual reality (VR) is an interactive computer-simulated environment which closely resembles reality in which users can interact with the virtual environment in real-time (Brey, 2014). One of the primary reasons gamification and VR were employed in cognitive research is to increase performance and motivation in target populations through immersive VR experience induced by multisensory stimulation and tangible user interfaces. For instance, tabletop-virtual reality gaming platform in the Eldergames project was developed to improve cognitive functions in older adults. Their findings showed that their interactive tabletop games with a pen-like input device were well accepted with regard to usability and reported to create a positive experience (Gamberini et al., 2009). In the context of cognitive assessment, a number of virtual environments have been developed to simulate real-life situations including city navigation (Zakzanis et al., 2009), school classrooms (Rizzo et al., 2000), a supermarket (Rizzo et al., 2000), a museum (Tarnanas, Tsolakis & Tsolaki, 2014) and a fire evacuation drill (Tarnanas et al., 2013, Tarnanas, Tsolaki & Tsolaki, 2014) for enhancing the ecological validity of the assessment.

In particular, the Smart Aging Platform (Zucchella et al., 2014), a first-person 3D virtual reality game was developed with the aim to evaluate the VR usability as a screening tool for pre-dementia conditions. Five tasks in the game simulated in real-world conditions were designed to assess multiple cognitive abilities. Due to its intuitive interface, the navigation within the virtual environment via touch interaction was found to be easy to learn for users even with little or no computer experience.

In another study of VR game-based cognitive assessment with more complex system setup involving multiple motion sensors, Tarnanas et al. developed a virtual reality day-out task (VR-DOT) and validated its psychometric properties as a screening measure for cognitive impairment. A variety of real-world scenarios were presented as part of a fire evacuation drill. The 3D immersive navigation system (see Figure 6) was designed to examine participants' executive functions to prioritise, plan and make decisions to evacuate safely from the building. The VR-DOT demonstrated strong psychometric properties in identifying people with cognitive impairment from cognitively normal individuals (Tarnanas et al., 2013). Furthermore, in their subsequent study, it was shown that VR-DOT scores could also be used as a marker to predict progression from mild cognitive impairment to dementia. Given the strong discriminative power, the authors argued that when combined with existing neuropsychological tests, the VR-DOT could provide additional predictive information at low costs in a noninvasive way (Tarnanas, Tsolaki & Tsolaki, 2014).

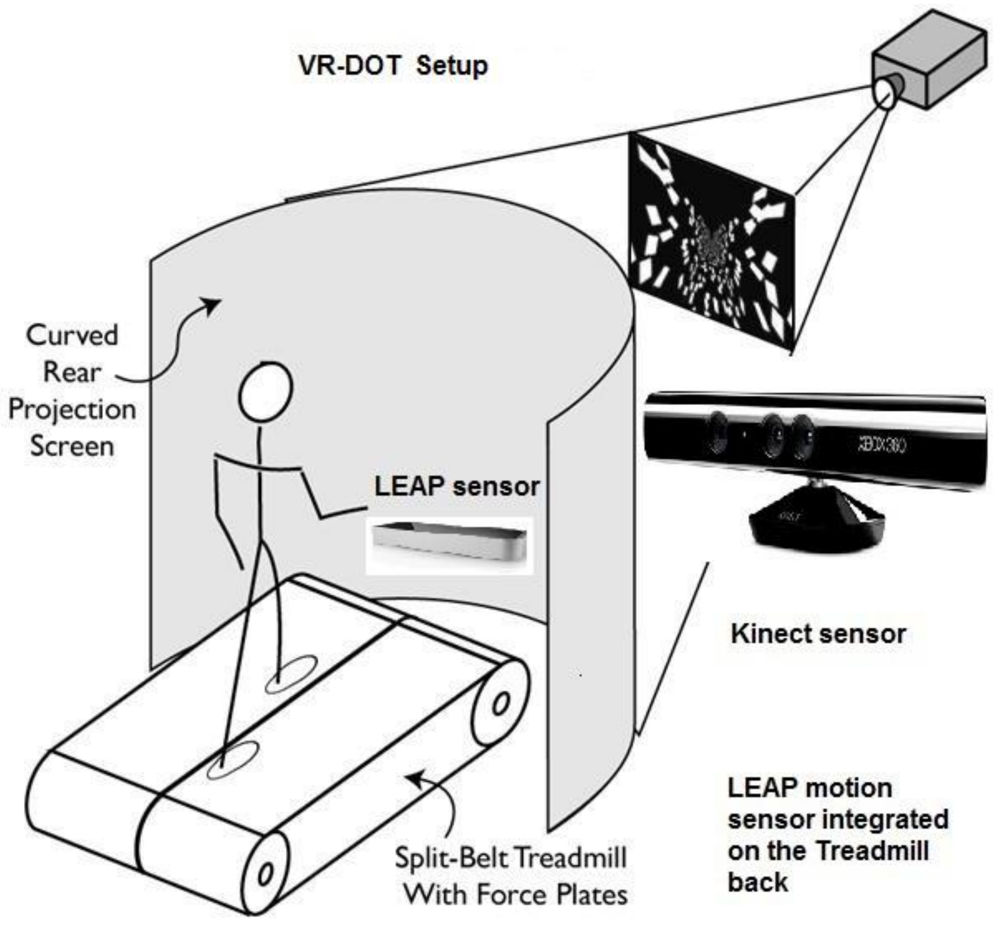


Figure 6: System setup for the experiments in VR-DOT

2.3.3. Mobile game-based assessment and screening

In the previous section, findings in prior research have shown how VR technology and multisensory gaming platforms could enhance personal engagement and participation in cognitive assessment. However, most of the VR approaches require space for equipment setup which is often wired and bulky, while others require specific sensors and hardware devices and are thus not feasible for running in a large-scale experiment. More importantly, these limitations make their application impractical in non-clinical settings, especially for home use, where clinicians aim to monitor changes in patients' cognitive status over time.

In contrast, the ubiquitous computing power of modern mobile devices offers promising solutions for data collection and processing for cognitive assessment and monitoring outside clinical settings. Mobile versions of serious games have been developed to simulate common daily activities such as cooking (Manera et al., 2015), and supermarket shopping (Zygouris et al., 2015), in order to assess and help improve cognitive functions among people with mild cognitive impairment (MCI). To complete tasks in the game scenarios on a tablet device, a multitude of cognitive processes were involved, e.g. object recognition, attention, visual search, memory and executive functions. Comparing in-game task performance and conventional cognitive assessments, e.g. MMSE and TMT, significant correlations between variables in the games and results from standard cognitive measures were found (Manera et al., 2015, Zygouris et al., 2015). With regard to discriminant validity, in Zygouris et al.'s study, MCI patients exhibited poorer performance on the virtual supermarket shopping game as compared to healthy older adults. Results have demonstrated that the game was sensitive to cognitive impairment and could be used to distinguish MCI patients from healthy adults (Zygouris et al., 2015). Similarly, differences in the game performance between patients with MCI and those with Alzheimer's disease (AD) were found in the Kitchen and Cooking (Manera et al., 2015). In that, AD patients' performed significantly poorer than MCI patients. This suggested that the game was sensitive to the severity of impairment in cognitive disorders and could be used to complement traditional clinical instruments for detecting progression of cognitive decline outside of clinical settings.

Unlike the simulation-based games that artificially represent real-world scenarios, by replicating a popular casual game, the more game-like attributes in Whack-a-Mole (Tong et al., 2016) (see Figure 7 for a screenshot) induced fewer feelings of being tested. The game incorporated a Go/No-Go discrimination task to measure cognitive inhibition. The significant correlations between median response time and cognitive test scores suggested that this in-game feature could be used as a predictor for cognitive status.

While numerous studies have demonstrated the effectiveness of game-based assessment on mobile platforms for diagnosis of cognitive disorders commonly found in ageing populations, other studies also examined the use of mobile serious games in screening and predicting cognitive changes in people with cognitive disorders other than dementia, for example, post-stroke cognitive impairment (Jung et al., 2019, H. Jung et al., 2019) and ADHD (Song, Yi & Park, 2020). By exploiting machine learning techniques, Neuro World demonstrated its predictive ability to quantify the post-treatment cognitive level of post-stroke patients based on cognitive scores at baseline and game performance features (Jung et al., 2019, H. Jung et al., 2019). A more recent study (Song, Yi & Park, 2020) has also shown that mobile serious games could be used to assess cognitive control deficits which are closely linked to ADHD. Their results provided empirical evidence for the feasibility of using mobile games, in ecological settings such as home, to identify children and adolescents who are at high risk of developing dysfunction in cognitive control.

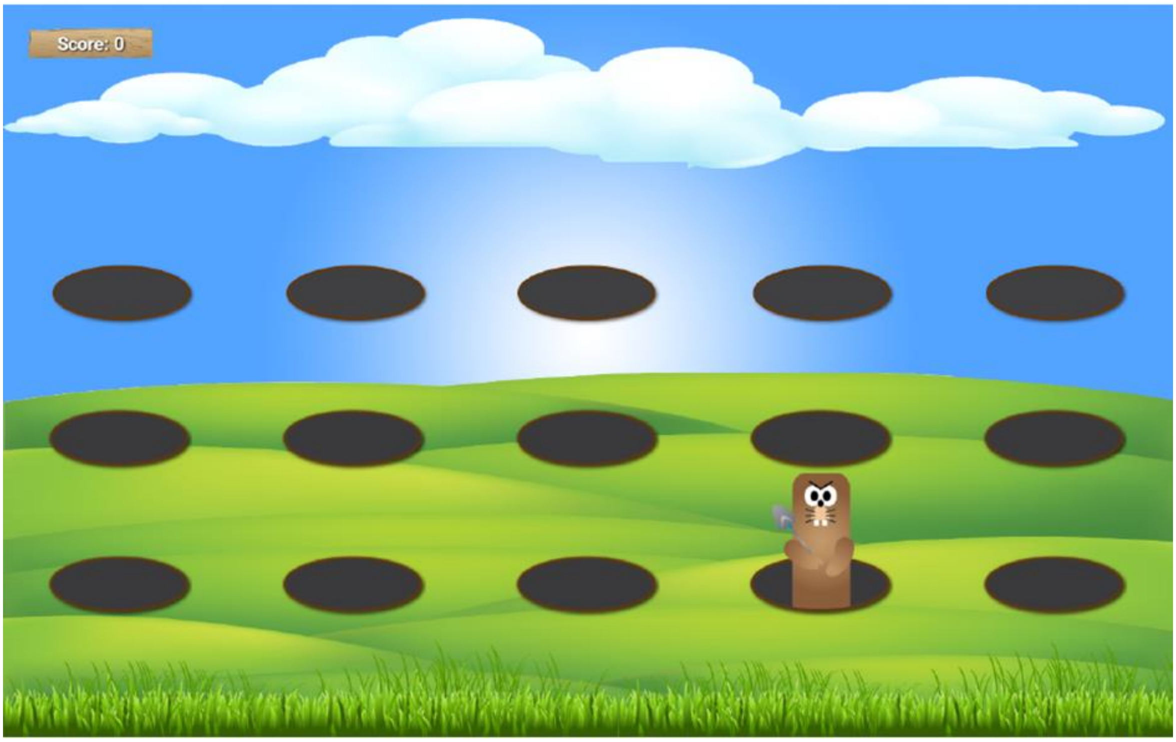


Figure 7: A screenshot of the Whack-a-Mole game

In summary, the literature review has provided encouraging evidence that cognitive tests can be gamified to increase motivation and engagement in research populations. In particular, even minimal gamification can be engaging enough to sustain participants' attention to complete tasks that were considered tedious and effortful in their non-game-like counterparts (McPherson, Burns, 2007, McPherson, Burns, 2008). Employing common daily activities or close-to-real life situations could further enhance the ecological validity of virtual environments (Tarnanas et al., 2013, Manera et al., 2015, Zygouris et al,. 2015). Given the ubiquitous nature of mobile devices, mobile game-based measures allow individuals to self-evaluate their cognitive functions in the home environment at a convenient time. This enables clinicians to monitor early signs of cognitive changes in the target groups outside of clinical settings. With regard to usability, it is worth noting that despite common misperceptions about the attitudes of older adults towards gaming technology, a systematic review reported that older adults enjoyed video games and benefited from game-based cognitive intervention (Kueider et al., 2012). This was supported by a recent report demonstrating that 23 per cent of the U.S. gamers were 50 years and older (Statista, 2019). Hence, these studies have emphasised the potential of serious games as highly engaging cognitive assessments to monitor changes in cognition outside of a clinical environment for populations with cognitive disorder across age groups.

Most of these papers examined the feasibility of mobile game-based measures with a focus on common cognitive disorders such as mild cognitive impairment and dementia. Only a few studies have investigated their use in other types of cognitive impairment. In particular, to my knowledge, no previous research has explored the use of mobile games in identifying alcohol-related cognitive impairment which is strongly associated with chronic excessive alcohol consumption behaviour. Given that cognitive impairment in alcohol-related dementia is relatively non-progressive and is reversible with abstinence in certain cases, early detection of alcohol dependence provides a great opportunity for timely intervention. Key terminology and related work in this area are discussed in the next section.

2.4. Alcohol Use Disorder

2.4.1. Definitions (ICD-10 and DSM-V)

Alcohol use is causally associated with a number of diseases, physical injuries, accidents, including psychological, social, and legal issues (National Institute on Alcohol Abuse and Alcoholism, 2020). Alcohol Use Disorder (AUD) is an umbrella term used to describe a harmful pattern of alcohol consumption leading to clinically significant impairment. The definitions for alcohol use disorders are determined by two major classification systems, i.e., the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD). The DSM has been widely used in the United States, while the ICD is more prevalent in Europe and other parts of the world (Hasin, 2003). The Diagnostic and Statistical Manual of Mental Disorders, 4th edition (DSM-IV) (Guze, 1995) and the International Classification of Diseases, 10th revision (ICD-10) (World Health Organization, 1993) define diagnostic criteria for allocating symptoms of AUD into two subcategories, i.e., harmful alcohol use and alcohol dependence. Despite sharing similar diagnostic criteria, the term "alcohol abuse" is used in DSM-IV, while ICD-10 describes the condition using the term "harmful alcohol use" coded as F10.1, instead. Likewise, ICD-10 uses the term "dependence syndrome" coded as F10.2 to refer to alcohol dependence (Babor et al., 2001, Guze, 1995). In both DSM-IV and ICD-10, to be diagnosed with AUD, individuals must exhibit a recurrent pattern of drinking behaviours meeting one or more of the criteria within a 12-month period.

In short, harmful alcohol use is a recurrent pattern of drinking behaviours during a 12-month period causing physical or psychological harm, or negative social consequences related to alcohol use (Hasin, 2003, Schuckit et al., 1994). Alcohol dependence is a more severe form of drinking problems in which an individual with alcohol dependence typically exhibits persistent alcohol cravings and withdrawal symptoms, leading to unsuccessful attempts to cut down or abstain from alcohol. This maladaptive pattern of alcohol use often continues in alcohol-dependent drinkers despite being aware of its harmful consequences. Increased tolerance to alcohol is also often developed, such that significantly higher quantities of alcohol are required to achieve the same alcohol's effects used to feel with the lower amount (Hasin, 2003). It is worth noting that under the current version of the DSM (DSM-V), both alcohol abuse and alcohol dependence have been integrated into a single unified category as alcohol use disorder (AUD). The symptoms are instead diagnosed with severity – mild, moderate, or severe (Robinson, Adinoff, 2016).

For simplicity, the terms "harmful alcohol use" and "alcohol dependence" will be used in this thesis to refer to the two distinct alcohol use disorders.

2.4.2. Risks associated with excessive alcohol use and alcohol dependence

The health survey report published by NHS Digital estimated that in 2018, 82% of adults in England drank alcohol during the past 12 months, with 49% of these adults used alcohol on a weekly basis (Population Health Team, NHS Digital, 2019). The amount of alcohol consumption and drinking behaviours are causally associated with alcohol-related health risks (both physical and mental). Approximately 1.2 million hospital admissions in England were contributed to alcohol consumption. Alcohol-related diseases and physical injuries were the primary reasons for these admissions (NHS Choices, 2020). Globally, the World Health Organization (WHO) estimates that 3 million people die prematurely every year as a result of excessive alcohol drinking, which is 5.3% of all global deaths (World Health Organization, 2018). Excessive alcohol drinking can impair brain functioning associated with decision making and inhibition controls, potentially causing social harms such as violent crime and anti-social behaviour, which often lead to legal problems (Population Health Team, NHS Digital, 2019).

Apart from social harms, long-term alcohol misuse often poses a substantial risk to several severe physical and mental health, for instance, high blood pressure, stroke, liver disease, neurological complications, depression, including dementia (Jauhar, Marshall & Smith, 2014, Rehm, 2011). Research has shown that excessive alcohol consumption can cause cumulative brain damage and cognitive dysfunction through life, even among the young (Jauhar, Marshall & Smith, 2014, Zeigler et al., 2005). Alcohol-related brain impairment can also cause problems with coordination, balance, and fine motor movement, including cognitive functioning (Jauhar, Marshall & Smith, 2014, Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). It has been found in an expanding number of studies that chronic heavy drinkers typically demonstrate deficits in specific cognitive functions, i.e., visuospatial, working memory, attention, and executive function (Jauhar, Marshall & Smith, 2014, Hermens et al., 2013). Extreme drinking at younger ages increases the risks of developing long-term cognitive impairment related to alcohol. Unlike other types of cognitive impairment, which typically demonstrate progressive cognitive decline over time, cognitive functions in young chronic alcohol misusers can improve or remain stable with continued alcohol abstinence (Jauhar, Marshall & Smith, 2014). Thus, early detection of early-onset alcohol-induced cognitive impairment would greatly facilitate timely intervention (Hermens et al., 2013).

2.4.3. Standard measures and limitations

Unfortunately, it is common for individuals with covert symptoms of alcohol-related health conditions to remain unrecognised until serious complications have developed. According to 2018 Public Health England, approximately more than half a million people in England were alcohol-dependent drinkers (Public Health England, 2019a). Only 18% of these adults with alcohol dependency ever received treatment (Public Health England, 2019b).

Where sufficient resources exist, alcohol dependence syndrome can be identified through an extensive series of diagnostic measures administered by trained medical staff. The diagnostic procedure often requires diagnostic interviews and other physical or psychological measures to establish a diagnosis. In low-resource settings, such as medical facilities with a shortage of trained clinicians, it is instead common to use alcohol screening instruments to identify those at risk for alcohol use problems with referral to further diagnostic evaluation for alcohol dependence only if required (Iglesias et al., 2018).

The Alcohol Use Disorders Identification Test (AUDIT) (Saunders et al., 1993, Babor et al., 2001) is one of the most widely accepted screening tools for harmful alcohol use and alcohol dependence in clinical practice. It consists of 10 questions (max score of 40) with regard to alcohol consumption behaviour and social problems caused by chronic drinking and excessive alcohol intake. In the detailed guidelines about the use of the AUDIT published by (Babor et al., 2001), the ten questions are grouped and categorised into three major domains, as described in Table 2. The key terms describing the three domains in the manual were defined by the World Health Organization (WHO) (Higgins-Biddle, Babor, 2018).

The terminology is consistent with ICD-10 definitions of dependence syndrome and harmful alcohol use except for hazardous alcohol use. In that, the term is only introduced by WHO to describe a pattern of alcohol consumption above the recommended limits, which potentially poses a risk of harmful consequences. It is not part of the diagnostic terms in ICD-10 (Higgins-Biddle, Babor, 2018).

Table 2: Domains and Item Content of the AUDIT

Domains	Question Number	Item Content
Hazardous Alcohol Use	1	Frequency of drinking
	2	Typical quantity
	3	Frequency of heavy drinking
Dependence Symptoms	4	Impaired control over drinking
	5	Increased salience of drinking
	6	Morning drinking
Harmful Alcohol Use	7	Guilt after drinking
	8	Blackouts
	9	Alcohol-related injuries
	10	Others concerned about drinking

A score of eight or more is typically used as the cut-off point for identifying individuals with alcohol problems (Babor et al., 2001). The AUDIT displayed high sensitivity and specificity values, which were superior to those of other screening instruments (de Meneses-Gaya et al., 2009).

The AUDIT-C, a shortened version of the AUDIT, was developed for use in busy medical settings. It adapts only the first three questions with regard to alcohol consumption of the original AUDIT. The summed scores of all items can range from 0 to 12. Cut-off scores of 5 or 6 are generally recommended for a positive screen with a high risk of alcohol problems (Khadjesari et al., 2017). Despite the compelling evidence of the validity and reliability of the tests, at times, clinicians face challenges to evaluate and interpret the results as responses can be ambiguous or evasive. Indeed, the tests rely heavily on self-responses, which can be deliberately controlled to avoid embarrassment and thus are subjective to potential biases (Babor et al., 2001). For instance, the actual volume of alcohol consumption is likely to be under-reported among alcohol drinkers (Gilligan et al., 2019). Such response biases, therefore, could lead to inaccurate screening results. To accurately quantify actual alcohol intake, asking for clarification and clinical observations are often required to probe for the most accurate responses when conducting the assessment (Babor et al., 2001). Most importantly, both AUDIT and AUDIT-C were not originally designed with the explicit purpose of identifying alcohol dependence. In fact, these screening measures are used to identify individuals with hazardous and harmful alcohol drinking patterns before developing dependence. Based on the original document, the AUDIT scores of 20 or above are suggested to affirm the need for further diagnostic evaluation for alcohol dependence (Babor et al., 2001, Higgins-Biddle, Babor, 2018). In other words, to indicate the possibility of alcohol dependence, the obtained AUDIT scores need to be much greater than the recommended cut-off widely used in primary care.

2.4.4. Current alcohol screening implementation and barriers

Given the high prevalence of alcohol use disorders in primary care and emergency departments (Barry et al., 2004, Forsythe, Lee, 2012), alcohol screening and brief intervention in these general healthcare settings could provide a great opportunity for early detection of harmful alcohol drinking patterns and offer timely treatment. Besides, this also gives healthcare practitioners an opportunity to determine whether patients' alcohol drinking could worsen their presenting conditions or adversely affect the use of medications they are currently receiving (World Health Organization, 2021). Due to the strong link to social stigma for being identified as alcoholism, people with alcohol-related problems are often reluctant to seek treatment at speciality medical facilities. Offering screening and treatment in primary care settings could be one of the strategies to reduce these barriers (Glass et al., 2017).

Therefore, alcohol screening and brief intervention in general healthcare settings have been recommended by national healthcare organisations in many countries to be part of routine clinical practice to improve screening rates and reduce unhealthy alcohol use in at-risk drinkers (Centers for Disease Control and Prevention, 2014, Glass et al., 2017, Forsythe, Lee, 2012, Zhang et al., 2017).

Several approaches have been used for alcohol screening in primary care practice, largely depending on clinical practitioners to determine which screening strategy would best suit their routine practices. Patients could be asked to perform self-screening using validated alcohol screening tools, such as the AUDIT, an alcohol screening questionnaire (Babor et al., 2001), in the waiting area. In some practices, alcohol screening is carried out during a clinical visit by primary care clinicians. Asking questions about quantity and frequency of alcohol use, clinical observation and formal screening tools could be used to identify alcohol-related problems (Fiellin, Reid & O'Connor, 2000). Diagnostic interviews could be further carried out by an experienced clinician to establish a reliable diagnosis (Iglesias et al., 2018).

According to the clinical guidelines of alcohol screening implementation in primary care by the Centers for Disease Control and Prevention in the US, all primary care patients should be screened for the full spectrum of alcohol-related problems and offered brief intervention when necessary. A very short screening measure (e.g., AUDIT-C with only three questions) could be used at the reception to first screen patients who exceed alcohol drinking limits. When screened positive, the full AUDIT with ten questions will be used to determine the potential of having harmful or dependent drinking behaviours. Such alcohol screening activities are likely to be performed by nursing staff, medical assistants or receptionists. When identified as at risk for alcohol use disorders, clinical advice and brief intervention are provided by physicians or nurse practitioners to raise awareness of harmful alcohol consumption patterns and motivate patients to seek speciality treatment (Centers for Disease Control and Prevention, 2014).

However, a systematic review on alcohol screening measures in the ED settings reported that although the AUDIT has been well-validated within the general population, its effectiveness in detecting harmful or dependent drinking patterns within the female population dropped substantially in the emergency settings (Reinert, Allen, 2002). In a systematic review (Jones, 2011), a variety of brief alcohol screening instruments (self-reported questionnaires), including the Fast Alcohol Screening Tool (FAST) (Hodgson et al., 2002), the Paddington alcohol Test (PAT) (Smith et al., 1996), the Rapid Alcohol Problem Screen (RAPS-4) (Cherpitel, 2000) and TWEAK (an acronym of the first letters of the keywords in the screening questions: tolerance, worried, eye-opener, amnesia, cutdown) (Russell et al., 1994) were assessed for their effectiveness in identifying alcohol use disorders in emergency settings. Although FAST showed the best performance in accurately identifying alcohol misuse patterns in emergency settings, the authors concluded that given the cost and time constraints, it seemed infeasible to use FAST to screen all ED patients. On the contrary, PAT, a screening tool originally developed to identify alcohol-related problems in emergency settings, appeared to be more cost-effective (Jones, 2011). This is in line with the guidelines of the National Institute for Health and Care Excellence in the UK which recommended that in such time-limited settings as the emergency departments, FAST or PAT would be the most appropriate screening tools. Alternatively, the full AUDIT should be used in other non-busy clinical settings (National Institute for Health and Clinical Excellence (Great Britain), 2010). In contrast to the US Centers for Disease Control and Prevention recommendations, when an individual is identified as alcohol dependent, UK primary healthcare professionals are suggested to refer a patient to relevant specialists rather than offering brief advice. A brief intervention would be provided only to those identified as harmful alcohol users (National Institute for Health and Clinical Excellence (Great Britain), 2010).

Despite the recommendations of national health organisations in numerous countries (Forsythe, Lee, 2012, Glass et al., 2017, Zhang et al., 2017), formal alcohol screening implementation in routine clinical practice reportedly remained inadequate. Only 2% of the emergency departments used formal screening instruments to identify patients with alcohol problems (Jones, 2011). Furthermore, the ED settings are usually busy and often in shortage of trained healthcare professionals for alcohol screening and brief intervention. Some ED nursing staff did not consider alcohol screening and intervention as part of their routines. Concerns over workflow disruption in the busy ED setting were expressed among ED nurses as it was difficult to allocate their time and attention to alcohol screening in addition to their busy and stressful routines (Karlsson et al., 2005). This is in line with the findings that lack of time posed an important barrier in implementing screening procedure in ED settings (Anderson et al., 2001). Many ED nurses also reportedly lacked confidence in carrying out the screening activities as they did not receive training on dealing with patients with alcohol presentations. Another attitudinal barrier is the reluctance of ED clinical staff to ask patients about their alcohol use, as patients might feel offended and react negatively to such questions (Anderson et al., 2001, Karlsson et al., 2005).

In addition to the aforementioned barriers, patients' attitudes towards their drinking habits and alcohol stigma also pose challenges in implementing alcohol screening and intervention in primary care. In particular, it was often cited in a number of studies that there was a significant difference in the attitude towards changes in drinking behaviours and receiving alcohol addiction treatment between alcohol-dependent individuals who seek help and those who are identified as alcohol use disorders through screening. Unlike those who are self-motivated to seek treatment, people with a positive alcohol screen may not feel that their drinking behaviour would be considered a problem and thus ignore the advice to reduce their alcohol consumption levels. They may also be unaware of the harmful consequences of continuing their excessive drinking habits. Given insufficient motivation, they often do not proactively seek medical attention for their drinking problem (Edlund, Booth & Feldman, 2009, SAITZ, 2010, Glass et al., 2017). Fear of perceived social stigma associated with alcohol use disorders is another major barrier facing many individuals with alcohol problems in seeking help from healthcare professionals (Mojtabai, Crum, 2013, Glass et al., 2017, Grant, 1997, SAITZ, 2010). Considering their alcohol harmful use the violation of social norms, many patients with alcohol use disorders often perceive public discrimination and therefore refuse to seek help because of the shame of alcoholism (Glass et al., 2017).

2.4.5. The use of computerised technologies to support AUD patients

Despite being regarded as the gold standard, the current traditional screening and interventions face substantial barriers to widespread accessibility and the adequate provision of healthcare services in resource-limited settings. The measures currently used in the field today are resource-intensive in terms of costs, time, and skilled health professionals (Fowler et al., 2016). For instance, cognitive-behavioural therapy (CBT), a face-to-face treatment to help alcohol-dependent patients to recognise and cope with their negative thoughts and situations that are likely to lead to alcohol relapse (AddictionCenter.com, 2020), typically involves a series of therapeutic sessions administered essentially by a trained therapist (AddictionCenter.com, 2020, Fowler et al., 2016). Given such limitations in the current modalities and a very low rates of treatment-seeking among alcoholic drinkers, it is not unexpected that a significant percentage of those with such a condition remains untreated (Cunningham et al., 2011) or relapse to alcohol use after being discharged from residential treatment (Gustafson et al., 2011).

In response to these concerns, a growing body of research has investigated the adoptions of computerised technologies in screening (Mumtaz et al., 2018, Mumtaz et al., 2017, Harris, Knight, 2014), interventions (Harris, Knight, 2014, Gonzalez, Dulin, 2015) and recovery support (Gustafson et al., 2011, Gustafson et al., 2014, Yoo et al., 2019) to improve screening and treatment success rates for alcoholism. In comparison to the traditional approaches that required face-to-face visits, the computer-based assessments and interventions showed the potential of being flexible, accurate, and cost-effective ways of screening, treatment, and delivering multiple-session recovery interventions (Harris, Knight, 2014).

2.4.4.1. Interventions and Recovery Support

With respect to interventions to support people in recovery from alcohol dependence, to reduce the burden on medical professionals, and encourage individuals to abstain from excessive alcohol drinking behaviours, the use of mobile technologies has been proposed and examined in a number of studies (Gustafson et al., 2011, Gustafson et al., 2014, Gonzalez, Dulin, 2015, Yoo et al., 2019, Agyapong et al., 2012, Suffoletto et al., 2012, Suffoletto et al., 2015). Many of these mobile-based support systems were developed around theoretical frameworks to improve the long-term intervention outcomes (Gustafson et al., 2011, Gonzalez, Dulin, 2015, Suffoletto et al., 2015). In general, the common key fundamentals in these frameworks contributing to behaviour change interventions are coping competence (ability to cope or avoid situations that may lead to alcohol use), social support, and autonomous motivation (Gustafson et al., 2011, Gonzalez, Dulin, 2015, Gustafson et al., 2014). One of the simplest forms of the behaviour change interventions was primarily delivered through text messaging, which allowed therapists to stay in touch with a large number of people in recovery from alcohol dependency regardless of their geological locations at low costs (Gustafson et al., 2011, Agyapong et al., 2012, Suffoletto et al., 2015, Mason et al., 2015).

In a series of recent studies (Gustafson et al., 2011, Gustafson et al., 2014, Yoo et al., 2019, Gustafson et al., 2016), Gustafson et al. proposed and evaluated the Addiction Comprehensive Health Enhancement Support System (A-CHESS) for mobile-based intervention for alcohol and substance use disorders (Figure 8) (Gustafson et al., 2011). Based on personal profile and conditions, supportive messages could be easily tailored to provide only information that is most relevant to each individual (Gustafson

Figure 8: A-CHESS, an example of mobile-based alcohol intervention systems

et al., 2011, Gustafson et al., 2014). In light of the ability of the Global Positioning System (GPS) to track the current location of mobile users, an alert could be sent via text messages to the person in recovery when approaching locations where he/she was deemed to be at high risk of alcohol relapse. In such a case, the mobile-based intervention system could also be configured to notify their selected family members or caregivers to provide additional assistance with relapse prevention (Gustafson et al., 2011). Furthermore, treatment counsellors could proactively monitor patients' risk of alcohol relapse, e.g., recent use of alcohol, the number of risky drinking days, and the number of abstinent days, through the integrated online periodic assessments (Gonzalez, Dulin, 2015, Gustafson et al., 2014, Suffoletto et al., 2015).

A mounting body of literature showed that such mobile-based systems could significantly reduce risky drinking behaviours measured in terms of units of alcohol per drinking days (Agyapong et al., 2012, Suffoletto et al., 2015), drinks per week (Gonzalez, Dulin, 2015) and the number of risky drinking days (Gustafson et al., 2014, Suffoletto et al., 2015). Increased cumulative duration of alcohol abstinence was also found among participants who received such computer-delivered interventions as compared to control groups (Gonzalez, Dulin, 2015, Gustafson et al., 2014). Given the prevalence of mobile devices today, these technology-assisted interventions show great promise to be a cost-effective way to sustain multiple-session interventions for alcohol recovery.

2.4.4.2. Screening

Alcohol screening is recommended for use in medical settings but still underutilised in primary care (Harris, Knight, 2014, Forsythe, Lee, 2012). Given this barrier and the low rate of seeking help among alcohol abusers, a large majority of drinkers with alcohol problems remain unrecognised. Barriers to effective screening implementation include lack of time and shortage of trained medical staff. Most importantly, conventional screening tests typically rely on self-report, which could be subject to deliberate bias to avoid embarrassment (Mumtaz et al., 2017). Often, clinicians need to use their own experience and clinical observations and repeatedly ask questions to probe for most accurate responses regarding their actual drinking behaviour (Babor et al., 2001).

In order to overcome these limitations, there has been an extensive number of studies that explored the use of computer technologies to allow more widespread implementation and to improve alcohol screening rates. Given the ubiquitous computing power of modern mobile devices, electronic screening can be used at home or in a waiting area, allowing patients to perform self-screening prior to a clinical appointment (Harris, Knight, 2014, Forsythe, Lee, 2012). Automatic feedback from such computer-based measures could provide an understanding of their current conditions and prepare them to discuss further when seeing a therapist. Furthermore, one of the reasons for the inadequate implementation of conventional alcohol screening was the fear of offending patients when asked about their drinking behaviour (Anderson et al., 2001). A relevant study found positive changes in attitudes among nurses when using the computer-assisted approach, as most of them found it easier to obtain patients' information about their alcohol consumption due to its simplicity (Bendtsen, Holmqvist & Johansson, 2007).

Increasingly, research has shown that responses obtained from computerised screening measures have been argued to be reliable and valid. In that, compared to face-to-face interviews and paper-based questionnaires, participants had a tendency to disclose more sensitive and potentially embarrassing information, such as higher levels of alcohol intake, on computerised self-report surveys (Forsythe, Lee, 2012, Beck, Guignard & Legleye, 2014, Wright, Aquilino & Supple, 1998). This seems to be associated with the level of trust in data privacy and the anonymity that computerised technology can offer (Choo et al., 2012). Various studies have also argued that health professionals could take advantage of these technology-based approaches to improve the detection of risky drinking behaviours for early intervention in adolescents who are familiar and highly engaged with technologies (Harris, Knight, 2014, Marsch, Bickel & Grabinski, 2007).

In addition to the particular technology-based screening mentioned above, neuroimaging technology has recently received attention from researchers given its potential to be used for screening and diagnosis of AUD patients. Several studies (Mumtaz et al., 2018) have investigated the use of Electroencephalography (EEG) for the identification of individuals at high risk for alcohol use disorder (Mumtaz et al., 2017, Faust, Yanti & Yu, 2013) and relapse prediction for detoxified patients (Mumtaz et al., 2018). Changes in brain activities were observed in AUD patients through electrophysiological measures recorded from multiple electrodes placed on different scalp locations. In particular, previous studies found significant differences in EEG-based features, such as spectral power, coherence, phase delay, and synchronization, when comparing AUD patients and controls (Bauer, 2001, Tcheslavski, Gonen, 2012). By applying machine learning methods to EEG signals, various computational models have been developed and evaluated for automatic identification of patients with alcohol problems. In a recent meta-analysis on EEG-based modalities for screening and diagnosis of AUD, these EEG-based classifiers, in general, demonstrated promising performance in screening AUD patients from healthy controls with relatively high accuracy (Mumtaz et al., 2018).

2.4.6. Limitations and research gaps in alcohol screening

Given the continuous advances in computerised screening and intervention methods, a body of literature has highlighted the advantages of such systems over conventional approaches in terms of costs, feasibility, and effectiveness. In that, the computer-assisted modes are relatively easy to implement at a lower cost while yet are able to provide comparable efficacy.

Nevertheless, these technology-based modalities have not yet been widely adopted for use in medical settings as compared to their traditional counterparts. One of the reasons may be that only limited research has investigated the validity and reliability of the computerised version. Furthermore, the current assessment methods, either paper-based questionnaires, face-to-face interviews, or their computerised versions, still heavily rely on retrospective self-responses, which can be unintentionally or deliberately false when reporting their alcohol consumption. These could mislead clinicians to misdiagnose patients, and their conditions may remain untreated.

As opposed to the self-report approaches, EEG-based screening has been argued to enable researchers to implicitly acquire data from brain activities, avoiding potential response biases that can be deliberately controlled. Based on EEG-based features, previous research has demonstrated very high accuracy in the identification of AUD patients. Nevertheless, setting up devices to get optimal electrode positioning for accurate EEG recordings could be time-consuming. Special training is therefore required for medical staff to administer such an EEG-based screening method. Such barriers make this technique less effective and receive little attention in clinical practice (Mumtaz et al., 2018).

These limitations have led a call for an alternative method that is quick and easy to administer, yet provides a reliable and accurate assessment to improve the screening rate and accuracy for the early detection of alcohol dependence (especially one appropriate for use outside of clinical settings). Section 2.3.3 provides examples of how mobile games could be adopted to assess cognitive abilities and identify people with cognitive impairment. In addition, prior work reviewed in this section has demonstrated that alcohol dependence is linked to both declines in cognitive abilities (Jauhar, Marshall & Smith, 2014, Hermens et al., 2013) and irregular motor function of patients' hands (Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). Given such findings, the use of smartphone games could potentially provide an engaging way to capture both of these types of discriminant factors and therefore help develop an automated system for the diagnosis of alcohol dependence. To provide further context of this motivation, the potential use of touch and motor patterns for identifying patients with health conditions is discussed in the next section.

2.5. Gesture and Device Motions

Mobile gameplay mainly involves touch gestures that users perform on the screen. In order to discover whether such gestures can be related to cognitive performance, this section explored a broader range of studies where hand movement has been shown to be related to cognitive abilities. Most existing literature in this domain focuses on people with diagnosed neurological disorders. Previous studies have shown that changes in fine motor abilities are commonly observed in patients with Alzheimer's disease, mild cognitive impairment (Schroter et al., 2003), schizophrenia (Tigges et al., 2000) and obsessive-compulsive disorder (OCD) (Mavrogiorgou et al., 2001). A series of comparative studies (Tigges et al., 2000, Mavrogiorgou et al., 2001, Schroter et al., 2003) investigated speed, quality and accuracy of kinematic handwriting movement using a digitising tablet in samples of various cognitively impaired patients. Significant impairment in the regularity of repetitive hand movement was detected through hand-motion parameters. For instance, patients with Schizophrenia differed from healthy controls in automation parameters (mean peak acceleration and the number of direction changes of velocity (NCV)) and regularity of stroke motion parameters (standard deviations of velocity, acceleration and stroke duration) (Tigges et al., 2000). Similarly, patients with Alzheimer's disease and mild cognitive impairment exhibited a lower degree of automation of hand movement in drawing repetitive circles compared to healthy controls. A significant negative correlation was also found between MMSE and NCV (Schroter et al., 2003). Mean stroke length in the writing task appeared to be shorter in patients with OCD than in healthy controls (Mavrogiorgou et al., 2001). Moreover, due to age-related cognitive declines, older adults were found to exhibit fine motor disturbance, for instance, slower velocity and higher variability in movement (Ketcham, Stelmach, 2004). These findings appear to be consistent with significant differences in finger dexterity between cognitively impaired patients (MCI and AD) and healthy age-matched controls reported in a more recent study (Suzumura et al., 2018). In that, patients with cognitive impairment reportedly exhibited lower abilities to control fine finger movement, for example, slower responses and higher contact duration fluctuation when compared to healthy adults. Collectively, these studies demonstrate that a higher degree of movement variability is correlated with declines in cognitive performance.

Over the past few years, there has been emerging interest in the use of sensors to measure behavioural interaction, particularly in serious games. Apart from precise data collection of in-game behaviours and performance, modern mobile devices are capable of sensing user-game interaction behaviour via built-in sensors such as accelerometers, gyroscope and magnetometer. A number of existing studies exploited these sensing capabilities to passively collect data about a user's interaction with their phone, their movement and surroundings in order to infer users' affective states (Gao, Bianchi-Berthouze & Meng, 2012) and health conditions (Sano, Picard, 2013, Anzulewicz, Sobota & Delafield-Butt, 2016). Gao et al. exploited touch patterns during gameplay to predict the self-reported emotional state of participants from a 4-class task and achieved up to 77% accuracy (Gao, Bianchi-Berthouze & Meng, 2012). A more recent study combined built-in mobile sensors with mobile phone usage and physiological signals for automatic discrimination of stress condition with above 75% classification accuracy (Sano, Picard, 2013).

Another study that investigated the use of motor patterns in an attempt to identify children with autism was conducted by Anzulewicz et al.. Two mobile games were employed on a smart tablet to collect touch and inertial movement patterns of the device during the gameplay (Figure 9). Their best machine learning model could identify children with autism from typically-developing children with 93% accuracy. With respect to the autism motor signature, they reported significant different gestural and inertial movement patterns in autistic children as compared to their age-matched controls. Specifically, children with autism demonstrated greater force, including faster and more distal gestures with greater variation in the given goal-directed motor tasks (Anzulewicz, Sobota & Delafield-Butt, 2016).

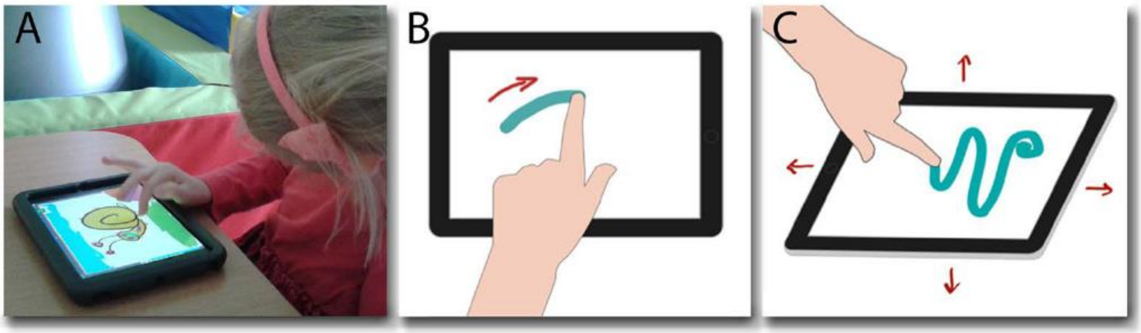


Figure 9: Movement patterns, i.e. touch interaction (B) and device motion (C) were sensed through the touch screen and the built-in inertial sensors

Overall, this body of literature provides encouraging evidence suggesting that the combination of behavioural data passively collected via multisensory input could produce more fruitful results for measuring cognitive abilities as well as identifying people with cognitive impairment.

2.6. Summary of Literature Review

In this chapter, topics related to cognitive impairments were discussed, mainly to provide definitions of basic cognitive functions and explore existing neuropsychological measures often used in clinical practice to assess cognitive abilities and identify common cognitive disorders. Despite the widespread use of paper-based assessment instruments, numerous academic publications have pointed out the limitations of these conventional clinical approaches for cognitive assessments in terms of costs, clinical-centred use, a lack of ecological validity and patients' motivation to engage. To address these barriers, a number of researchers have been investigating technological approaches to enhance personal engagement and motivation in cognitive assessment and screening. Several studies highlighted the advantages of computerised measures over traditional approaches. In particular, such technology-assisted modalities allow better control of stimuli presentation, more accurate measurement and self-administration.

The literature review continued by identifying prior studies where the use of gamification, especially in conjunction with behavioural data collected via built-in sensors, have been explored for clinical assessment and screening in the home environment. Key features extracted from these mobile sensors including touch-based interaction, accelerometer, gyroscope, GPS and microphone along with sophisticated machine learning techniques have been exploited for building efficient classification models on both mobile applications and gaming platforms. To date, little is known about how touch-based interaction and device motion patterns are linked with cognitive abilities. Therefore, an exploratory study was carried out (see Chapter 3) to determine the existence of such relationships. Then continued to review the literature and prior research related to alcohol use disorders which are associated with dysfunctional cognitive abilities known as alcohol-related brain damage (ARBD). Prior work has shown that cognitive and motor deficits resulting in continued disruption of hand movement are commonly found among alcoholics. However, no study to date has considered the use of mobile games and user-game interaction via multisensory input in identifying people with alcohol dependence. For that reason, another study was carried out (see Chapter 4) to address this research gap and investigate the potential of mobile game-based measures in self-screening for alcohol dependence outside of clinical settings.

Chapter 3: Exploring the Touch and Motion Features in Game-Based Cognitive Assessments

The previous chapter discussed how computer and mobile technology could be adopted to address the limitations of traditional paper-based cognitive measures in early detection of cognitive impairment allowing frequent monitoring of cognitive changes, particularly in the home environment (section 2.2.3). Studies also showed that cognitive tasks, which are often viewed as effortful and repetitive, could be gamified to enhance participants' engagement and increase their motivation to self-assess their cognitive status frequently in ways that are interactive and fun (section 2.3). However, only a few studies so far have investigated the use of gestural interaction and device movement as markers for evaluating cognitive abilities. In this chapter, we examine the feasibility of using off-the-shelf mobile games and user-game interaction patterns with a focus of touch gesture and device motion in cognitive assessment.

Although section 2.5 of the previous chapter identified prior research examining the differences in such user-interaction patterns between patients with clinical conditions and a group of healthy controls, it is important to note that most of these studies have explored hand movement in non-time-dependent tasks, such as handwriting. However, gameplay hand movement is closely related to user reactions to game stimuli. The characteristics of touch gestures in games are highly dependent on the time the user perceives the game stimuli, and often the limited time they have to perform a specific gesture. Therefore, the shape, speed and length of a gesture can be different, depending on the time it takes to perceive a game trigger. For example, a slow response time in identifying a game object that a player needs to interact with (e.g. in "Fruit Ninja" spotting a fruit that is about to move out of the screen) could result in a faster and more erratic gesture in order to complete the gesture in the reduced time available. Previous studies have shown that mental fatigue (Langner et al., 2010) and age (Deary, Der, 2005) adversely affect the speed of processing resulting in slower reaction time. This means that in certain games, faster and more erratic gestures could be an indicator of slower response time to visual stimuli, and therefore indicative of cognitive decline.

Therefore, the study in this chapter was carried out to gain a better understanding of how user-game interaction features could be linked to cognitive abilities. The results of this study were published as a journal article in IMWUT

(Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies) (Intarasirisawat et al., 2019).

A broad set of mobile games were developed and employed in this study to examine the influence of game mechanics on touch patterns. As the young generation, often considered as “digital native”, would be more familiar with touch interactions on smartphones and game technology compared to other age groups, they were then chosen as a target population in this study. Nevertheless, most individuals from this age group are often cognitively intact and likely to exhibit scores very close possible maximum. Therefore, it is likely that these samples would have low variability in test scores. For this reason, mental fatigue-inducing tasks were explored with an aim to induce temporary cognitive decline to improve data variability in the cognitive assessment scores.

3.1. Mental Fatigue and Cognitive Performance

Studies demonstrate the declined performance on specific cognitive domains is associated with other independent factors such as mental exhaustion, medication, and psychiatric comorbidity (Collie, Darby & Maruff, 2001, Wilson, 2014, Boise et al., 1999).

Mental fatigue is a psychological state induced by prolonged periods of demanding cognitive activities (Marcora, Staiano & Manning, 2009, Smith et al., 2016, Boksem, Meijman & Loris, 2005). When individuals become fatigued, feelings of tiredness and lack of energy are generally reported. Mental fatigue has an adverse effect on cognitive performance in various domains, for example, attention, response inhibition, planning and processing speed (Smith et al., 2016). A 100-mm visual analogue scale – fatigue (VAS-F) (Lee, Hicks & Nino-Murcia, 1991) is commonly used in many studies for the mental fatigue assessment (Smith et al., 2016, Shigihara et al., 2013, Ishii et al., 2015).

To establish a mental fatigue condition, different mental fatigue-inducing tasks have been employed in several studies. (Boksem, Meijman & Lorist, 2005) asked participants in their experiment to perform a visual attention task for 3 hours without rest. The task required participants to respond when a letter appeared at the relevant positions and ignore other cues displayed in the wrong positions. (Marcora, Staiano & Manning, 2009) induced mental fatigue in participants by using AX-continuous performance test (AX-CPT) for 90 minutes. Participants were required to press the right button or otherwise the left button when a target cue (letter A) or a probe cue (letter X) appeared on the screen, respectively. Other letters were invalid cues or probes, and thus they were expected to inhibit their response (Marcora, Staiano & Manning, 2009). However, the mental fatigue-inducing approaches in these studies (Boksem, Meijman & Lorist, 2005, Marcora, Staiano & Manning, 2009) require participants to perform mental fatigue-inducing tasks for a long period of time. Participants might be discouraged to take part in such a long session in a study. On the contrary, the 2-back test (see Figure 10) employed in a series of recent studies (Shigihara et al., 2013, Ishii et al., 2015), required participants to perform such a cognitive task for 30 minutes to establish a mental fatigue condition. This is a much shorter time compared to the cognitive tasks proposed in other studies. In the test, participants were continually presented with a series of letters on a screen. They were required to respond as quickly as possible when the presented letter was the same as the one that had appeared two presentations before.

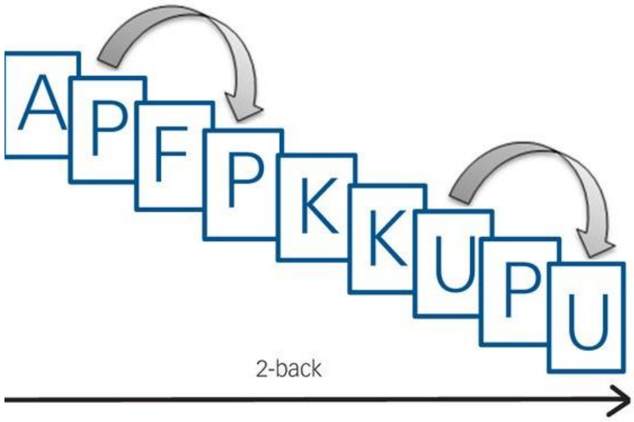


Figure 10: Example of sequential letters in the 2-back test

Thus, given the short time required to make participants mentally exhausted, the 2-back test was chosen as a cognitive task to induce a temporary cognitive decline in this study. It is also worth noting that this study does not particularly aim to investigate the effect of mental fatigue on cognitive performance, but such a mental fatigue-inducing task was only used to improve the data variability in participants' cognitive scores.

3.2. Research Questions

Existing work has demonstrated a potential relationship between cognitive performance and hand movement/gestures. A set of research questions was formulated to explore how these observations are reflected in the domain of smartphone games. In particular, this study aims to explore the extent to which the shape and timing of gestures could be related to changes in cognitive abilities.

1) Are the swipe length and shape of touch gestures related to changes in cognitive performance?

Considering the related work in writing exercises, there are strong indications that changes in cognitive performance could be related to changes in the length and shape of hand movements. Although gameplay touch interactions are different in nature compared to those of handwriting — gestures are time-dependent, and triggered by other stimuli — it is anticipated that the nature of the gesture shape could demonstrate statistically significant correlations with different cognitive abilities.

2) Is the speed of touch gestures related to changes in cognitive performance?

Speed in the game interaction is mainly related to responses to visual stimuli. In that respect, the temporal characteristics of gestures would be related to the time needed for a person to respond to such stimuli. Previous work has established that reduced cognitive performance is linked to increased response time to stimuli. This study aims to explore how such an increase in response time can be related to the timing characteristics of touch gestures.

3) Are the characteristics of the physical movement of the mobile device related to changes in cognitive performance?

It is anticipated that in smartphone gameplay, the device movements are predominantly influenced by the user's touch gestures as they interact with the game. Assuming that RQ1 and RQ2 have revealed correlations between touch gestures and cognitive performance, it is interesting to explore further if device movements, as captured by the smartphone's sensors, are also correlated with changes in cognitive performance.

In order to answer these research questions, a controlled study was conducted to capture gameplay information from a range of users and analyse them with respect to differences in cognitive abilities.

3.3. Materials and Methods

In this study, participants were asked to play games to assess their cognitive performance. The objective of the study was to find links between how they use touch gestures in popular games and their cognitive performance as measured through established cognitive function tests.

3.3.1. Participants

In this study, 22 healthy participants between the ages of 18-34 years were recruited through email invitations for voluntary participation in the study via the university mail lists. Volunteers were offered a £20 gift voucher as an incentive for taking part in the study. Potential participants were excluded if they were critically ill, diagnosed with neurological or psychiatric disorders, diagnosed with Parkinson's disease or arthritis, currently receiving psychoactive medication, blind or colour-blind, unable to understand verbal English instruction or considered to be excessive video gamers (with a playing time of more than 3 hours a day). Initially, 10 females and 12 males were recruited. After reviewing all collected data, 1 participant was later excluded from the analysis for accidentally resetting a game and so was unable to continuously play the game over the given time period. The final data set hence consisted of 21 participants (9 females and 12 males), 10 of whom use English as their first language. All participants are right-handed. Participants reported that recently they only played mobile games at most 2-3 days a week, with 71% saying that their average gaming session time was less than an hour, while 24% and 5% played average sessions of 1-2 hours and 2-3 hours respectively.

This study was approved by the Research Ethics Advisory Group of the School of Engineering and Digital Arts, University of Kent, UK (Ref. No. 0721617). All participants provided written informed consent after a complete description of the study.

3.3.2. Data Collection Procedure

Cognitively normal individuals without any diagnosed conditions were recruited to participate in this study. Under normal conditions, measuring the cognitive abilities of such individuals using standardised cognitive assessment instruments would typically exhibit scores within a narrow range closer to the maximum possible scores (Schroter et al., 2003). Considering that the possible low variation in cognitive scores within our subjects could limit the extent of the correlation analysis findings, therefore, a prolonged mental task was introduced in this study to induce a temporary decline in cognitive performance. Specifically, the study was carried out in two sessions on two separate days. In one of the sessions, a selected mental fatigue task was used to stimulate mental exhaustion, which induced a decline in participants' cognitive performance. The session with the intervention was solely introduced in our experimental design with a particular aim to improve data variability in paper-based cognitive assessment scores.

The experiment was conducted individually in a quiet room. All participants played two sessions two weeks apart, with one session starting with the mental fatigue task. Block randomisation was used for session type, splitting participants into two groups A and B. Groups were therefore roughly balanced in terms of gender and English as a first language, with group A experiencing the mental fatigue task in session 1. In order to reduce the effect of prior game experience in the study, in their first session, participants received instructions on how to play the games and were asked to play each game for 10 minutes to familiarise themselves with the gameplay. Participants were instructed to play the games while being seated on a chair without an armrest. They were advised to hold the device with one hand and play the game with another hand. Only one finger was allowed to touch the screen at a time (see Figure 11). The justification for asking players to play two-handed is that playing games with a single hand would make it difficult to access certain screen areas, e.g. top left corner. Moreover, with single hand playing, hand size and finger length are likely to influence the stroke patterns, and this would therefore potentially introduce confounding factors leading to spurious associations.

3.3.3.1. Control Session

All participants were asked to perform a set of cognitive measures (see section 3.3.4) and then to play three games in succession, 10 minutes per game, without breaks. All games were pre-installed on a Samsung S6 device, without a screen protector. The sequence of the games was also randomised to avoid order effects.

3.3.3.2. Mental Fatigue-Induced Session

In this session, participants followed the same steps described in the basic session, except that they were required to perform a mental fatigue-inducing task for 30 minutes prior to taking a series of cognitive ability tests. To induce cognitive overload, a 2-back test was used, in which participants were continually presented with a series of letters and instructed to respond as quickly and correctly as possible when the displayed letter was the same as the one that had appeared two presentations ago

(Shigihara et al., 2013). The aim of the mental fatigue-inducing task was to induce a broader range of cognitive ability scores for our participants. A wider range in cognitive abilities across the study could help highlight potential correlations more clearly.

Figure 11: A graphic displaying the body positioning, finger placement and hand grasp participants were advised to adopt during touchscreen interaction while playing the games.

3.3.3. Games

The three games used in the study were: Tetris, Fruit Ninja and Candy Crush Saga. Games were selected based on: being easy to learn, being highly engaging for most players, and involving intensive touch interactions (rich in data). The three games were chosen together for a diversity of gameplay characteristics in order to explore different demands on cognitive function, i.e. visuospatial in Tetris (Lau-Zhu et al., 2017), response inhibition and attention in Fruit Ninja (Liu et al., 2015) and visual search in Candy Crush Saga. In order to passively collect interaction data on touch, sensor and gameplay, we developed our own versions of these three games based on the available assets (Unity3D, 2017a, Unity3D, 2017b, Unity3D, 2017c) in Unity3D asset store. Several modifications were implemented to allow the games to keep track of touch interactions and physical motions through built-in sensors, including gameplay activities. In order to precisely capture their hand movements, participants were instructed to hold the phone in their hand and not to place it on the table while playing. To simplify touch interactions, games were modified to support only single touch events (one finger on the screen at a time).

Figure 12: A screenshot of a variation of Fruit Ninja in Unity3D asset store

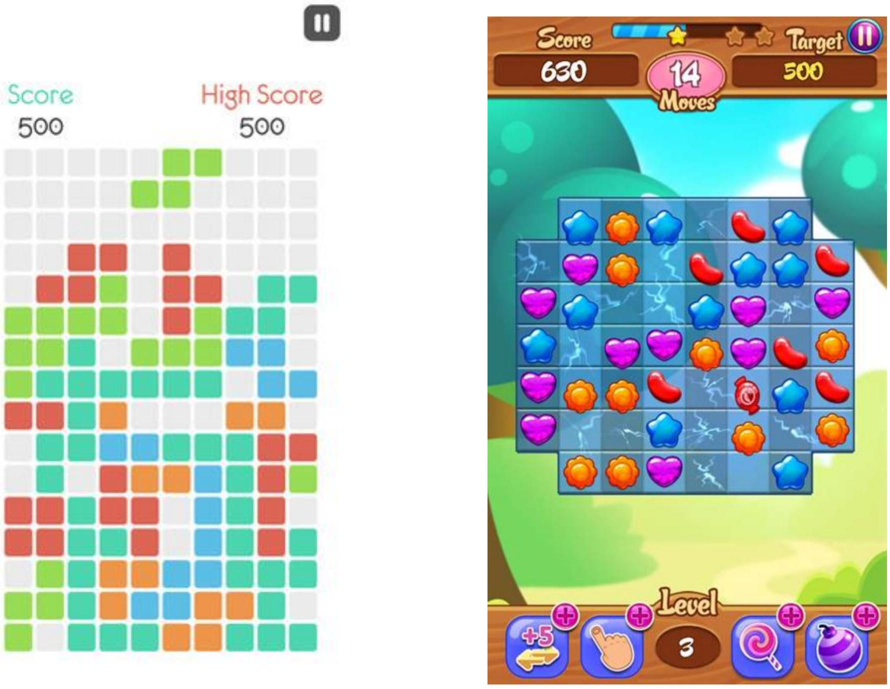


Figure 13: A screenshot of a variation of Tetris (Left) and Candy Crush Saga (Right) in Unity3D asset store

Fruit Ninja: To win points, players have to slice fruit randomly thrown in the air with a blade using their fingers to swipe across the screen. The game instantly ends if three pieces of fruit are missed, or players slash bombs that are occasionally thrown onto the screen (see Figure 12 for a screenshot).

Tetris: The shape matching game consists of four square blocks each. A random sequence of shapes falls at progressively increased speeds. Players are required to manipulate the falling shape with the goal to complete a 10-block horizontal line without gaps. When such a line is created, it disappears, and all blocks above the deleted line will fall. Swiping left/right is to move the shape to the left/right one block unit at a time while swiping down is to force it to fall into the stack instantly. Tapping the screen is to rotate it by 90 degrees (see Figure 13 for a screenshot).

Candy Crush Saga: In this puzzle match-3 game, players have to swipe the screen to swap two adjacent candies vertically or horizontally to match coloured candies in a combination of three or more to earn points. The matched row or column is then eliminated from the board, making candies above them fall into empty spaces. The game continues with new candies falling from the top until the entire board is filled. When matching special candies with others, it will clear a whole line of candies in the direction of the stripes. In order to pass each level, players must complete the challenge which may require a minimum score or to collect all target ingredients (see Figure 13 for a screenshot).

3.3.4. Measures

Global cognitive functioning was measured using ACE-III, a cognitive screening instrument used in the assessment of attention, memory, language and visuospatial function (Hodges, 2007). In this study, only results from ACE-III's subtasks were used to measure cognitive abilities in attention, memory and visuospatial domains. Higher values indicate increased cognitive performance and vice versa.

Attention (ATN) refers to the participants' ability to stay focused on target stimuli or tasks over a long period of time. It is anticipated that ATN would have a significant influence on performance in all three games.

Memory (MEM) is the ability to maintain information over time. Working memory is usually engaged when performing spatial and visual tasks to recall information that has been recently perceived. Demands on this particular cognitive function are most relevant to the game of Tetris as players are required to remember the current stack of shapes in order to decide where particular shapes may fit to clear a number of rows. We did not expect Candy Crush and Fruit Ninja to place particular demands on memory.

Visuospatial ability (VISP) refers to the ability to understand spatial relationships between objects. It is anticipated that VISP cognitive function to be most relevant to Tetris as the ability to identify the relationship between the falling shape and the current stack is key to performance. Fruit Ninja places slightly different demands on VISP function, namely on how to determine the distance between falling items and the bottom edge of the screen. We did not expect Candy Crush to place particular demands on VISP function.

Trail Making Test Part A and B (TMTA and TMTB, respectively) were used to measure participants' visual search, processing speed, including visual attention. However, in addition to the previous cognitive domains, TMTB also tests participants' mental flexibility (Tombaugh, 2004). The longer time spent to complete TMT tasks indicates a decline in cognitive performance and vice versa. Both measures were regards as relevant to all three games.

Response Inhibition (RESIN) was measured by the Stroop Colour-Word test (Hodges, 2007, Homack, Riccio, 2004). Higher values indicate a decline in cognitive performance and vice versa. It is anticipated that RESIN is most relevant to Fruit Ninja in that participants must inhibit their responses to bombs (no-go stimuli) and Candy Crush as participants should not make a random move or the first match they see but rather make a deliberate move strategically to win more points.

Therefore, in this present work, we investigated associations in different sets of cognitive domains specific to each particular game as described above and listed in Table 6.

3.4. Data Processing

3.4.1. Outlier Removal

Prior to the analysis, the score distribution of each cognitive task was examined to detect if there were unusually large or small values among all observations. By using the standard deviation method, the observations with values greater than three standard deviations above or below the mean are considered potential outliers.

When examining closer to these observations, two samples appear to coincide with unusual events during the experiment, including a participant restarting a task without the clock being restarted and a participant reporting being distracting from the task by a procedural error. Therefore, for the TMT-A task, the sample of participant no.1 in the control condition and the sample of participant no.8 in the mental fatigue-induced condition were considered outliers and excluded from the analysis.

3.4.2. Cognitive Scores

As the mental fatigue-inducing task was introduced into the study to gain greater variability in cognitive assessment scores, data variability in terms of the distribution of normalised cognitive assessment scores in both sessions was evaluated using mean, interquartile range (IQR) and stand deviation (SD). In the session with the mental fatigue-inducing task, noticeably higher degrees of variation were found in attention (IQR increased from 0.17 to 0.25, SD increased from 0.15 to 0.24 and mean declined from 0.91 to 0.81) and TMT-A (IQR increased from 0.30 to 0.33 while SD and mean remained roughly the same. Similarly, in TMT-B, the mean increased from 0.27 to 0.33 though IQR and SD remained relatively the same.

Furthermore, a paired-samples t-test was conducted to compare cognitive performance between the control and mental fatigue-induced conditions. The results indicate that attention scores were significantly higher for the control condition ($M=17.48$, $SD=0.873$) than for the mental fatigue-induced condition ($M=16.86$, $SD=1.459$), $t(20)=2.444$, $p<.05$, $d=0.701$). However, no significant difference was found in other cognitive domains.

These results indicate that the mental fatigue-inducing task (2-back) does have an effect on cognitive performance in the attention domain. Specifically, the results suggest the 2-back task could temporarily induce a cognitive decline in the attention domain with a medium effect size of 0.701. These results are broadly in line with the findings in previous studies that mental fatigue can induce declines in cognitive performance, including, executive attention, sustained attention, alternating attention, response inhibition and planning (Tanaka, Ishii & Watanabe, 2015).

3.4.3. Features

3.4.3.1. Touch Data

In this initial exploration, it was aimed to assess the relationship between touch interaction dynamics and cognitive scores. For each gestural touch interaction, we recorded a series of coordinates of the finger contact areas on the screen with timestamps. To identify possible touch feature patterns, quiver plots in Figure 14 and Figure 15 were used for visual inspection to display each corresponding pair of data points as a vector with an arrowhead. Each swipe renders a line with arrowheads by connecting all data points within that individual interaction. Lines are drawn in different colours to represent the directions of swipes. Coordinates of tap interactions are plotted with 'X' markers. Values in the horizontal and vertical axes represent touchpoints on Samsung S6 screen with the display resolution of 1440 x 2560 pixels.

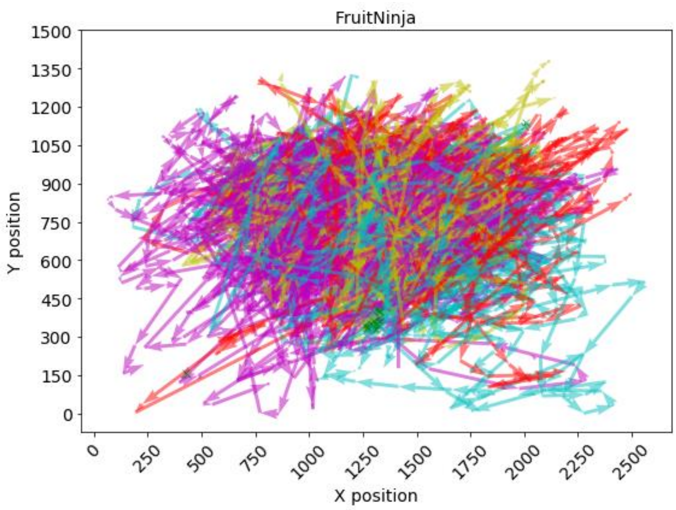


Figure 14: Touch patterns of an individual participant in Fruit Ninja

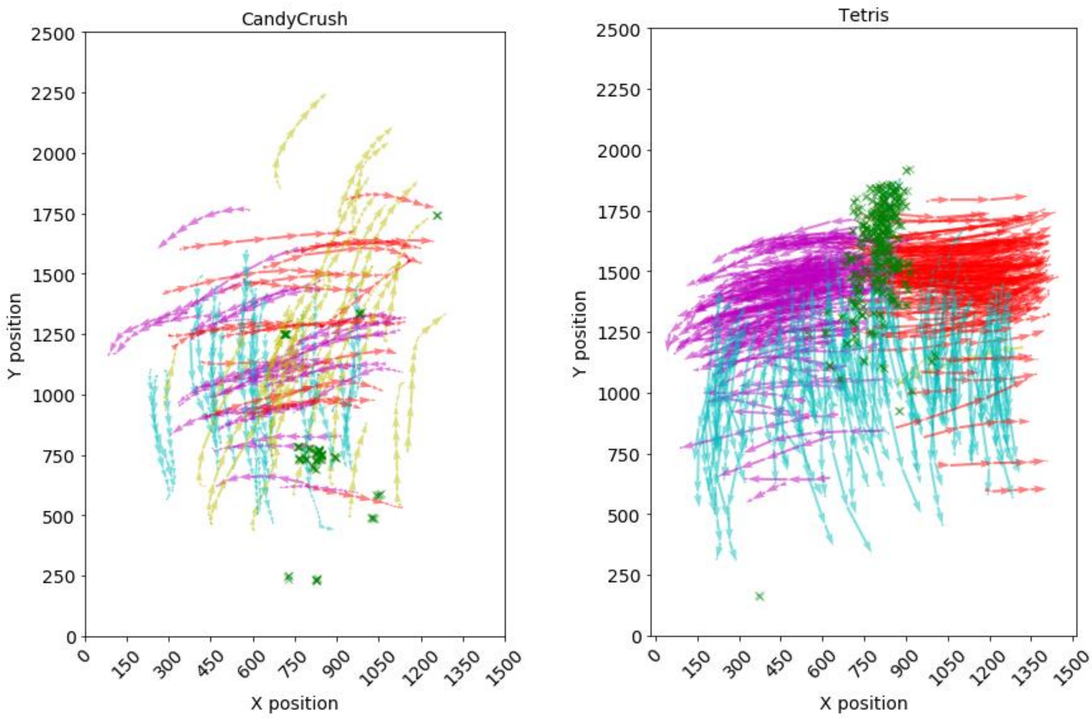


Figure 15: Touch patterns of an individual participant in Candy Crush Saga (left) and Tetris (right)

In particular, the swipe gestures made throughout the entire gameplay were classified into four directions, i.e. up, right, down and left based on the suggestion proposed by Bevan et al. (Bevan, Fraser, 2016) that directions of swipes affect the characteristics of swipe gestures. Importantly, features were measured in different directions because it was anticipated that different game mechanics could potentially influence gestural characteristics in particular directions. For instance, in Tetris, swiping left or right is to move the falling shape to the corresponding direction one step at a time regardless of the performed swipe length. In contrast, players are likely to swipe their finger down to drop the piece as quickly as possible when they feel confident of the target location. Therefore, a lower number of longer and faster downward swipes, as compared to horizontal swipes, were expected. Furthermore, it was reported in the neuroscientific literature that hemispheric utilisation bias demonstrates a strong influence on visuospatial attention. Particularly, individuals with a left hemisphere (LH) utilisation bias exhibited difficulty in selectively attending to stimuli presented on the left visual field (Spencer, Banich, 2005). Since participants are all right-handers who commonly demonstrate left-hemisphere dominance (Taylor, Heilman, 1980), these right-handed individuals were expected to display attentional bias to in-game stimuli appearing on the right. This led us to anticipate differences in gestural characteristics between leftward and rightward directions.

Different colours were used to indicate swipe directions in the plots. Swipe direction was determined using a swipe angle calculated from the sum of distances in x and y axes using the arctan2 function as denoted in Equation 1.

$$swipe\ angle = arctan2\left(\frac{Y_{dist\_sum}}{X_{dist\_sum}}\right) \times \frac{180}{\pi} \tag{1}$$

Based on the equation, output angles are between -180 and 180 degrees. Swipe direction was subsequently determined using an output angle, as illustrated in Figure 16.

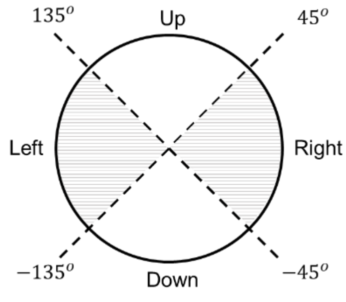


Figure 16: The four quadrants defining the general direction of a swipe

A full circle, which represented 360 degrees in one full rotation, was split into four 90 degree quadrants. A swipe was labelled with the corresponding direction of the quadrant in which the swipe angle landed. From the visual inspection of the touch patterns, certain plots revealed patterns that seemed to be unusual as several swipes shared the same data points in the lower-left area of the plots. It was speculated that these touch data points were mistakenly captured when participants' palm touched the screen by chance while holding the phone in their hand. These faulty records were automatically identified by thresholding the distance between two data points within a given swipe and then removed from further analysis. Four measures, specifically, total number, length, speed and directness index, were used to extract an initial set of features across the four directions of swipes, including taps.

It is worth pointing out that directness index is a feature to quantify the "straightness" of a swipe. If a swipe is carried out in a perfectly straight line, the directness index will be one whereas the value will be greater than one in a curved swipe. The features were extracted and computed per session based on the functions denoted in Table 3.

Table 3: A full table of initial touch features

Features	Function
Total Number of Swipes by Direction*	N
Total Number of Taps	N
Mean Length of Swipes by Direction*	$\bar{l} = \frac{\sum_{i=1}^{N} l_i}{N}, where$ $l_i = \sum_{j=1}^{n_i - 1} \sqrt{(x_{i,(j+1)} - x_{i,j})^2 + (y_{i,(j+1)} - y_{i,j})^2}$ n_i *is the number of data points in the* i^{th} *swipe interaction*
Mean Speed of Swipes by Direction*	$\bar{v} = \frac{\sum_{i=1}^{N} v_i}{N}, where$ $v_{i,j} = \frac{(l_{i,(j+1)} - l_{i,j})}{(t_{i,(j+1)} - t_{i,j})}$ $l_{i,j} = \sqrt{(x_{i,(j+1)} - x_{i,j})^2 + (y_{i,(j+1)} - y_{i,j})^2}$
Mean Directness Index of Swipes by Direction*	$\bar{d} = \frac{\sum_{i=1}^{N} d_i}{N}, where$ $d_i = \frac{l_i}{\sqrt{(x_{i,n_i} - x_{i,j})^2 + (y_{i,n_i} - y_{i,j})^2}}$

*Up, right, down, left

Due to differences in gameplay styles, participants tended to perform distinct touch gesture patterns in each game. Different subsets of the original touch-based features were chosen from the full table for each game.

Tetris. Horizontal swipes move blocks to the left or right and tapping the screen rotates the blocks by 90 degrees. Swiping downward forces the blocks to fall into the bottom stack instantly. This could indicate confidence in the location where a falling block will fall with its current orientation. As upward swipes have no function in the game, all features in the upward direction were excluded. Performed swipes exhibited a low degree of variability in directness indexes (M=1.04, SD=.10). This result indicates that the game mechanics were in favour of straight swipes. Therefore, features associated with directness index were excluded accordingly.

Fruit Ninja. Looking over the touch plots, the swipe gestures in Fruit Ninja were clearly more idiosyncratic than in other games. Most swipes were drawn continuously in erratic zigzag patterns. As a result, the swipe length increased significantly in contrast to the number of swipes, which considerably declined. As the number of swipes and taps were not much different between participants, these features were excluded. Owing to the arbitrary zigzag move, a single swipe was largely performed in multiple directions. It was impossible to label a swipe with a single direction. Instead of extracting gesture features by direction, it made more sense to extract features on all swipe gestures together (irrespective of direction). Performed swipes exhibited a great degree of variability in directness indexes (M=25.48, SD=35.11) than in other games. The DI feature was, thus, included.

Candy Crush. Unlike Tetris tapping the screen does nothing in Candy Crush. Thus, the number of taps was not included in the feature list. Performed swipes exhibited a low degree of variability in directness indexes (M=1.07, SD=.11). This result indicates that the game mechanics were in favour of straight swipes. Therefore, features associated with directness index were excluded accordingly.

Touch features included in the analysis for each game are listed in Table 4.

3.4.3.2. Sensor Data

In order to allow us to explore if there is any movement pattern associated with cognitive performance, device motions during gameplay were captured using the built-in 3D accelerometer and gyroscope. Although the primary function of the accelerometer is to determine changes in acceleration associated with gravity in three different directions, it can also identify the orientation of the phone when it is stationary. When the phone is held upright, and the screen faces towards a person, the x-axis is horizontal and positive in the rightward direction. The y-axis is vertical and positive in the upward direction. The z-axis is positive in the outward direction from the screen. Values are captured in the range of (-1g, +1g) for each axis. When no other acceleration force is applied, the accelerometer measures only the gravity acceleration. For example, when the phone is held upright, the measured value will be (0, -1g, 0) in Unity3D.

Table 4: Extracted touch features for each game

Feature	**Tetris**	**Fruit Ninja**	**Candy Crush**
Total Number of Swipes by Direction*	✓		✓
Total Number of Swipes in Horizontal or Vertical	✓		✓
Total Number of Swipes	✓		✓
Total Number of Taps	✓		
Mean Length of Swipes by Direction*	✓		✓
Mean Length of Swipes in Horizontal or Vertical	✓		✓
Mean Length of Swipes	✓	✓	✓
Mean Speed of Swipes by Direction*	✓		✓
Mean Speed of Swipes in Horizontal or Vertical	✓		✓
Mean Speed of Swipes	✓	✓	✓
Mean Directness Index of Swipes		✓	

*Right, left and down in Tetris and all four directions in Candy Crush

The rotational motion was captured using the gyroscope. The speed of rotation around each axis is measured in radians per second. When the phone is rotated counter-clockwise, the rotation will be positive. By contrast, the rotation will be negative when turning the phone in a clockwise direction.

In addition to raw values from the three axes, the magnitude of a 3D vector was also included as a basic attribute for feature extraction. This study aims to investigate the physical movement rather than orientation. Therefore, the standard deviation of the eight basic attributes (four from each sensor) was included as features to describe variation in physical movement. The mean and the sum of the acceleration and speed of rotation magnitude are also included. As a result, twelve features were extracted from sensor data per session for each game.

3.4.3.3. Gameplay Data

Although it is not part of the main research questions, it is yet interesting to explore associations between gameplay patterns and cognitive performance, based on the significant findings from a number of related studies (Manera et al., 2015, Tong et al., 2016, Zorluoglu et al., 2015). Despite sharing the same characteristics of being highly engaging and easy to play, each game has its own gameplay and rules, which is very much distinct from others. Therefore, different sets of gameplay features were extracted per session from each game as listed in Table 5.

Table 5: Extracted gameplay features for each game

Feature	Description
Tetris	
Max score	The maximum score achieved in the entire session
Max total taps per shape*	The maximum number of taps
Mean total taps per shape*	The average number of taps
Max total swipes per shape*	The maximum number of swipes
Mean total swipes per shape*	The average number of swipes
Max total interactions per shape*	The maximum number of taps
Mean total interactions per shape*	The average number of taps
Max rows completed per shape*	The maximum number of rows completed
Mean rows completed per shape*	The average number of rows completed
Fruit Ninja	
Max score	The maximum score achieved in the entire session
Mean overall air time	The average time a ball was in the air including the missing balls
Mean air time before being cut	The average time a ball was in the air before being cut
Max air time before being cut	The maximum time a ball was in the air before being cut
Min air time before being cut	The minimum time a ball was in the air before being cut
Mean cut position x	The average cut position in x-axis
Mean cut position y	The average cut position in y-axis
Candy Crush	
Max level	The maximum level reached in the entire session
Max score	The maximum score achieved in the entire session
Max score in level**	The maximum score achieved in each level
Percentage of switches by direction***	The percentage of candy switches made in each direction

*Based on actions performed before a single shape fell into the stack
**Level 1, 2, 3, and 4.

3.5. Results

Prior to our data analyses, samples from participants no.1 and no.8 were identified as outliers in measuring TMT-A in the control condition and the mental fatigue-induced condition, respectively, leaving a final data set of 20 samples to analyse with TMT-A in each condition.

One of the key objectives in this study was to examine the degree to which association exists between mobile gameplay behaviour and cognitive abilities. Spearman's rank correlation coefficients were computed to assess the relationship between pairs of variables for each condition separately. For ease of reading, the acronyms in Table 7 are used throughout the rest of this chapter.

Table 6: Acronym Table

Acronym	Description	Tetris	Fruit Ninja	Candy Crush
ATN	Score from attention subtasks in ACE-III	✓	✓	✓
MEM	Score from memory subtasks in ACE-III	✓		
VISP	Score from visuospatial subtasks in ACE-III	✓	✓	
TMTA	Time spent completing the task in TMT part A	✓	✓	✓
TMTB	Time spent completing the task in TMT part B	✓	✓	✓
RESIN	Response inhibition in the Stroop test		✓	✓

3.5.1. Touch Data

Overall for touch data, we found a few pairs of variables showing significant correlations consistently in both conditions. This includes the mean speed of swipe and RESIN in Fruit Ninja ($r=.482$, $p<.05$ and $r=.558$, $p<.01$ for the control and mental fatigue-induced conditions, respectively) and the mean length of downward swipes and RESIN in Candy Crush ($r=.488$, $p<.05$ and $r=.499$, $p<.05$ for the control and mental fatigue-induced condition, respectively).

Table 7: Correlation between each touch feature and cognitive performance in Tetris in the control condition

Feature	ATN	MEM	VISP	TMTA	TMTB
Total Number of Rightward Swipes	0.353	0.115	0.299	0.281	0.154
Total Number of Leftward Swipes	0.430	0.404	0.410	0.049	-0.056
Total Number of Horizontal Swipes	0.413	0.257	0.292	0.209	0.079
Total Number of Downward Swipes	**0.439***	0.111	0.418	0.129	0.284
Total Number of Swipes	**0.464***	0.180	**0.439***	0.167	0.130
Total Number of Taps	0.350	0.270	0.268	-0.074	0.264
Mean Length of Rightward Swipes	0.061	-0.088	-0.075	0.239	**0.455***
Mean Length of Leftward Swipes	0.205	0.213	0.042	0.083	0.401
Mean Length of Horizontal Swipes	0.163	0.101	0.052	0.099	0.417
Mean Length of Downward Swipes	0.086	-0.286	0.103	0.173	0.109
Mean Length of Swipes	0.173	-0.057	0.042	0.186	0.427
Mean Speed of Rightward Swipes	0.322	0.118	0.163	0.290	0.301
Mean Speed of Leftward Swipes	**0.485***	**0.526***	0.310	0.005	0.206
Mean Speed of Horizontal Swipes	0.401	0.301	0.202	0.165	0.294
Mean Speed of Downward Swipes	0.208	-0.212	0.184	0.260	0.031
Mean Speed of Swipes	**0.446***	0.214	0.305	0.251	0.121

*p<.05 and **p<.01

[See acronym description in Table 7]

Table 8: Correlation between each touch feature and cognitive performance in Tetris in the mental fatigue-induced condition

Feature	ATN	MEM	VISP	TMTA	TMTB
Total Number of Rightward Swipes	-0.008	**0.541***	0.180	**0.485***	-0.154
Total Number of Leftward Swipes	-0.159	**0.467***	0.141	0.202	-0.118
Total Number of Horizontal Swipes	-0.008	**0.512***	0.244	0.341	-0.069
Total Number of Downward Swipes	-0.198	0.178	0.356	0.200	0.075
Total Number of Swipes	-0.063	0.431	0.229	0.383	0.010
Total Number of Taps	-0.312	0.292	0.328	0.068	0.088
Mean Length of Rightward Swipes	0.275	0.087	0.302	0.370	0.119
Mean Length of Leftward Swipes	**0.581****	0.192	0.347	0.326	0.100
Mean Length of Horizontal Swipes	**0.454***	0.100	0.317	0.352	0.095
Mean Length of Downward Swipes	0.016	-0.289	-0.089	0.290	0.123
Mean Length of Swipes	0.253	-0.054	0.156	0.385	0.016
Mean Speed of Rightward Swipes	0.109	0.118	0.137	0.395	0.166
Mean Speed of Leftward Swipes	0.405	0.197	0.184	**0.502***	0.095
Mean Speed of Horizontal Swipes	0.288	0.138	0.178	**0.504***	0.147
Mean Speed of Downward Swipes	0.012	-0.197	0.005	0.346	0.045
Mean Speed of Swipes	0.159	0.007	0.196	0.414	0.045

*p<.05 and **p<.01

[See acronym description in Table 7]

Table 9: Correlation between each touch feature and cognitive performance in Fruit Ninja in the control condition

Feature	ATN	VISP	TMTA	TMTB	RESIN
Mean Length of Swipes	-0.058	-0.341	0.206	0.026	0.388
Mean Speed of Swipes	-0.225	-0.393	0.189	0.119	**0.482***
Mean Directness Index of Swipes	-0.143	-0.315	0.220	0.075	0.396

*p<.05 and **p<.01

[See acronym description in Table 7]

Table 10: Correlation between each touch feature and cognitive performance in Fruit Ninja in the mental fatigue-induced condition

Feature	ATN	VISP	TMTA	TMTB	RESIN
Mean Length of Swipes	0.125	-0.300	0.117	0.009	0.222
Mean Speed of Swipes	0.287	-0.274	0.039	0.122	**0.558****
Mean Directness Index of Swipes	0.047	-0.241	0.104	0.145	0.144

*p<.05 and **p<.01

[See acronym description in Table 7]

Table 11: Correlation between each touch feature and cognitive performance in Candy Crush in the control condition

Feature	ATN	TMTA	TMTB	RESIN
Total Number of Rightward Swipes	-0.398	-0.245	0.135	0.177
Total Number of Leftward Swipes	-0.162	-0.330	0.082	0.057
Total Number of Horizontal Swipes	-0.012	0.004	-0.008	0.034
Total Number of Upward Swipes	-0.306	-0.320	0.020	0.314
Total Number of Downward Swipes	-0.381	-0.392	0.012	0.101
Total Number of Vertical Swipes	-0.378	-0.315	-0.159	0.213
Total Number of Swipes	-0.422	-0.355	0.073	0.149
Mean Length of Rightward Swipes	0.037	-0.314	0.091	0.299
Mean Length of Leftward Swipes	-0.098	-0.229	0.058	**0.469***
Mean Length of Horizontal Swipes	-0.030	-0.206	0.087	**0.455***
Mean Length of Upward Swipes	-0.040	-0.262	0.177	0.226
Mean Length of Downward Swipes	-0.096	-0.126	0.353	**0.488***
Mean Length of Vertical Swipes	-0.063	-0.229	0.349	0.417
Mean Length of Swipes	-0.068	-0.289	0.231	0.422
Mean Speed of Rightward Swipes	-0.079	-0.186	0.121	**0.510***
Mean Speed of Leftward Swipes	-0.131	-0.081	-0.053	**0.509***
Mean Speed of Horizontal Swipes	-0.168	-0.146	0.055	**0.614****
Mean Speed of Upward Swipes	-0.152	-0.083	0.184	**0.600****
Mean Speed of Downward Swipes	-0.119	-0.056	0.132	**0.471***
Mean Speed of Vertical Swipes	-0.105	-0.095	0.195	**0.519***
Mean Speed of Swipes	-0.163	-0.105	0.097	**0.587****

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 12: Correlation between each touch feature and cognitive performance in Candy Crush in the mental fatigue-induced condition

Feature	ATN	TMTA	TMTB	RESIN
Total Number of Rightward Swipes	-0.022	-0.291	0.034	0.053
Total Number of Leftward Swipes	-0.134	-0.063	-0.216	-0.241
Total Number of Horizontal Swipes	0.339	0.132	0.247	-0.131
Total Number of Upward Swipes	-0.303	-0.117	-0.193	-0.137
Total Number of Downward Swipes	-0.097	-0.274	-0.144	-0.203
Total Number of Vertical Swipes	-0.026	-0.058	0.005	-0.098
Total Number of Swipes	0.026	-0.146	-0.047	-0.157
Mean Length of Rightward Swipes	0.284	-0.015	0.160	0.314
Mean Length of Leftward Swipes	**0.501***	-0.125	0.056	0.142
Mean Length of Horizontal Swipes	0.383	-0.081	0.070	0.331
Mean Length of Upward Swipes	0.378	-0.125	0.179	0.127
Mean Length of Downward Swipes	0.403	-0.009	0.239	**0.499***
Mean Length of Vertical Swipes	**0.446***	-0.068	0.225	**0.453***
Mean Length of Swipes	0.386	-0.080	0.204	0.379
Mean Speed of Rightward Swipes	0.326	-0.125	0.065	0.212
Mean Speed of Leftward Swipes	0.431	-0.122	0.030	0.161
Mean Speed of Horizontal Swipes	**0.439***	-0.132	0.047	0.199
Mean Speed of Upward Swipes	0.365	-0.077	0.127	-0.003
Mean Speed of Downward Swipes	0.431	-0.072	0.164	0.344
Mean Speed of Vertical Swipes	0.410	-0.017	0.158	0.212
Mean Speed of Swipes	**0.434***	-0.072	0.123	0.203

*p<.05 and **p<.01
[See acronym description in Table 7]

3.5.1.1. Swipe Length and Cognitive Performance

In Candy Crush, there was a positive correlation between RESIN and the mean length of downward swipes (r=.488, p<.05 and r=.499, p<.05 for the control and mental fatigue-induced condition, respectively). The results imply that increases in swipe length in the downward direction were correlated with declines in response inhibition ability. Similar results were also found in the control condition, where RESIN was significantly associated with the mean length of leftward swipes (r=.469, p<.05) and horizontal swipes (r=.455, p <.05). A coherent result was also found in the mental fatigue-induced condition as there was a significant correlation between the mean length of vertical swipes and RESIN (r=.453, p<.05). Taken together, these results suggest that increases in swipe length were correlated with declines in response inhibition. Interestingly, the results also seem to imply that increases in swipe length were correlated with decline in mental flexibility and processing speed, given the positive correlation found between TMTB and the mean length of rightward swipes ($r=.455$, $p<.05$) in the control condition of Tetris.

It was worth noting that in Candy Crush, there were positive correlations between ATN and the mean length of left swipes ($r=.501$, $p<.05$) and vertical swipes ($r=.446$, $p<.05$) in the mental fatigue-induced condition. Similar results were also found in the mental fatigue-induced condition in Tetris, where ATN was positively correlated with the mean length of leftward swipes ($r=.581$, $p<.01$) and horizontal swipes ($r=.454$, $p<.05$). These results seem to imply that longer swipes are correlated with increases in attention.

3.5.1.2. Swipe Speed and Cognitive Performance

There was a positive correlation between RESIN and the mean speed of all swipes in both conditions of Fruit Ninja ($r=.482$, $p<.05$ and $r=.558$, $p<.01$ for the control and mental fatigue-induced condition, respectively). In the control condition of Candy Crush, all swipe speed-related features showed positive correlations with RESIN ($r>.471$, $p<.05$), especially the mean speed of upward swipes ($r=.600$, $p<.01$), horizontal swipes ($r=.614$, $p<.01$) and all swipes ($r=.587$, $p<.01$). Collectively, this seems to indicate that increases in the swipe speed were correlated with declines in response inhibition ability.

In addition, ATN was significantly correlated with the mean speed of horizontal swipes ($r=.439$, $p<.05$) and all swipes ($r=.434$, $p<.05$) in the mental fatigue-induced condition of Candy Crush, whereas ATN was positively linked to the mean speed of leftward swipes ($r=.485$, $p<.05$) and all swipes ($r=.446$, $p<.05$) in the control condition of Tetris. Taken together, these results could imply that increases in swipe speed were correlated with increased attention.

Furthermore, the results also showed a significant correlation between MEM and the mean speed of leftward swipes in the control condition of Tetris ($r=.526$, $p<.05$). This seems to suggest that increases in swipe speed were correlated with increased performance on memory.

3.5.1.3. Directness Index and Cognitive Performance

The directness index is a feature that defined the shape of the touch interaction, whether it is a curved or a straight swipe gesture. This feature is only included in Fruit

Ninja for analysis. However, no signification correlation was found between the mean directness index of swipes and cognitive performance.

3.5.1.4. Total Number of Touch Interactions and Cognitive Performance

The total number of all swipes was significantly correlated with VISP (r=.439, p<.05) and ATN (r=.464, p<.05) in Tetris under the control condition. A significant correlation was also found between the total number of downward swipes and ATN (r=.439, p<.05). In addition, MEM was positively correlated with the total number of interactions features in the mental fatigue-induced condition, including the total number of rightward swipes (r=.541, p<.05), leftward swipes (r=.467, p<.05) and horizontal swipes (r=.512, p<.05). There was also a significant correlation between the total number of rightward swipes and TMTA (r=.485, p<.05). Taken together, these results seem to suggest that increases in the total number of interactions were correlated with increased performance on attention, visuospatial abilities and memory but declines in performance on processing speed.

3.5.2. Sensor Data

Overall, our results showed some significant correlations between device motion patterns and cognitive abilities. However, inconsistent results were observed to some extent, especially in the rotational speed-related features and cognitive performance.

3.5.2.1. Acceleration-related Features and Cognitive Performance

The sum acceleration magnitude in Tetris showed a positive correlation with ATN (r=.450, p<.05) and a negative correlation with TMTA (r=-.445, p<.05) in the mental fatigue-induced and control conditions, respectively. A similar result was found in the control condition in Fruit Ninja, where the SD acceleration on the x-axis was negatively correlated with TMTA (r=-.457, p<.05). These significant correlations imply that increases in these features were linked to increases in performance on attention and processing speed.

Interestingly, VISP was found to be negatively correlated with the sum acceleration magnitude (r=-.495, p<.05) in the mental fatigue-induced condition in Tetris. This implies that increases in the sum acceleration magnitude were correlated with increases in visuospatial abilities.

3.5.2.2. *Rotational Speed-related Features and Cognitive Performance*

The device motion patterns yielded a mixed picture of the relationships between the rotational movement-related features and RESIN. There were significant positive correlations between RESIN and the mean rotational speed magnitude (r=.434, p<.05) and the SD rotational speed around the z-axis (r=.592, p<0.1) and the sum of rotational speed magnitude (r=.465, p<.05) in the mental fatigue-induced condition in Fruit Ninja. Furthermore, in the control condition, TMTB showed significant correlations with the SD rotational speed around the x-axis (r=.462, p<.05) and the z-axis (r=.434, p<.05). Similarly, TMTA was significantly correlated with the SD rotational speed around the x-axis (r=.635, p<.01) and the SD rotational speed magnitude (r=.583, p<.01) in Tetris under the mental fatigue-induced condition.

However, in Candy Crush, a mixed picture of the relationships between the rotational speed-related features and RESIN emerged. In particular, the SD rotational speed magnitude was positively correlated with RESIN in the control condition (r=.462, p<.05), while the sum of rotational speed magnitude was negatively correlated with RESIN in the mental fatigue-induced condition (r=-.462, p<.05).

Table 13: Correlation between each sensor feature and cognitive performance in Tetris in the control condition

Feature	ATN	MEM	VISP	TMTA	TMTB
Mean Acceleration Magnitude	0.026	-0.204	-0.302	0.140	0.109
Sum Acceleration Magnitude	-0.201	-0.204	0.170	**-0.445***	-0.005
SD Acceleration on X axis	-0.040	0.033	0.028	-0.081	-0.130
SD Acceleration on Y axis	-0.023	-0.092	-0.088	0.069	0.071
SD Acceleration on Z axis	-0.054	-0.090	-0.139	0.182	0.386
SD Acceleration Magnitude	-0.247	-0.143	-0.199	0.257	0.310
Mean Rotational Speed Magnitude	-0.100	0.051	0.073	0.035	0.045
Sum Rotational Speed Magnitude	-0.156	0.023	0.083	-0.015	0.051
SD Rotational Speed around X axis	0.016	0.221	0.018	0.254	0.174
SD Rotational Speed around Y axis	-0.177	-0.031	0.010	-0.008	-0.047
SD Rotational Speed around Z axis	-0.212	-0.216	0.067	0.104	0.110
SD Rotational Speed Magnitude	-0.058	-0.024	0.041	0.066	0.014

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 14: Correlation between each sensor feature and cognitive performance in Tetris in the mental fatigue-induced condition

Feature	ATN	MEM	VISP	TMTA	TMTB
Mean Acceleration Magnitude	0.315	0.112	0.360	-0.044	-0.097
Sum Acceleration Magnitude	**0.450***	0.180	0.317	-0.383	-0.194
SD Acceleration on X axis	-0.048	-0.009	**-0.495***	-0.020	-0.051
SD Acceleration on Y axis	-0.014	0.236	0.182	0.202	0.208
SD Acceleration on Z axis	-0.176	0.288	-0.161	0.226	0.003
SD Acceleration Magnitude	-0.128	0.077	-0.161	0.224	-0.191
Mean Rotational Speed Magnitude	0.132	0.083	-0.199	0.302	0.147
Sum Rotational Speed Magnitude	0.183	0.144	-0.121	0.272	0.149
SD Rotational Speed around X axis	-0.036	0.219	-0.149	**0.635****	0.229
SD Rotational Speed around Y axis	0.331	0.122	-0.171	0.352	0.142
SD Rotational Speed around Z axis	0.322	0.047	0.056	0.371	0.110
SD Rotational Speed Magnitude	0.234	0.115	-0.192	**0.583****	0.174

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 15: Correlation between each sensor feature and each cognitive performance in Fruit Ninja in the control condition

Feature	ATN	VISP	TMTA	TMTB	RESIN
Mean Acceleration Magnitude	-0.142	-0.354	0.087	0.329	0.179
Sum Acceleration Magnitude	-0.210	0.098	-0.068	-0.291	-0.217
SD Acceleration on X axis	0.049	-0.184	0.075	0.191	0.116
SD Acceleration on Y axis	-0.096	-0.145	**-0.457***	0.187	0.106
SD Acceleration on Z axis	-0.215	-0.082	-0.402	0.125	0.244
SD Acceleration Magnitude	-0.289	-0.212	0.024	0.229	0.145
Mean Rotational Speed Magnitude	-0.119	-0.292	0.086	0.356	0.147
Sum Rotational Speed Magnitude	-0.194	-0.292	0.084	0.288	0.127
SD Rotational Speed around X axis	0.068	-0.178	-0.033	**0.462***	0.122
SD Rotational Speed around Y axis	-0.182	-0.307	0.120	0.251	0.168
SD Rotational Speed around Z axis	-0.082	-0.354	0.116	**0.434***	0.036
SD Rotational Speed Magnitude	-0.026	-0.207	0.044	0.371	0.130

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 16: Correlation between each sensor feature and each cognitive performance in Fruit Ninja in the mental fatigue-induced condition

Feature	ATN	VISP	TMTA	TMTB	RESIN
Mean Acceleration Magnitude	0.046	0.272	-0.226	-0.035	0.223
Sum Acceleration Magnitude	-0.213	-0.101	0.388	0.142	0.065
SD Acceleration on X axis	0.017	-0.039	-0.356	-0.244	0.162
SD Acceleration on Y axis	-0.186	-0.356	-0.153	0.058	0.282
SD Acceleration on Z axis	0.056	-0.184	-0.272	0.110	0.179
SD Acceleration Magnitude	0.013	-0.025	-0.071	-0.106	0.312
Mean Rotational Speed Magnitude	0.102	-0.024	0.054	-0.006	**0.434***
Sum Rotational Speed Magnitude	0.076	-0.060	0.077	0.073	**0.465***
SD Rotational Speed around X axis	-0.106	-0.024	0.320	0.190	0.183
SD Rotational Speed around Y axis	-0.143	-0.104	0.021	-0.149	0.370
SD Rotational Speed around Z axis	0.020	-0.153	0.032	-0.055	**0.592****
SD Rotational Speed Magnitude	-0.237	-0.106	0.033	-0.077	0.403

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 17: Correlation between each sensor feature and each cognitive performance in Candy Crush in the control condition

Feature	ATN	TMTA	TMTB	RESIN
Mean Acceleration Magnitude	0.166	-0.060	-0.030	-0.142
Sum Acceleration Magnitude	0.350	0.248	0.073	0.071
SD Acceleration on X axis	-0.238	-0.271	-0.342	0.073
SD Acceleration on Y axis	0.278	-0.051	-0.147	0.149
SD Acceleration on Z axis	-0.117	0.027	-0.026	0.394
SD Acceleration Magnitude	-0.334	0.165	0.395	0.382
Mean Rotational Speed Magnitude	-0.222	0.095	0.253	0.387
Sum Rotational Speed Magnitude	-0.091	0.159	0.252	0.395
SD Rotational Speed around X axis	-0.037	0.314	0.332	0.349
SD Rotational Speed around Y axis	-0.264	-0.036	0.235	0.429
SD Rotational Speed around Z axis	-0.231	0.137	0.390	0.362
SD Rotational Speed Magnitude	-0.201	0.194	0.368	**0.462***

*p<.05 and **p<.01
[See acronym description in Table 7]

Table 18: Correlation between each sensor feature and each cognitive performance in Candy Crush in the mental fatigue-induced condition

Feature	ATN	TMTA	TMTB	RESIN
Mean Acceleration Magnitude	0.062	-0.131	-0.265	-0.353
Sum Acceleration Magnitude	0.028	0.438	0.121	-0.292
SD Acceleration on X axis	-0.134	-0.165	-0.034	0.030
SD Acceleration on Y axis	0.067	-0.177	0.105	0.192
SD Acceleration on Z axis	0.093	0.020	0.227	0.136
SD Acceleration Magnitude	-0.159	0.077	0.055	-0.153
Mean Rotational Speed Magnitude	-0.050	0.057	0.104	-0.432
Sum Rotational Speed Magnitude	-0.125	0.063	0.077	**-0.462***
SD Rotational Speed around X axis	-0.203	0.290	0.277	-0.182
SD Rotational Speed around Y axis	0.032	0.005	-0.014	-0.327
SD Rotational Speed around Z axis	0.144	-0.364	0.084	0.204
SD Rotational Speed Magnitude	-0.025	0.009	0.075	-0.127

*p<.05 and **p<.01
[See acronym description in Table 7]

3.5.3. Gameplay

Overall, the results demonstrate some statistical significance between gameplay patterns and cognitive abilities, especially in the max score-related features. These seem to suggest that poorer performance in gameplay were linked to poorer cognitive performance. Nevertheless, contradicting results also emerged in some of these gameplay specific features, particularly the number of interactions in Tetris and the percentage of switches in Candy Crush.

3.5.3.1. Max Score and Cognitive Performance

The max score showed a negative correlation with TMTA (r=-.558, p<.05) in Tetris in the control condition, while the max score was significantly correlated with RESIN (r=-.539, p<.05) in Fruit Ninja in the mental fatigue-induced condition. Even though no significant correlation was found between the max score and cognitive scores in both conditions in Candy Crush, TMTA was significant correlated with the level2 max score (r=-.456, p<.05) and the level3 max score (r=-.449, p<.05) for the mental fatigue-induced and control conditions respectively. Taken together, these significant correlations imply that increased performance, reflected in the max score-related features, was correlated with increases in cognitive performance on processing speed and response inhibition ability.

3.5.3.2. Game Response Time and Cognitive Performance

In Fruit Ninja, the minimum air time before being cut was significantly correlated with ATN ($r=-.524$, $p<.05$) in the mental fatigue-induced condition. However, no signification was found between such a feature and cognitive performance in the control condition.

3.5.3.3. Number of Interactions per Shape and Cognitive Performance

The numbers of touch interactions players made per shape before a shape fell into the stack in Tetris were calculated in terms of taps and swipes. The analysis yielded a mixed picture of results. In the control condition, the maximum number of total taps per shape was significantly correlated with ATN ($r=.475$, $p<.05$) and VISP ($r=.519$, $p<.05$), while the maximum number of total taps per shape was positively correlated with MEM ($r=.467$, $p<.05$) in the mental fatigue-induced condition. A coherent result was found in the control condition that the maximum number of total interactions was positively correlated with ATN ($r=.476$, $p<.05$). These results seemed to imply that the increases in the total number of interactions per shape were correlated with increases in attention and visuospatial abilities. However, contradictory results emerged in the mental fatigue-induced condition, where negative correlations were found between VISP and the mean total number of taps ($r=-.579$, $p<.01$) and the mean total number of interactions ($r=-.550$, $p<.05$).

3.5.3.4. Percentage of Candy Switches and Cognitive Performance

In Candy Crush in the mental fatigue-induced condition, the percentage of candy switches made in the upward direction showed a significant correlation with ATN ($r=.489$, $p=.05$) while the percentage of candy switches made in the rightward direction was negatively correlated with TMTA ($r=-.517$, $p<.05$).

3.6. Discussion

This study investigates the possible use of popular mobile games with a strong track record in user engagement and re-playability to assess cognitive function by examining the links between cognitive performance and user-game interaction behaviour. In particular, this exploratory study focuses on examining whether touch interaction and device motion can be potentially used as predictive features for cognitive assessment. It was acknowledged that the analysis was evaluated with a relatively small number of healthy participants. However, the study has shown statistically significant results (with p-value < .01 in some cases) that provide compelling evidence to support the presence of the correlations.

3.6.1. Addressing Research Questions

3.6.1.1. RQ1: Are the swipe length and shape of touch gestures related to changes in cognitive performance? And RQ2: Is the speed of touch gestures related to changes in cognitive performance?

Overall, we found some evidence that several swipe speed features were positively correlated with RESIN, implying that increases in swipe speed in these games were associated with decreases in performance on response inhibition. Similarly, our results seem to indicate that increases in swipe length in the game context were significantly correlated with decreased performance on response inhibition. These findings demonstrate a diversion from the previous handwriting studies where cognitively impaired patients tended to exhibit slower hand movement than their healthy peers (Tigges et al., 2000, Mavrogiorgou et al., 2001, Schroter et al., 2003, Rosenblum et al., 2013, Kawa et al., 2017). In a similar fashion, our findings are also in contrast with previous studies on traditional handwriting in which the mean stroke length was significantly shorter among patients with a clinical condition associated with cognitive impairment, including Obsessive-Compulsive Disorder (OCD) (Mavrogiorgou et al., 2001) and Parkinson's disease (Rosenblum et al., 2013) as compared to healthy controls.

These seemingly contradictory findings could be explained by the differences in user intention and attentional demands between gameplay and handwriting tasks. In healthy adults, handwriting is a well-learned movement, which can be executed automatically without conscious attention (Longstaff et al., 2001, Tucha, Paul & Lange, 2001). On the contrary, given the inherent intent of games to keep players engaged, players were constantly bombarded with visual and auditory stimuli, resulting in high demand for attentional resources. It is, therefore, speculated that while designed for engagement, such game mechanics forces players to provide appropriate responses as quickly as possible within a limited time frame. The underlying motivation to gain scores as much as possible could lead to more erratic and faster gestures.

In addition, such impulsive touch patterns in games could be explained by the well-known concept of the dual thinking system described by Kahneman as thinking fast and slow (Kahneman, 2011). In that, the impulsivity in touch patterns would be spontaneous responses with a strong incentive drive towards rewards, i.e., scores in the game context, leading to impaired inhibition control. Such rapid and effortless movement may indicate that their swipe interactions heavily rely on System 1 (fast thinking) rather than System 2 (slow thinking) to inhibit their automatic responses to negative cues.

However, another research study reported the opposite findings demonstrating faster hand movement in cognitively impaired children than their healthy peers. In particular, it was found that children with Attention Deficit Hyperactivity Disorder (ADHD) and Developmental Coordination Disorder (DCD) exhibited significantly faster but less accurate gestures in a hand-drawing task as compared to typically developing children (Flapper, Houwen & Schoemaker, 2006). These findings are in line with our results, although derived from a different population and context.

Overall, significant correlations observed in this study seem to demonstrate possible relationships between touch patterns and cognitive performance. Therefore, the potential use of these touch features as input for a screening tool to detect a medical condition related to cognitive impairment will be further examined in Chapter 4.

3.6.1.2. RQ3: Are the characteristics of the physical movement of the mobile device related to changes in cognitive performance?

The bivariate analysis of sensor data provides only weak or inconclusive evidence for the relationships between cognitive performance and device motion during the gameplay. Seemingly consistent results could only be found in Fruit Ninja, where rotational speed-related features showed positive correlations with TMTB and RESIN in the controlled and mental fatigue-induced conditions, respectively. Specifically, these results seem to suggest that a higher degree in the rotational movement was correlated with reduced performance on mental flexibility and inhibition control. This seems to be coherent with the aforementioned findings with regards to touch-based features in Section 3.6.1.1 that more rapid and active interactions with the device correspond to poorer performance on response inhibition. It seems reasonable to speculate that the rapid screen interaction may generate such a high degree of device movement. However, only some evidence was found in the mental fatigue-induced condition of Fruit Ninja, where swipe speed was significantly correlated with several rotational movement-related features. No significant correlation was found in the control condition. These correlation results provide weak evidence that the significant correlations between cognitive performance and device motion features in Fruit Ninja were influenced by the rapid touch interaction.

Although it is not possible to draw any strong conclusions whether these device motions features alone can be used as proxy markers for changes in cognitive performance, it is worth investigating in future studies the potential of the device motions features as input when combined with other user-game interaction features to develop classification models for the identification of people with cognitively impaired conditions.

3.6.1.3. Game Performance Patterns

Findings in prior studies provided indicative evidence of associations between game performance metrics and cognitive abilities in various domains, such as inhibition control, attention, processing speed and working memory (Manera et al., 2015, Zygouris et al., 2015, Tong et al., 2016, Song, Yi & Park, 2020). As expected, significant correlations found in the study are in line with these findings. In particular, associations of our game score features across the three games with cognitive performance suggest that higher-performing players tend to demonstrate better cognitive performance, especially in processing speed and inhibitory control. Furthermore, a negative correlation between attention scores and the minimum air time before being cut in Fruit Ninja supports previous findings of associations between in-game response time-related features and cognitive abilities. In that, increases in response time are correlated with declines in cognitive performance, such as inhibition control, visual attention and processing speed (Manera et al., 2015, Tong et al., 2016).

Furthermore, Spencer et al. suggested that individuals with left hemisphere dominance tended to exhibit a strong attentional bias to the right visual field (Spencer, Banich, 2005). To some extent, the results from our game-based study converge with these findings. In particular, in Candy Crush, significant correlations between the candy switches made in the rightward direction and processing speed was observed, but no significance was found between the percentage of candy switches made in the leftward direction and cognitive scores. Given that all participants were left-hemisphere dominant (right-handed), it is speculated that this discrepancy could be related to the strong attentional bias of left hemisphere individuals to stimuli on the right visual field (Spencer, Banich, 2005) that may potentially influence the interaction patterns and our correlation results. However, this study does not have sufficient evidence, future research should be carried out to demonstrate such a link. Nevertheless, such results could be indicators that future research should examine the influence of this attentional bias of both right-handed and left-handed users on user-game interaction patterns.

3.6.2. Game Mechanics, Cognitive Demand and Gestural Characteristics

It is worth noting that swipe gestures only show significant correlations with particular cognitive capacities in particular games. We believe that this could be due to the differences in the game mechanics and cognitive demands required in particular games. For instance, several features related to the total number of swipes were significantly associated with ATN, VISP and MEM in Tetris. Conversely, such relationships were not found in Candy Crush. It is speculated that the differences in the swipe characteristics among these games are potentially influenced by the game mechanics and related cognitive demand of the given game tasks. In particular, Tetris demands attention and visuospatial functions to determine the spatial relations to complete a row of blocks, whereas Candy Crush requires visual search capacity to locate and make a move to create a possible match of items. Furthermore, the underlying game objective of gestural interaction may have some influence on swipe characteristics (Burnett et al., 2013). The results from the paired samples t-test seem to provide evidence to support our speculation. The results indeed indicated that there was no difference between the speed of horizontal and vertical swipes in Candy Crush ([$M=-27.35$, $t=-.473$, $p=.64$], [$M=14.01$, $t=.30$, $p=.77$] in control and mental fatigue-induced conditions, respectively) whereas the speed of horizontal swipes was significantly different from downward swipes in Tetris ([$M=-936.7$, $t=-5.923$, $p<.01$], [$M=-1056.59$, $t=-6.485$, $p<.01$] in control and mental fatigue-induced conditions, respectively). Based on our speculation, it could be explained that in Candy Crush, swipes in all four directions were solely to swap item positions resulting in no speed difference in these gesture directions. Conversely, downward swipes in Tetris, which were carried out at a much faster speed comparing to swipes in horizontal directions, could indicate players' confidence in the target location and the intention to force the block to fall as quickly as possible.

In addition, the touch plots in Figure 14 and Figure 15 clearly illustrated that the swipe patterns in Fruit Ninja were considerably distinct from those observed in the other two games. Such zigzag swipe patterns across the screen could indicate attempts to slice multiple items in a single swiping interaction without lifting a finger. Furthermore, the relationship between swipe speed and RESIN found in Fruit Ninja could be explained by the influence of the game mechanics and cognitive demands. In that, players were likely to swipe at a faster speed when multiple items were thrown up in the air simultaneously in order to slice all these items before they fell off the screen. However, at the same time, the game mechanics also forces players to inhibit their responses to negative cues (bombs). Taken together, these observations seem to point to the possibility that gestural characteristics are likely to be influenced by game mechanics and respective cognitive demand.

Based on the discussion outlined above, the insights realised from this study could offer a number of recommendations and considerations for designing a practical game-based cognitive assessment instrument. In designing games to help assess cognitive performance, game mechanics can be designed to target specific cognitive abilities. For instance, assessing visuospatial functions would be possible within games where the user is expected to identify positions, orientations and shapes of visual stimuli relative to the game environment in space. Furthermore, game mechanics should involve user gestures that are triggered by such visual stimuli. These features would allow the capture of such gestures and explore features such as length, shape and orientation of gesture to discover changes in visuospatial abilities. These game mechanics can be found in shape matching games like Tetris and other traditional Shape Sorter games. Augmenting such games with time constraints is also a feature that can help capture changes in the player's processing speed and response to visual stimuli. Furthermore, the underlying game objectives of performing specific gestures to manipulate visual stimuli should be linked to cognitive demand reflecting the player's ability to understand spatial relations, for example, tapping the screen to rotate an object or swiping down to drop an object with the correct orientation into the correct gap in Tetris. Specifically, the latter swipe down gesture in Tetris could demonstrate high confidence in identifying spatial relations between the presented stimuli and the game environment.

More generally, within the mechanics of any games, certain gestures can potentially play the role of demonstrating the players' confidence in understanding and responding to visual stimuli in the game. These gestures can be exploited in the same way as the vertical gesture in Tetris to identify correlations with cognitive abilities.

Lastly, games that require intensive touch interactions, such as taps and swipes within a time constraint game duration, can help generate significant gesture data points, which subsequently can help identify changes in cognitive abilities. However, it should be considered that the intensity and cognitive demand by a game could potentially hinder user retention. Indeed, finding the right balance in the level of game intensity and user satisfaction is a broader challenge for the design of any computer games.

3.6.3. Limitations and Future Directions

It should be acknowledged that there are a number of limitations in this study. The main limitation is its relatively small sample size, which limits the reliability of the results, thereby leading to inconclusive findings. Most importantly, the study results must be interpreted with caution, given that over-testing multiple pairs of variables based on a single data set is likely to introduce spurious correlations. Although adjusting the significance level using the Bonferroni correction could be used to avoid spurious positives, the threshold is very stringent, which may result in discarding significant observations (false negatives). Nevertheless, the presence of the relationships found in this study seems to indicate the potential in exploring machine learning techniques to examine the predictive capability of these extracted features for cognitive assessments. Therefore, it is a question of future research to investigate whether user-game interaction behaviour can be used to identify patients with cognitive impairment and explore the long term changes in cognitive abilities for such individuals.

Besides the limited sample size, according to the participant exclusion criteria, the study results are also restricted to non-excessive gamers. For these reasons, the findings of this exploratory study cannot be generalised to a wider population. Apart from the fatigue-inducing task, the in-game events, such as making wrong moves in the game, may also have an additive fatigue-inducing effect on the subsequent cognitive performance within the game. Therefore, the game order was randomised while the gameplay duration on each game was kept to a minimum to minimise this influence on our measures. Moreover, in this experiment, data collection was under controlled lab conditions in that participants were asked to use only one finger to interact with the device at a time. This may not truly reflect their natural gameplay behaviour in a non-experimental environment. Future work should consider the potential effect of multi-touch gestures to validate the findings drawn from this study. Long-term studies in users' natural environment will also help shed light on the practicality of deploying such a system in the real world.

3.7. Conclusions

In this chapter, we explored the feasibility of using gesture and movement data in mobile games to identify patterns that are associated with cognitive performance in cognitively healthy individuals under induced mental fatigue condition. As discussed in

Section 2.3.3, the majority of previous studies in this field focuses on using gameplay performance as features in cognitive assessment. To the best of our knowledge, this is the first piece of work that investigates such links between patterns of touch interaction and device motions in these particular mobile games and cognitive performance.

Although the results of this study are inconclusive and not consistently supporting previous findings in prior handwriting studies, the observed significant correlations indicate the potential of the proposed touch interaction and device motion features as promising features for developing a game-based cognitive assessment, including a screening measure for a clinical condition related to cognitive impairment. Given that the inconclusive results may have been impacted by the limited number of samples, further exploration with larger sample sizes would enable researchers to obtain more reliable results and the generalisation of the findings.

Our work relied on the use of existing popular games to demonstrate these effects. This is a strong indicator that our findings can be applied or incorporated in a range of existing games with a strong track record in user engagement.

In the main study discussed in the next chapter, these proposed user-game interaction features will be included as input to examine the feasibility of using casual mobile games to identify cognitively impaired individuals, specifically those with alcohol dependence from health controls.

Chapter 4: An Automated Mobile Game-based Screening Tool for Patients with Alcohol Dependence

In chapter 3, we have examined the relationships between cognitive performance and the proposed user-game interaction features, particularly the touch interaction and device motion features. This chapter demonstrates the use of mobile games and user-game behavioural features in a clinical application. In particular, we focused on the feasibility of using the proposed game-based features to classify alcohol-dependent patients and healthy individuals. The results reported in chapter 3 provide some indications that different game mechanics inherent in each game could place particular cognitive demands on players and potentially influence touch interaction patterns. The game selection in this study was based on these game design recommendations discussed in 3.6.2 in the previous chapter.

In addition to the findings in the previous chapter, the current study reported in this chapter was motivated by the findings from previous studies, discussed in section 2.5, which demonstrated that individuals with several medical conditions associated with cognitive impairment exhibited reduced fine motor skills. In particular, it was found in a recent study that by using a tablet to measure finger dexterity, patients with MCI and Alzheimer's Disease demonstrated significantly slower responses and higher contact duration fluctuation when compared to healthy adults (Suzumura et al., 2018). Furthermore, touch gestures and device movement patterns were used as key features in an automated screening tool to identify children with autism from typically-developing children (Anzulewicz, Sobota & Delafield-Butt, 2016) . Collectively, this body of literature provides encouraging evidence suggesting that the combination of user-game behavioural data passively collected via multisensory input could produce fruitful results for identifying people with cognitively impaired conditions, especially with fine motor disturbance. Most importantly, prior work has demonstrated that alcohol dependence is strongly linked to both declines in cognitive abilities (Jauhar, Marshall & Smith, 2014, Hermens et al., 2013), and irregular motor function of patients' hands (Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). Given that the interaction mode in mobile games typically involves touch gestures and device motions, we consider that smartphone games have the potential to capture both of these types of discriminant factors and therefore help develop an automated system for the diagnosis of alcohol dependence to overcome the limitations of current alcohol screening tools discussed in section 2.4.3 and 2.4.6.

The results of this study were published as a journal article in IMWUT (Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies) (Intarasirisawat et al., 2020).

4.1. Approach

Alcohol dependence is often manifested with specific cognitive and physiological changes such as cognitive decline (Hermens et al., 2013, Jauhar, Marshall & Smith, 2014) and changes in the motor functions of their hands (Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). We consider that both of these changes can influence the way users interact with mobile games. In particular, prior work has shown that both game performance metrics and characteristics of touch gestures during gameplay are correlated with cognitive decline (Intarasirisawat et al., 2019). Furthermore, potential alcohol dependence related changes in motor function may be manifested in the movement of the mobile device, and the way touch gestures are performed during gameplay.

These considerations have led us to explore the design of a game-based diagnosis tool that aims to identify people with alcohol dependence. Specifically, the intended system is based around the augmentation of existing smartphone games, such as Tetris, Fruit Ninja, and Unblock Puzzle (see section 4.3 for details), with the ability to collect data about the user performance, touch gestures on the screen, and device movement recorded through the smartphone's accelerometer and gyroscope. Our objective is to develop a classifier that can identify individuals with alcohol dependence, using these signals as input. To this end, a controlled study involving 40 individuals diagnosed with alcohol dependence and a control group of 40 healthy individuals was carried out. The datasets from multiple gameplay sessions were used to train and validate a classifier for the diagnosis of alcohol dependence.

4.2. Data Collection

This study protocol was approved by the University of Kent Psychology Research Ethics Committee, UK (Ref. No. 201815420117865237). All participants gave written informed consent to participate after a complete description of the study.

The study was carried out at two locations, i.e., a speciality substance use disorder hospital and a university, for the patient and the control (healthy participants) groups, respectively. It is worth noting that participants in the patient group were clinically diagnosed with alcohol dependence. Only those who were admitted to a residential treatment program after being detoxified were recruited to enter the study, given the fact that patients, during the detoxification phase, often experience effects of withdrawal and can be easily tired and unable to focus on tasks at hand (Chris Elkins, 2020). The experiments were conducted individually in a quiet room. All participants completed the AUDIT (Allen et al., 1997) and the Hospital Anxiety and Depression Scale (HADS) (Snaith, 2003) questionnaire prior to commencing the data collection session. Those in both groups, who scored a total of 8 points or higher in either Anxiety or Depression categories, were excluded from the study. It is worth noting that the use of the Hospital Anxiety and Depression Scale (HADS) was recommended by a clinical consultant who works closely with our research group. In particular, with the aim to evaluate symptoms of both anxiety and depression, the Patient Health Questionnaire (PHQ-9) was not chosen as it was designed to assess only depression severity (Hansson et al., 2009). Given that Beck Depression Inventory-II (BD-II) consists of 42 items when combining items from both anxiety and depression subscales, BD-II is a longer test when compared to HADS, which has only 14 items in total. Additionally, BD-II is licensed while HADS can be used for free (Phan et al., 2016). HADS was, thus, chosen in our study.

A growing number of studies have shown that chronic binge drinkers typically demonstrate deficits in specific cognitive functions, i.e., visuospatial ability, working memory, attention, and executive function (Hermens et al., 2013, Jauhar, Marshall & Smith, 2014). Participants' cognitive function was therefore examined by a research assistant who has received clinical training in cognitive assessment administration. The cognitive assessment battery included the Mini-Mental State Examination (MMSE) (Tombaugh, McIntyre, 1992), the Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005), and the Stroop Colour-Word Test (Homack, Riccio, 2004). These cognitive measures assess a variety of cognitive functions, including orientation, attention, memory, language, executive function, and inhibition control. Participants were given an introduction on how to play all three games pre-installed on a mobile phone (Samsung S6) without a screen protector. To reduce the effect of participants' prior game experience in the study, they were asked to familiarise themselves with the games, each game for 5 minutes. Participants were instructed to hold the phone firmly with one hand and play the games with another hand while sitting on a stationary chair without an armrest. The instruction on handgrip and body posture was to eliminate the effects of hand size and finger length on the touch patterns and to maximise phone movement. Only one finger was allowed on the screen at one time to simplify touch interactions in the analysis.

No data was recorded during this game training session. Afterwards, participants were asked to play each of the three games for 10 minutes in random order to avoid order effects. After the completion of each game, touch interaction, device motions, as well as gameplay activities collected during the gameplay, were stored on the phone.

4.3. Mobile Games

In this study, we used three casual games on the mobile platform, i.e., Tetris, Fruit Ninja, and Unblock Puzzle. Previous studies (Hermens et al., 2013, Jauhar, Marshall & Smith, 2014) have shown that long-term excessive alcohol use commonly found in alcohol-dependent drinkers is strongly associated with cumulative brain damage impairing cognitive functions (e.g., attention, visuospatial function, executive function and decision-making). Apart from being highly engaging and easy to learn, the three games were selected based on their particular game mechanics that place specific cognitive demands, particularly in the domains which are often found impaired in patients with alcohol dependence, i.e. visuospatial function in Tetris (Lau-Zhu et al., 2017), executive function in Fruit Ninja (Liu et al., 2015), and problem-solving in Unblock Puzzle. The games were developed based on game assets in the Unity3D asset store to replicate the look and feel of their commercial version. The games were modified to allow touch interactions, device motions, and gameplay activities to be tracked through built-in sensors on the mobile device. Data were continuously recorded with timestamps at the sampling rate of maximal 30Hz. The games automatically ended after 10 minutes and stored the data in JSON files.

It is worth noting that in this work, we used the same Tetris and Fruit Ninja games as described in section 3.3.3 while Unblock Puzzle (Unity3D, 2018) was newly introduced to this study. In Unblock Puzzle, players are required to rearrange the given blocks with different shapes of pipes in order to make the ball roll to the goal block. Once completed, players are moved up to the next level where the level of difficulty gradually increased, e.g. the number of sliding tiles to solve the puzzle. Scores are calculated based on the number of moves to resolve the puzzle in each level.

Figure 17: A screenshot of a variation of Unblock Puzzle in the Unity3D asset store.

4.4. Participants

There were two groups of participants, an experimental group of alcohol-dependent patients and a control group of healthy adults.

4.4.1. Experimental Group

The study sample was drawn from adult male patients admitted to a residential treatment program for alcohol detox and rehabilitation at the hospital. Patients were only considered for inclusion if they: i) were diagnosed with alcohol dependence according to ICD-10 criteria (coded as F10.2) (World Health Organization, 2017); ii) abstained from alcohol consumption for at least two weeks prior to the study, and iii) were attending the rehabilitation phase of treatment. Potential study participants were contacted and screened for eligibility by the research assistants who were the counsellors of the treatment program.

4.4.2. Control Group

Age and gender-matched healthy adults were recruited through public advertising for voluntary participation in the study. Volunteers were given £10 for their research participation upon the completion of the data collection session. Potential participants were excluded if they: i) consumed alcohol in the past 24 hours; ii) had symptoms of hazardous or harmful alcohol use as screened by AUDIT (at the cut-off point of 8); iii) had a medical history including severe mental illness, drug or alcohol abuse; or iv) were receiving psychoactive medication.

In addition, potential participants in both groups were excluded if they: i) were under 18 years old; ii) had visual conditions affecting daily activities; iii) were diagnosed with Parkinson's disease; iv) had symptoms of generalised anxiety disorder or depression screened by HADS; v) were unable to use smartphones through touch controls, or vi) played video games excessively over 3 hours a day in the past 6 months. Informed consent of 46 patients and 45 healthy participants were acquired, with six patients and five control participants excluded due to exclusion criteria. Thus, the final sample was comprised of 40 alcohol-dependent patients (37 right-handers and 3 left-handers) and 40 healthy participants (37 right-handers and 3 left-handers).

All included participants were male aged between 24 – 65 and had completed primary education (as a minimum). We computed two-tailed independent-samples t-tests for the comparison of alcohol-dependent patients (AD) and healthy controls. The mean age of alcohol-dependent participants ($M=42$, $SD=10.29$) was comparable with healthy adults ($M=40.75$, $SD=10.20$). There was a significant difference in mean AUDIT scores between patients and controls ($t49.649=30.135$, $p < 0.001$). Overall, patients with alcohol dependence had significantly lower cognitive performance in all measures as compared to healthy controls ($p<0.05$). The participants' clinical characteristics are shown in Table 19.

Table 19: Summary of participant characteristics

Variable	AD Patients (n=40)	Healthy Controls (n=40)	P-Value (two-tailed)
Gender (female/male)	0/40	0/40	N/A
Handedness (right/left)	37/3	37/3	N/A
Age(years) [mean(SD)]	42.08 (10.29)	40.75(10.20)	0.82
AUDIT [mean(SD)]	35.95 (6.62)	2.28 (2.47)	0.000
MMSE score [mean(SD)]	26.85 (2.92)	28.10 (1.33)	0.001
MMSE score distribution			
MMSE <=24	7	0	
MMSE 25 -30	33	40	
MoCA score [mean(SD)]	21.67 (4.66)	26.33 (2.73)	0.003
MoCA score distribution			
MoCA <= 25	32	14	
MoCA 26-30	8	26	
TMTA completion time [mean(SD)]	49.68 (28.71)	25.07 (7.35)	0.000
Response Inhibition [mean(SD)]	0.29 (1.06)	0.27 (0.22)	0.035

4.5. Data Processing and Feature Selection

User game interaction patterns were captured for 10 minutes during the gameplay session. Raw data of three different data types, i.e., touch, device motion, and gameplay, were recorded in separated JSON files. In order to avoid inaccurate data analysis, data cleansing was carried out to eliminate irrelevant data samples, i.e., the faulty touch data points at the edges of the phone, which were speculated to occur while participants were holding the phone in their palm. The data were then converted into XLS format prior to feature extraction. Features were computed using the entire data samples from each participant. The min-max scaling method was used to transform the features' values to the range of 0 to 1.

4.5.1. Touch Data

To remove artefacts from the collected samples, touch coordinates were plotted to identify unintentional touches with participants' palm along the edge of the phone. These faulty touches were removed by thresholding the distance and speed between two data points within a given touch interaction. Four measures: count, length, speed and directness index were used to extract features across the four directions of swipes as proposed in the study in the previous chapter (see section 3.4.3.1).

Table 20: Extracted touch features for each game

Feature	Mean and SD	Tetris	Fruit Ninja	Unblock Puzzle
Total number of swipes by direction[a]		✓		✓
Total number of swipes in horizontal[b] or vertical[c]		✓		✓
Total number of overall swipes		✓		✓
Total number of taps		✓		
Swipe length by direction[a]	✓	✓		✓
Swipe length in horizontal[b] or vertical[c]	✓	✓		✓
Overall swipe length	✓	✓	✓	✓
Swipe speed by direction[a]	✓	✓		✓
Overall swipe speed	✓	✓	✓	✓
Starting point on the x-axis of swipes by direction[a]	✓	✓		✓
Starting point on the y-axis of swipes by direction[a]	✓	✓		✓
Starting point on the x-axis of swipes in horizontal[b] or vertical[c]	✓	✓		✓
Starting point on the y-axis of swipes in horizontal[b] or vertical[c]	✓	✓	✓	✓
Starting point on the x-axis of overall swipes	✓	✓	✓	✓
Starting point on the y-axis of overall swipes	✓	✓	✓	✓
Center of mass on the x-axis of overall swipes	✓		✓	
Center of mass on the y-axis of overall swipes	✓		✓	
Directness index[d] of swipes by direction[a]	✓	✓		✓
Directness index[d] of swipes in horizontal[b] or vertical[c]	✓	✓		✓
Directness index[d] of overall swipes	✓	✓	✓	✓

[a]Right, left and down in Tetris and all four directions in Unblock Puzzle

[b]Denote swipes in both left and right directions

[c]Denote swipes in both up and down directions

[d]A feature to quantify the swipe straightness. Its value is computed by the total distance of an interaction divided by the displacement. As such, the value of 1 indicates a perfectly straight line, while a curved swipe has a greater value.

Previous studies have shown that chronic alcohol abuse or withdrawal can cause a tremor or uncontrolled shaking of hands in patients with alcohol dependence (Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). Therefore, less consistent touch movement patterns, precisely, a higher degree in movement variability in patients was anticipated. As a result, the mean value and the standard deviation of features were computed except for the count features. Research findings also suggested that different game mechanics and cognitive demands associated with the given game tasks made some swipe characteristics patterns more relevant than others (Intarasirisawat et al., 2019). Hence, different subsets of touch-based features were chosen for each game, as listed in Table 20.

4.5.2. Sensor Data

It was anticipated that patients with alcohol dependence would exhibit different device motion patterns from healthy adults during the gameplay session. Therefore, device acceleration and rotational motion were captured using the built-in 3-dimensional motion sensors. Based on the entire samples within the allotted game time, a total of 16 features were computed using the mean and the standard deviation values in each axis, including the magnitude of the 3D vector for acceleration and rotational motion.

Table 21: Extracted gameplay features for each game

Feature	Description
Tetris	
Max_score	The maximum score achieved in the allotted game time
Mean_first_response_x_pos	The average position on the x-axis of the first response on the screen of each falling shape
Mean_first_response_y_pos	The average position on the y-axis of the first response on the screen of each falling shape
Mean_stack_height	The average stack height when touch interaction performed on the screen
Mean_delta_first_response_y_pos_stack_height	The mean difference between the position on the y-axis of the first response and the stack height
Mean_response_time	The average response time of all touch interaction on each falling shape
Mean_time_to_first_response	The average response time of the first response on the screen of each falling shape
Mean_no_of_taps_per_shape	The average number of taps performed on each falling shape
Mean_no_of_horizontal_swipes_per_shape	The average number of horizontal swipes performed on each falling shape
Mean_no_of_down_swipes_per_shape	The average number of downward swipes performed on each falling shape
Mean_no_of_swipes_per_shape	The average number of overall swipes performed on each falling shape
Fruit Ninja	
Max_score	The maximum score achieved in the allotted game time
No_of_times_to_startover	The number of times the game was started over
Mean_overall_air_time	The average time a ball was in the air including the missing balls
Mean_air_time_before_being_cut	The average time a ball was in the air before being cut
Mean_cut_x_pos	The average cut position in x-axis
Mean_cut_y_pos	The average cut position in y-axis
Unblock Puzzle	
Max_level	The maximum level achieved in the given duration
Mean_response_time	The average response time of all touch interactions in the given duration
Mean_response_time_to_complete_level	The average response time of touch interactions to complete a level in the given duration
Mean_total_time_to_complete_level	The average total time to complete a level in the given duration
Mean_complete_level_no_of_moves	The average number of moves performed to complete a level in the given duration

4.5.3. Gameplay Data

Previous studies have shown that gameplay performance was associated with standard cognitive measures (Lumsden et al., 2016, Tong et al., 2016). Most alcoholics exhibit cognitive impairment in multiple domains, especially, visuospatial function, executive functions, and memory (Martin, Singleton & Hiller-Sturmhofel, 2003, Oscar-Berman et al., 1997). Thus, gameplay metrics were included as features. The game interaction and activities are shaped by a set of rules and game mechanics defined explicitly in the game. Therefore, different sets of gameplay features for each game were extracted as listed in Table 21.

4.6. Model Validation

In this work, three supervised machine-learning methods were employed to classify patients with alcohol dependence and healthy controls: Logistic Regression (LR), Linear Support Vector Machine (LSVM), and Random Forest (RF). "Alcohol Dependence' and 'Healthy Controls' were used as our class labels. Samples from participants, who were clinically diagnosed with alcohol dependence and were admitted to a residential treatment program, were labelled as 'alcohol dependence'. Samples from healthy participants were labelled as 'healthy control'. Only in the control group of healthy participants, the AUDIT with the cut-off point of ≥ 8 was used to screen symptoms of hazardous or harmful alcohol use. As a result, participants in the control group with an AUDIT score ≥ 8 were excluded from the study. As the observed class labels were balanced (40 patients and 40 healthy controls), classification accuracy was used to evaluate the models' performance. K-fold cross-validation technique was applied when building models to generalise our results to unseen data. In particular, stratified K-fold cross-validation (K = 10) was used to generate test sets with a balanced distribution of classes. In each iteration, the models' performance was assessed on a random selection of 4 patients and 4 healthy adults. After feature scaling, feature selection was performed within the cross-validation on the training sets using the Correlation-based Feature Selection algorithm (CFS) (Hall, 1999) to remove collinear features. In each K-fold iteration, grid-search with 10-fold cross-validation was used for hyper-parameter tuning to maximise the model classification accuracy. Hyperparameters and their value ranges used in grid search are listed in Table 22.

Table 22: Lists of hyperparameters used for parameter tuning

Tuning Hyperparameters			
Algorithm	**Parameter**	**Values**	**Type**
Logistic Regression	C	[0.5, 1, 1.5, 3, 5, 7, 10]	Searched
	penalty	['l2']	Fixed
	class_weight	['balanced']	Fixed
	random_state	[9]	Fixed
	max_iter	[500]	Fixed
SVM	C	[0.1, 0.5, 1, 1.5, 3, 5, 7, 10]	Searched
	kernel	['linear']	Fixed
	random_state	[9]	Fixed
	probability	[True]	Fixed
Random Forest	max_features	[0.2, 0.3]	Searched
	min_samples_leaf	[1,3]	Searched
	min_samples_split	[4,5]	Searched
	n_estimators	[130]	Fixed
	n_jobs	[n_cpu]	Fixed
	random_state	[9]	Fixed
	criterion	['gini']	Fixed
	bootstrap	[True]	Fixed

The optimal parameters returned from the grid search were used to retrain the model with the entire training sets. The models' performance on the completely unseen test sets were evaluated using the corresponding selected features for each iteration. The average model performance was calculated based on the accumulative model performance from all iterations, as illustrated in Figure 18. It is noteworthy that owing to a procedural error during the data collection, the recording was incomplete in one of the participants and therefore was excluded, leaving a final data set of 79 samples to analyse with Unblock Puzzle.

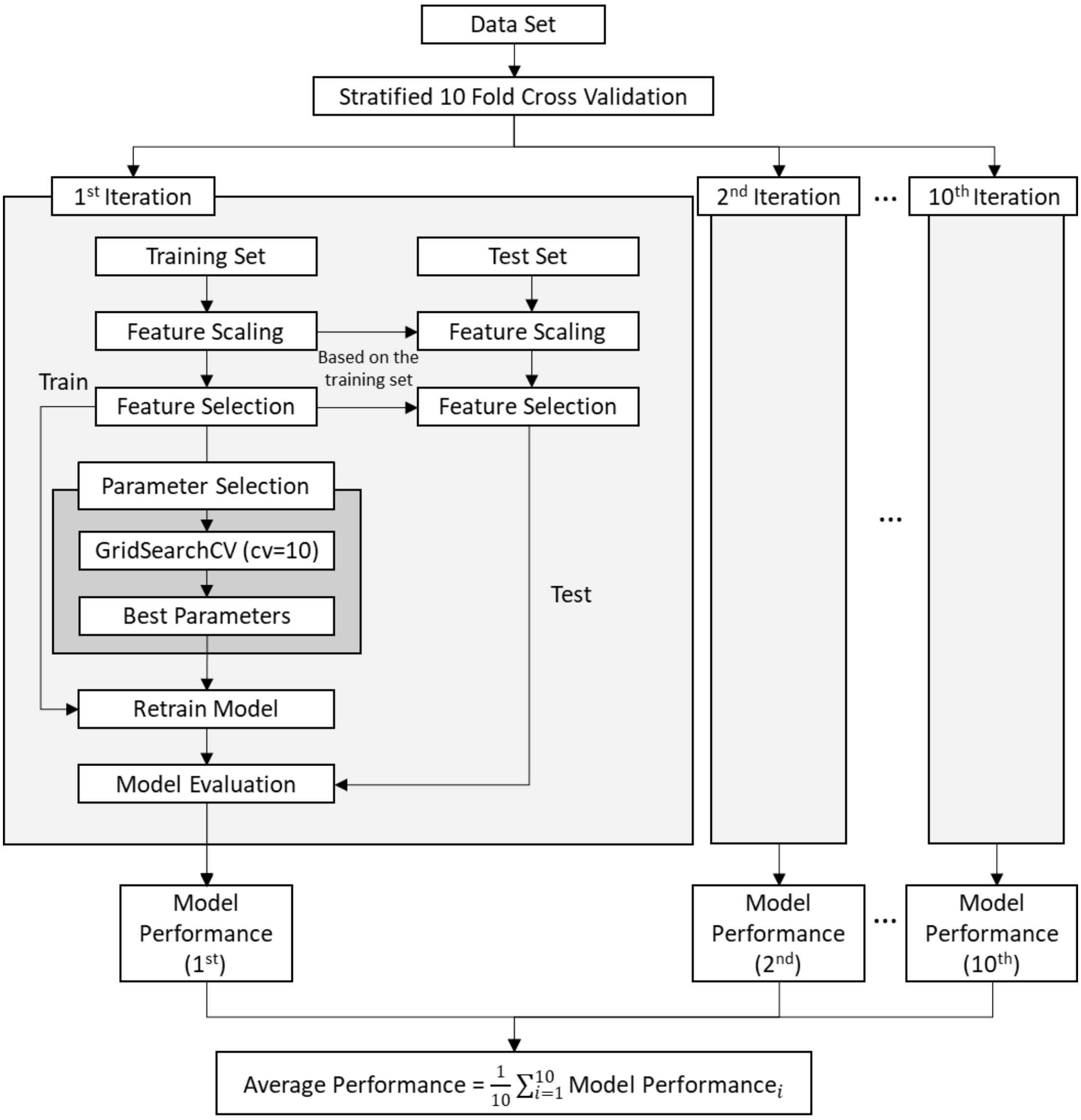


Figure 18: Illustrates the model evaluation with stratified 10-fold cross-validation

Quantitative comparisons were made on classifier performance over five different feature sets to investigate the effect on accuracy. Particularly, the feature sets included Touch (T), Sensor (S), Gameplay (G), Combined Touch and Sensor (TS), and Combined Touch, Sensor and Gameplay (TSG). Table 29 – Table 34 in Appendix list the hyperparameter sets for each algorithm that yield the best model performance for each iteration using combined TS and TSG of 10-minute samples as input.

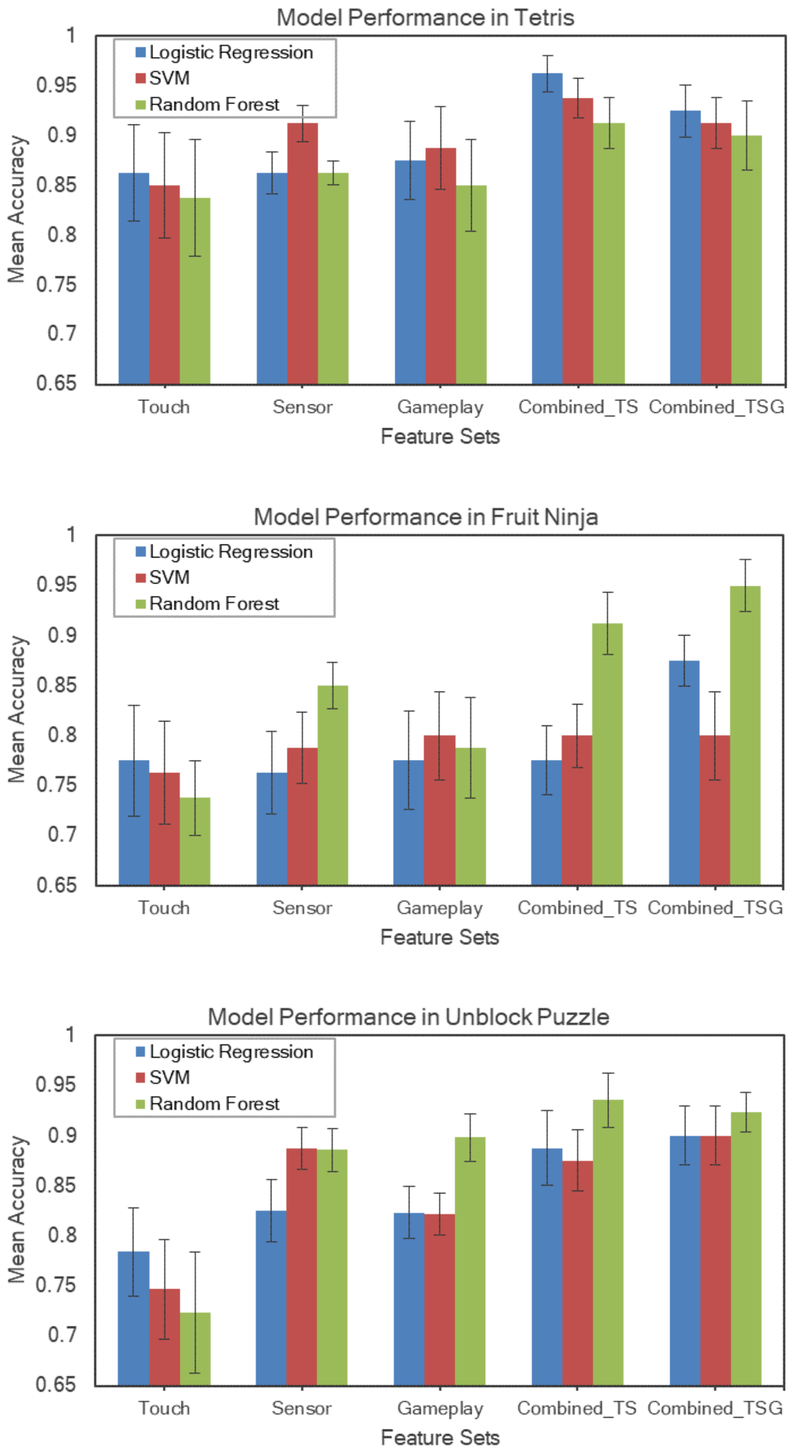


Figure 19: Illustrates the 10-fold cross-validation performance of each classifier over five different data types using data taken from the three games

Mean accuracy and standard error of the mean were computed for each classifier, as shown in Figure 19. By comparing the overall results, classifiers built on Tetris features performed better than those of Fruit Ninja and Unblock Puzzle. Using combinations of multiple feature sets (touch, sensor, and gameplay) as input improved the models' performance in classification accuracy as compared with using a single set of features. Logistic Regression yielded the highest mean accuracy of 0.96 when using the ensemble of touch and sensor features from Tetris.

However, with the same feature sets, Random Forest outperformed other classification algorithms in general, where the mean accuracies were well above 0.90 in the other two games. Moreover, the low standard errors of the mean accuracy (0.02 – 0.03) found in these classifiers indicate that the models generalised well against unseen data.

The main aim of developing these classification models was to investigate their effectiveness as a quick and accurate diagnostic instrument for the identification of alcohol-dependent patients. In current clinical practice, diagnostic interviews are used to diagnose patients with alcohol dependence according to ICD-10 criteria. Despite being regarded as a gold standard, these clinical interviews require trained clinicians to administer and often involve a series of additional measures to establish a reliable diagnosis, e.g., physiological tests and cognitive assessments (Iglesias et al., 2018). In order to support diagnostic team members, this novel game-based diagnostic tool was aimed to provide accurate results within a short time. Therefore, the study further examined the classifier performance on different gameplay durations, i.e., 3, 4, 5, 6, 7, 8, 9, and 10 minutes. For this reason, the first part of the original 10-minute data was truncated for the given durations accordingly. Based on the findings above, Logistic Regression and Random Forest achieved the best accuracies. Therefore, these classification models were selected and trained on the combinations of multiple feature sets (TS and TSG). Table 35 - Table 40 in Appendix list the hyperparameter sets for each algorithm that yield the best model performance for each iteration using combined TS and TSG of 3-minute samples as input.

The average classification accuracies of Logistic Regression and Random Forest were evaluated against the combined TS and the combine TSG feature sets, as shown in Table 23 and Table 24, respectively. When using the combined TSG, both classifiers yield better overall performance for the given durations in Fruit Ninja and Unblock Puzzle. In contrast for Tetris, the mean accuracy for TSG was slightly lower than TS for most durations.

With regard to classification methods, Random Forest classifiers generally outperformed Logistic Regression models in most cases, especially on input with short gameplay durations of 3 – 6 minutes. In particular, even with the gameplay durations as short as 3 minutes, the random forest was able to give relatively high classification accuracies of 0.94, 0.89, and 0.95 in Tetris, Fruit Ninja, and Unblock Puzzle respectively.

Table 23: Mean accuracies of Logistic Regression Classifiers

Duration	**Tetris**		**Fruit Ninja**		**Unblock Puzzle**	
	TS	**TSG**	**TS**	**TSG**	**TS**	**TSG**
10 Minutes	**0.96 (0.02)**	0.93 (0.03)	0.78 (0.03)	**0.88 (0.03)**	0.89 (0.04)	**0.90 (0.03)**
9 Minutes	**0.95 (0.03)**	0.90 (0.03)	0.80 (0.04)	**0.84 (0.03)**	0.88 (0.03)	**0.90 (0.03)**
8 Minutes	**0.93 (0.03)**	0.91 (0.03)	0.83 (0.04)	**0.85 (0.04)**	0.87 (0.04)	**0.90 (0.03)**
7 Minutes	**0.93 (0.03)**	0.91 (0.03)	0.76 (0.04)	**0.84 (0.04)**	0.89 (0.03)	**0.90 (0.03)**
6 Minutes	**0.91 (0.03)**	0.90 (0.03)	0.75 (0.04)	**0.83 (0.04)**	0.89 (0.03)	**0.93 (0.03)**
5 Minutes	0.89 (0.04)	**0.91 (0.03)**	0.80 (0.05)	**0.85 (0.03)**	0.89 (0.03)	0.89 (0.03)
4 Minutes	0.89 (0.03)	**0.90 (0.03)**	0.79 (0.05)	0.79 (0.04)	**0.90 (0.02)**	0.87 (0.02)
3 Minutes	**0.89 (0.03)**	0.88 (0.03)	0.78 (0.04)	0.81 (0.05)	0.89 (0.03)	**0.90 (0.03)**

[a](1 standard error either side of the mean)

[b]Table numbers in boldface highlight a better feature set in classification performance between combined TS and combined TSG

Table 24: Mean accuracies of Random Forest Classifiers

Duration	**Tetris**		**Fruit Ninja**		**Unblock Puzzle**	
	TS	**TSG**	**TS**	**TSG**	**TS**	**TSG**
10 Minutes	**0.91 (0.03)**	0.90 (0.03)	0.91 (0.03)	**0.95 (0.03)**	**0.94 (0.03)**	0.92 (0.02)
9 Minutes	0.91 (0.03)	**0.93 (0.03)**	0.84 (0.02)	**0.90 (0.02)**	0.94 (0.03)	**0.96 (0.02)**
8 Minutes	0.91 (0.03)	**0.93 (0.03)**	0.86 (0.02)	**0.93 (0.02)**	0.92 (0.03)	**0.94 (0.02)**
7 Minutes	0.91 (0.03)	0.91 (0.03)	0.88 (0.03)	**0.91 (0.02)**	0.91 (0.03)	**0.95 (0.02)**
6 Minutes	**0.94 (0.02)**	0.91 (0.03)	0.85 (0.03)	**0.86 (0.03)**	0.94 (0.02)	**0.95 (0.02)**
5 Minutes	**0.93 (0.03)**	0.90 (0.04)	0.86 (0.04)	**0.90 (0.03)**	0.92 (0.02)	**0.95 (0.02)**
4 Minutes	0.91 (0.03)	**0.93 (0.03)**	0.85 (0.04)	**0.91 (0.03)**	0.89 (0.04)	**0.93 (0.03)**
3 Minutes	**0.94 (0.03)**	0.93 (0.03)	0.86 (0.04)	**0.89 (0.03)**	0.90 (0.04)	**0.95 (0.02)**

[a](1 standard error either side of the mean)

[b]Table numbers in boldface highlight a better feature set in classification performance between combined TS and combined TSG

It is also worth noting that the best performing model on 10-minute samples was the Logistic Regression on combined TS features of Tetris with 0.96 accuracy. However, the model performance continued to decline when reducing the gameplay duration in which the performance dropped to 0.89 when training on 3-minute samples. By contrast, Random Forest classifiers on Unblock Puzzle data using all features performed consistently well above 0.92 across different gameplay durations. The mean accuracies only changed slightly within the range of 0.92 – 0.95 over the given durations. In general, Fruit Ninja seemed to yield the worst classification performance among the three games.

It was observed that there was a somewhat mixed picture of classification performance among the three games when reducing the allotted game time. Specifically, irrespective of the algorithm used for the classifier, model performance in Fruit Ninja and Unblock Puzzle seemed to remain relatively stable for different durations (with a slight drop when using shorter intervals of data as input). In Tetris, however, the two classifiers seemed to be affected differently with changes in duration. Logistic Regression demonstrated a downward trend in performance similar to the other two games, while the Random Forest classifiers seemed to perform slightly better when using shorter intervals of Tetris data as input. Although the differences were very small to consider them significant, anecdotally, such patterns could be explained by the differences in gameplay mechanics and the inherent nature of the two machine learning algorithms. Nevertheless, this study does not have sufficient evidence to draw a conclusion.

The study further examined the sensitivity and specificity of the classification models, as they are more common measures for assessing the performance of clinical tests (Maxim, Niebo & Utell, 2014). Sensitivity refers to the ability of the clinical test to correctly identify those patients with the condition while specificity tells us how well the tests can correctly identify those without the condition. Therefore, we evaluated and compared the sensitivity and specificity of Logistic Regression and Random Forest classifiers on 3-minute data and 10-minute data, as presented in Table 25 and Table 26.

Overall, all classifiers showed promising classification performance in terms of sensitivity (0.80 – 0.98) and specificity (0.75 – 0.98). In particular, using 10-minute samples, the Logistic Regression classifier on combined TS features of Tetris yielded the highest sensitivity of 0.98 with a specificity of 0.95. On the contrary, the highest specificity of 0.98 was obtained from the classifiers using the ensemble of all features of Fruit Ninja and Unblock Puzzle but with lower sensitivities of 0.93 and 0.83, respectively. These results suggest that the Logistic Regression classifier on 10-minute combined TS features of Tetris has the best capability in screening patients. On the other hand, by using 10-minute samples and all feature sets, the Logistic Regression model on Unlock Puzzle and the Random Forest model on Fruit Ninja seem to be better options for diagnosis purposes in which a high specificity value is preferred.

Table 25: Sensitivity and specificity of Logistic Regression Classifiers

Game	3-Minute Samples				10-Minute Samples			
	Combined TS		Combined TSG		Combined TS		Combined TSG	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
Tetris	0.85 (0.04)	0.93 (0.04)	0.83 (0.06)	0.93 (0.04)	0.98 (0.02)	0.95 (0.03)	0.90 (0.05)	0.95 (0.03)
Fruit Ninja	0.80 (0.05)	0.75 (0.09)	0.80 (0.05)	0.83 (0.08)	0.80 (0.06)	0.75 (0.07)	0.90 (0.04)	0.85 (0.05)
Unblock Puzzle	0.83 (0.06)	0.95 (0.03)	0.88 (0.06)	0.93 (0.04)	0.83 (0.05)	0.95 (0.05)	0.83 (0.06)	0.98 (0.02)

[a](1 standard error either side of the mean)

Table 26: Sensitivity and specificity of Random Forest Classifiers

Game	3-Minute Samples				10-Minute Samples			
	Combined TS		Combined TSG		Combined TS		Combined TSG	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
Tetris	0.98 (0.02)	0.90 (0.05)	0.93 (0.04)	0.93 (0.04)	0.95 (0.03)	0.88 (0.05)	0.90 (0.05)	0.90 (0.04)
Fruit Ninja	0.85 (0.05)	0.88 (0.07)	0.85 (0.05)	0.93 (0.05)	0.88 (0.06)	0.95 (0.03)	0.93 (0.05)	0.98 (0.02)
Unblock Puzzle	0.93 (0.04)	0.88 (0.07)	0.95 (0.03)	0.95 (0.03)	0.93 (0.05)	0.95 (0.03)	0.93 (0.04)	0.93 (0.04)

Considering our aim to reduce the administration time, the classifiers on 3-minute samples still showed promising results, particularly those based on the Random Forest algorithm. Using combined TSG features of Unblock Puzzle, the model achieved a sensitivity of 0.95 and specificity of 0.95. Interestingly, the aforementioned algorithm on the combined TS features of Tetris had the highest sensitivity of 0.98 but a lower specificity value of 0.90. These results demonstrate that even for the relatively short duration of 3 minutes, our game-based classifiers yielded consistently high sensitivities and specificities with low standard errors of the mean. The 10-fold cross-validation performance of the models indicates that our game-based approach provides the ability to effectively diagnose alcohol-dependent patients with overall good generalisation capabilities and short administration time.

4.7. Feature Importance

Further investigations into appropriate game features and their importance can provide useful insights to improve classification performance, model complexity, and speed. To this end, the study further investigated which user-game interaction features are most important for building the automated game-based measure for screening patients with alcohol dependence. The analysis was conducted on the Random Forest classifier on the ensemble of all feature sets of Unblock Puzzle as the model shows the best classification performance among the compared classifiers on 3-minute samples.

Tree-based models such as the Random Forests use node impurity or information gain to split nodes and construct an ensemble of decision trees. For each tree, feature importance is determined by the amount of information gained from the feature weighted by the number of observations in the node. The model provides feature importance scores by averaging values of feature importance across all decision trees. The higher the importance score, the more informative the feature is. In this work, we ran 10-fold cross-validation on Random Forests and ranked the feature importance scores using the *feature_importances_* attribute in the scikit-learn machine learning library. Feature selection was performed in the data processing step to maximise the classification accuracy by removing redundant features and thus improve the interpretability of the classification model. In that, the Correlation-based Feature Selection (CFS) technique was performed within the cross-validation to select a subset of relevant features out of all original features.

Feature importance values at each cross-validation iteration were extracted to determine the overall ten top-ranked features with the highest median variable importance. Test statistics were introduced to examine whether there was a significant difference between patients and control groups. Due to the small sample size, the Shapiro-Wilk test was used to determine the normality of the selected features. In a most of the features (8 out of 10), the results indicated that the data significantly deviated from normal distributions ($p<0.05$). Therefore, the statistical results were derived from the non-parametric Mann Whitney U Test, as shown in Table 27.

Table 27: Top 10 features with the highest median feature importance

Feature	Type	Feature Importance (Median)	Median Feature Value		U Test Statistic[b]	p value (two-tailed)
			Controls	Patients		
Mean Acceleration Magnitude	Sensor	0.228	0.996	1.028	202	< .001
Mean Response Time to Complete Level	Gameplay	0.174	1963.84	5787.93	60	< .001
Mean Response Time	Gameplay	0.126	1598.60	4377.47	142	< .001
Max Level	Gameplay	0.097	9	4	140	< .001
Mean Speed Swipe Up	Touch	0.048	2945.74	1627.54	196	< .001
Mean Speed Swipe Right	Touch	0.038	2623.65	1642.09	232	< .001
Mean Total Time to Complete Level	Gameplay	0.027	12468.67	25135.9	276	< .001
Mean Length Swipe Left	Touch	0.020	553.63	428.32	331	< .001
Mean Speed Swipe Left	Touch	0.019	2541.73	1501.30	273	< .001
Standard Deviation Acceleration Magnitude	Sensor	0.013	0.040	0.041	762	0.86

[a]Bonferroni critical value p<0.005 (0.05/10)

[b]$n_{control}$ = 40, $n_{patient}$=39

Results of the statistical analysis revealed significant differences (p<0.001) in all these features between the two groups except for the standard deviation acceleration magnitude. The mean acceleration magnitude by far is the strongest predictive variable with the highest median feature importance value. As such, patients tend to exhibit a statistically larger degree of device movement (1.028) comparing to healthy controls (0.996). The finding is consistent with previous research, where hand tremors are commonly found in patients with alcohol dependence (Jauhar, Marshall & Smith, 2014, Deik, Saunders-Pullman & San Luciano, 2012, Martin, Singleton & Hiller-Sturmhofel, 2003, Trevisan et al., 1998). It is therefore not unexpected to find that the device motion feature could be an important marker to discriminate patients from healthy controls. With regard to the gameplay performance, patients demonstrated lower performance comparing to healthy adults in terms of the mean response time to complete level (patients=5787.93, controls=1963.84), the overall response time (patients=4377.47, controls=1598.60), the max level completed (patients=4, controls=9), including the mean total response time (patients=25135.9, controls=12468.67). These seem to be coherent with the findings in several studies (Jauhar, Marshall et al. 2014, Deik, Saunders-Pullman et al. 2012, Martin, Singleton et al. 2003, Trevisan, Boutros et al. 1998). In that, long-term excessive alcohol consumption can cause problems with cognitive functioning, in this context, adversely affecting gameplay performance in such high cognitive demand tasks. Furthermore, significant differences in touch patterns between both groups were observed.

Specifically, patients' swipe patterns are significantly shorter and slower as compared to healthy controls.

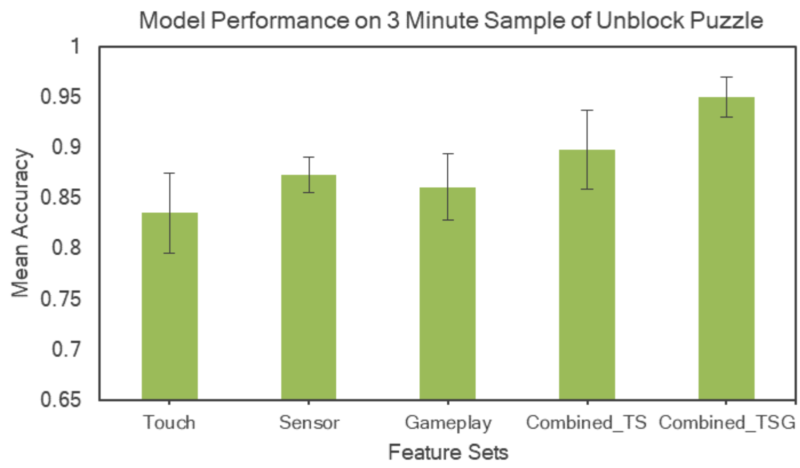


Figure 20: Illustrates the 10-fold cross-validation performance of Random Forest Classifier over five different data types using 3-minute data taken from Unblock Puzzle

In addition, the comparison of the classification performance over different feature sets was made to investigate whether the use of a combination of all feature sets can significantly improve classification accuracy comparing to the use of device motion-based features alone. As shown in Figure 20, when using only a single set of features as input, the classification performance is 0.84, 0.87, 0.86 for touch, sensor, and gameplay, respectively. By using the combination of all sources of features, the classification accuracy significantly improved to 0.95. These results appear consistent with the earlier findings with 10-min samples (see Figure 19), where the model performance was maximised by using an ensemble of multiple feature sets as input.

4.8. Participants' Feedback

At the end of the experiment session, a brief interview was carried out to obtain participants' views regarding the acceptability and practical application of the game-based approach. Most participants (65 out of 80) reported enjoying themselves and being engaged with the games. Moreover, the game-based method was reported to reduce their anxiety as compared to the paper-based version. Nevertheless, the majority of them (69 out of 80) found their game experience in Tetris quite frustrating due to difficulty in controlling the Tetris block movement with touch. Unlike the traditional controls, on a touchscreen, players have to drag their finger left or right to move the falling shape. As such, many participants expected that the touched piece would move proportionally based on the distance the finger has moved on the screen.

The fact that the block only moves one block unit at a time might be confusing, which may lead to a less engaging game experience. More training may have been beneficial to allow participants to familiarise themselves with the game controls. On the other hand, several participants highly enjoyed the Unblock Puzzle as the in-game tasks challenge their problem-solving skills and creativity. Despite requiring improvement in certain areas, most participants nonetheless felt comfortable and relaxed during the gameplay. These overall positive feedbacks suggest that the game-based screening platform is well-accepted with regard to usability.

4.9. Discussion

This work presents a novel approach based on machine learning algorithms to provide an alternative method for home-based screening for alcohol dependence. This study particularly examines the use of user-game interaction features from the three popular mobile games to classify patients and healthy adults. The ensemble of features extracted from 10-minute samples through touch interaction, device motion, and gameplay performance was used as input for the proposed classification models. A set of evaluation metrics, specifically the accuracy, sensitivity, and specificity, were used to quantify the classifier performance on entirely independent data sets using a stratified 10-fold cross-validation scheme. Our Logistic Regression classifier based on Tetris samples was capable of identifying the alcohol dependence condition with the accuracy of 0.96. The relatively high sensitivity of 0.98 indicates that our game-based model could be used as an effective screening tool for such a condition. A practical implementation of such a screening instrument should not only provide accurate and reliable outcomes but should also be inexpensive and time-efficient. Our classifiers show the promise to provide such an instrument as they perform consistently well even with sample lengths of 3 minutes in terms of accuracy, sensitivity, and specificity.

Generally, in medical screening and diagnosis, there is always a trade-off between specificity and sensitivity, and the decision must be made based on their relative clinical importance. In the screening process, it is important to identify as many patients with the condition as possible. Missing cases could lead to delayed treatment or no treatment at all. As a result, for early detection of health conditions, a screening tool with a high sensitivity value is preferred. In contrast, high specificity allows healthcare professionals to regard individuals as having a condition confidently. Thus, specificity is a useful attribute in a diagnostic procedure to avoid provoking anxiety, including unnecessary follow-up tests and treatment (Maxim, Niebo et al. 2014). Despite a slightly lower specificity of 0.90, results show that TS features of Tetris samples with the Random forest classifier has the best screening properties (sensitivity of 0.98) when compared to other classifiers. Nevertheless, considering the trade-off between false positive and false negatives, the Random Forest model using the combined TSG features of Unblock Puzzle is recommended as it has the best combination of specificity (0.95) and sensitivity (0.95) for a reliable screening instrument.

However, apart from the performance of the screening instrument, the computational complexity of each algorithm is another important factor to take into consideration when implementing the classifiers in clinical practice. The time complexity required for building the model varies depending on the sample size, the number of features and the performance of the machine running the codes. For instance, a comparative study by Sahin et al. (Sahin, Colkesen & Kavzoglu, 2020) investigated the computational time in a binary classification problem to estimate the landslide susceptibility among various machine learning algorithms, including Random Forest and Logistic Regression. Their results showed that Logistic Regression required significantly less execution time for training and testing stages when compared to Random Forest (0.095s and 98.44s). This is in line with the findings from the study by Brik et al. (Brik et al., 2019), where comparisons among several machine learning algorithms, including Logistic Regression and Random Forest, were made in terms of training time and testing time to predict the risk of system disruption in Industry 4.0. Their findings demonstrated that Logistic Regression required less computational time for training the model when compared to Random Forest (0.43s and 1.02s, respectively), while the runtime for testing the model was considerably shorter when compared with the training time for both algorithms (0.01s to 0.43s and 0.05s to 1.02s for Logistic Regression and Random Forest, respectively) (Brik et al., 2019).

Even though Random Forest may take substantially longer to train the model than Logistic Regression, the execution time for classification would be more important to consider in terms of computational costs as the model needs to be trained only once to be used to perform actual classification on unseen samples. Given the previous findings above and the computational power of current computers, the difference in testing time between pre-trained models based on Logistic Regression and Random Forest algorithms would be hardly noticeable. However, such a difference would become more pronounced when the model complexity grows.

Thus, in a general classification problem, a robust and highly accurate model would be preferable. However, in a clinical scenario where a real-time screening is required, researchers and practitioners may have to consider the trade-off between model classification performance and computational complexity for runtime classification on unseen samples.

4.9.1. Comparison to Conventional Screening Tools

To fully evaluate the performance and practicality of our proposed game-based method, it is essential to compare the results with current clinical screening tests. In 2009, a systematic review of alcohol use disorder screening instruments evaluated an exhaustive number of studies on the validation of AUDIT and AUDIT-C as screening instruments for alcohol-related problems (de Meneses-Gaya et al., 2009). Derived from the review, Table 28 reveals the screening and diagnostic performance of AUDIT and AUDIT-C for identifying alcohol dependence found in previous studies (Rumpf et al., 2002, Giang et al., 2005, Dawson et al., 2005, Seale et al., 2006). The findings show that both tests were sensitive to alcohol dependence with sensitivity above 0.82 at relative cut-off points.

Of note, at a cut-off point of 5, the AUDIT-C yielded a relatively high sensitivity of 0.94, which appears to be superior to that of the full-scale version. Nonetheless, the specificity was only 0.58 (Seale et al., 2006). In other words, 42% of non-alcohol dependent individuals were misclassified. Slightly lower sensitivity values were found in other studies, i.e., 0.88 (Rumpf et al., 2002) and 0.82 (Dawson et al., 2005). However, the results yielded significant improvement in specificity (>= 0.80). Among these studies, Giang et al. reported a sensitivity of 0.88 and a specificity of 0.77 using the full AUDIT to identify alcohol dependence (Giang et al., 2005). Nevertheless, these studies seem to present varying empirical results with very low specificities. One possible explanation could be that these conventional screening tools typically involve questionnaire techniques which heavily rely on respondents' feedback. It was found that several patients with alcohol-related problems are unable to quantify the actual amount of their alcohol consumption (Gilligan et al., 2019). Their responses may also be confounded with dishonest answers to avoid embarrassment. Thus, these self-reported response biases may lead to inaccurate and unreliable results (Mumtaz et al., 2018).

Table 28: Sensitivity and specificity of paper-based screening tools for alcohol dependence

Study	Test	Cutoff	Sensitivity	Specificity
Giang, Spak et al. 2005	AUDIT	7 or 8	0.88	0.77
Rumpf, Hapke et al. 2002	AUDIT-C	4	0.88	0.81
Dawson, Grant et al. 2005	AUDIT-C	6	0.82	0.80
Seale, Bolti et al. 2006	AUDIT-C	5	0.94	0.58

Comparing to the results obtained from our game-based classification models, based on 3-minute samples from the Unblock Puzzle game, the Random Forest classifier was found to have identified the alcohol dependence condition at a greater sensitivity (0.95) and specificity (0.95) than the conventional paper-based instruments. Besides the excellent sensitivity for such a condition, the screening process using our proposed game-based approach is as brief as 3 minutes, which is comparable or even faster than the paper-based modalities.

However, these findings should be interpreted with caution, considering the differences in population style screening. In particular, in our study, healthy controls were recruited from the general population using the AUDIT scores with the cut-off point of 8. However, samples with alcohol dependence were drawn from inpatients in a residential treatment program for alcohol use disorders in a speciality medical facility. As a result, the difference between alcohol-dependent and healthy control groups is more pronounced in terms of alcohol use and underlying symptoms. On the contrary, figures in table 28 were based on the data samples derived from a general population (Rumpf et al., 2002, Dawson et al., 2005, Giang et al., 2005) or primary care patients (Seale et al., 2006). Identifying people with alcohol dependence within the respective population could be more challenging as people with alcohol problems but less severe conditions were also included in the samples. Furthermore, the alcohol-dependent group in our study were alcohol detoxified as part of the residential treatment program, while all samples, including those labelled as alcohol dependent in these studies (Rumpf et al., 2002, Giang et al., 2005, Dawson et al., 2005, Seale et al., 2006), were not exposed to any intervention. Thus, these studies may not be ideal comparators for our game-based alcohol screening approach. Nonetheless, the study results demonstrate that our game-based classifier could be a promising screening tool for identifying patients with alcohol dependence.

4.9.2. Comparison to EEG-based Screening Tools

Other than the traditional paper-based tools, a number of literature reviews reported the clinical relevance between various electroencephalogram (EEG) features and the alcohol use disorder, for instance, inter-hemispheric coherence and phase delay (Herrera-Díaz et al., 2016). Another review, published in 2018, identified several studies that evaluated the clinical application of EEG-based methods to classify patients with alcohol problems and healthy adults (Mumtaz et al., 2018). Various machine learning techniques were employed on EEG signals recorded from multiple scalp electrodes in response to stimuli or cognitive events. The EEG-based classifiers showed a great capability in detecting AUD patients. Overall, the machine learning techniques utilised in these studies achieved relatively high accuracies (>0.90) (Mumtaz et al., 2018).

Similarly, the classification models of Mumtaz et al. employed the EEG features computed from each of 19 electrode signals. These EEG data were captured in participants' resting state with 5-min of eye-closed and 5 min of eyes-open. By integrating all EEG features, their classifiers yielded similar results with an accuracy of 0.89 (Mumtaz et al., 2017). Even though the EEG modalities show very promising results, these technology-based screening methods have a number of barriers to applying in field settings. For instance, artefacts caused by eye movement and muscle activities need to be removed prior to data analysis (Mumtaz et al., 2017). Most importantly, the EEG data acquisition often takes a long time for equipment set-up and calibration to ensure precise placement of multiple electrodes on the scalp. For these reasons, it can be administered only by trained clinical staff within clinical premises. These limitations make the EEG approach less effective and not popular in clinical practice as compared to the conventional paper-based tools (Mumtaz et al., 2018).

On the contrary, our proposed method exploits the sensing capabilities of mobile devices to passively collect the user-game interaction behaviours from the 3-minute gameplay. With the entertaining features of the games, it is anticipated that individuals would be less likely to have test anxiety as reported in (Lumsden et al., 2016) and, therefore, this game-based measure could potentially promote self-screening for early detection of potential alcohol dependence. As well as providing accurate outcomes, the game-based approach is relatively fast and inexpensive (as it can be installed on almost any smartphones). In addition, the game-based screening instrument is robust, portable and requires only minimal effort to implement. As such, our automated system could be adapted by health professionals as a home-based screening tool to help identify individuals who are at risk of having a subtle sign of the alcohol dependence condition.

4.9.3. Clinical Implications

Considering the short administration time, engaging nature and promising classification performance, our game-based approach seems to be well-aligned with the clinical guidelines from some national health organisations for implementing alcohol screening in general healthcare settings. In particular, this study introduced a novel screening method that offers a simple, fast, inexpensive, and non-intrusive approach without asking about patients' drinking habits and therefore is not likely to induce feelings of being offended or fears of being judged by others. In primary care settings where patients often spend a significant amount of time waiting for healthcare services, patients could be asked to perform self-screening for alcohol dependence using our game-based method. However, it would be more challenging to implement such screening in the ED settings where most patients attend with serious illnesses or injuries that need urgent medical attention. The most likely scenario is to offer the game-based alcohol self-screening to patients with a sub-critical condition when not many patients are presenting to the ED. Besides, our game-based instrument could be used to identify those at high risk of alcohol dependence among patients who visit rehabilitation centres for ongoing treatment and recovery. Identifying alcohol relapse is another scenario of use, where our game-based screening tool could be prescribed to outpatients who have been discharged after undergoing alcohol detoxification and a rehabilitation program.

Given that patients with alcohol problems often lack the motivation to seek help from healthcare providers (Edlund, Booth & Feldman, 2009, SAITZ, 2010, Glass et al., 2017), screening results should not be directly released to patients. Instead, physicians should be informed of the screening results and take appropriate actions, such as to provide brief counselling, referrals to further diagnosis and appropriate treatment when screened positive. Furthermore, this approach could help avoid unnecessary anxiety patients might feel after learning about the health risks and perhaps feeling lost if they cannot reach a healthcare professional.

4.9.4. Limitations and Future Work

Despite the promising results, the findings of this study are subject to two major limitations. First, since almost all patients admitted to the speciality facility where the experiment was carried out are male, we restricted our sample collection to males exclusively. Second, in order to remove the possible confounding factors, individuals with excessive gaming experience or symptoms of anxiety or depression were excluded from our study. As our proposed technique focuses on the use of touch interaction and device motion, a tremor symptom found in other cognitive disorders could have an adverse impact on our technique and potentially confound our results. Therefore, we also excluded individuals with health conditions often exhibiting hand tremors (e.g. Parkinson's disease) from our study. In addition, impaired visuomotor coordination and hand-eye coordination could adversely affect participants' gameplay performance and user-game behavioural patterns. Therefore, visually impaired individuals were excluded. For these reasons, our results should be interpreted with caution. Due to this limited scope, our results cannot be generalised to the entire relevant subgroup of our target population. These limitations could be overcome by further research to investigate the potential effects of these factors on model classification performance and validate the findings we drew from this study.

It is worth noting that the variations in levels of game difficulty over the course of the games could potentially have impacts on classification performance in these games. For example, in Tetris, players can only play on a single level, where the game speed remains stable along the course of the game. However, the gameplay becomes more difficult when the falling shapes are stacked up high close to the upper boundary. Due to there being a shorter amount of time to place blocks, there are periods of greater and lesser difficulty, partly depending on early choices and partly on chance, within the game. It is speculated that players with better visuospatial function can anticipate and mitigate against these periods of greater difficulty and hence its choice as a tool to distinguish between those with impairment of that function and those without. In Unblock Puzzle, given that the game places demands on cognitive function related to problem-solving, we speculate that as the level of difficulty gradually increases when progressing through levels, patients with impaired problem-solving abilities would take longer to solve the puzzle, leading to completing fewer levels when compared to healthy individuals. This is indeed in line with the results in Table 27, where the maximum level achieved by alcohol-dependent patients was found to be significantly lower than that of healthy participants. However, in the present work, we do not have sufficient data to perform an in-depth analysis whether such variations in levels of game difficulty over the course of the games could potentially affect our classification technique based on user-game behaviours. This issue might be addressed in future research.

Future research could examine the feasibility of using such gameplay behaviour patterns to determine the risk of relapse in detoxified alcohol-dependent patients. The practical implementation in a large-scale setting may require additional features such as an automatic notification system to notify the results to clinicians so that timely intervention and appropriate treatment strategies can be given to prevent further development of more severe conditions.

4.10. Conclusions

The primary objective of this study is to explore the use of mobile game-based interaction features in automated screening for a clinical condition associated with cognitive impairment. To our knowledge, this is the first work that evaluates the application of user-game interaction patterns in game-based classifiers for screening and diagnosis of an alcohol dependence condition. Our approach relies on the capture of interaction patterns during gameplay, while potential patients engage with popular mobile games on smartphones. The captured signals include gameplay performance, touch gestures, and device motion, with the intention of identifying patients with alcohol dependence. We evaluate the classification performance of various supervised learning algorithms on data collected from 40 patients and 40 age-matched healthy adults. The results show that patients with alcohol dependence can be automatically identified accurately using the ensemble of touch, device motion, and gameplay performance features on 3-minute samples (accuracy=0.95, sensitivity=0.95, and specificity=0.95). In addition, it is found that the mean acceleration magnitude is the most important indicative feature in discriminating patients from healthy individuals.

Overall, this study presents our novel game-based approach as a fast and inexpensive home-based self-screening tool. In comparison with the paper-based and EEG-based methods, our models demonstrated equal or superior classification performance in terms of accuracy, sensitivity, and specificity. We envision that our home-based self-screening instrument could be used to establish a practical and cost-effective screening strategy to increase screening rates for early detection of alcohol dependence in primary care, hospitals or rehab centres.

The next chapter will provide a conclusion to the studies in this thesis. Furthermore, research contributions and the implications of this thesis, including future research, will be discussed.

Chapter 5: Discussion and Conclusion

In chapter 3 and 4, the results from the two empirical studies exploring the use of touch interaction and device motion features in mobile game-based measures were discussed. This chapter summarises and presents some closing thoughts on the key findings discussed in the preceding chapters. First, the chapter discusses how the key research questions in this thesis are addressed in greater detail. The chapter then highlights the key contributions and implications of this research. Finally, the general limitations of the work and possible directions of future research are presented.

5.1. Research Questions Addressed

1. *Do implicit user-game interaction patterns, i.e. touch interaction and device motion, correlate with cognitive performance?*

This research question was addressed through the quantitative analysis reported in Chapter 3. In the study, a set of features, including touch interaction, device motion and gameplay activities were extracted from user-game interaction data passively collected while participants were playing the games. Spearman's rank-order correlation was used to analyse the associations between the proposed features and cognitive performance measured by traditional paper-based cognitive tests. The findings suggest that there is some indication of user-game interaction patterns being linked to cognitive performance. Although not all significance was found among the same pairs of variables in both control and mental fatigue-induced conditions, several significant relationships were identified between cognitive abilities and extracted touch features measured in dimensions of speed and length. In particular, the negative associations found between cognitive performance and such swipe features could imply that longer and faster swipes, in the context of these games, were correlated with declines in response inhibition and visual search. However, the positive correlations with performance in attention seemed to imply that increases in swipe length and speed were significantly linked to increased attention.

These findings seem to contradict, in part, the findings in the previous handwriting literature where slower and shorter mean stroke were found in patients with cognitive impairment when compared to their healthy peers (Kawa et al., 2017, Mavrogiorgou et al., 2001, Rosenblum et al., 2013, Schroter et al., 2003, Tigges et al., 2000). A possible explanation could be that handwriting is a muscular movement, which can be performed almost automatically without conscious attention in healthy adults.

However, the nature of interactive games that require players to be attentive to multiple stimuli and the underlying users' intention to undertake the game's challenges could influence the patterns of touch-based interactions in the game context. Such differences between both tasks in the attentional demands and the underlying intent of touch interactions may thus result in such contradictory findings.

With regard to device motion patterns, the statistical results in Chapter 3 revealed a mixed picture of significant correlations between device motion features and several cognitive abilities. As a result, this study could not provide conclusive evidence for the relationships between cognitive performance and such a feature set alone. This could be due to the small sample size and the participant recruitment of the study, which was limited to healthy adults only. Given that irregular patterns in fine motor function are commonly observed in individuals with cognitively impaired conditions (Schroter et al., 2003, Mavrogiorgou et al., 2001, Tigges et al., 2000, Anzulewicz, Sobota & Delafield-Butt, 2016), therefore, further efforts with a larger sample size and individuals with a medical condition associated with cognitive impairment are required to examine the underlying relationships between the device motion patterns within the game context and cognitive performance.

Despite the inconclusive results drawn from the study, the significant relationships observed between user-game interaction patterns and cognitive performance provide some indications that it is worth further examining the potential of using such proposed features as input in a novel implicit screening measure for a clinical condition associated with cognitive impairment.

2. *Do game mechanics and related cognitive demand influence gestural characteristics?*

This question was addressed through the findings from the exploratory study in Chapter 3. In particular, significant correlations between gestural features and specific cognitive measures were found only in some games. For instance, the total number of swipes in several directions in Tetris demonstrates significant associations with attention, visuospatial abilities and memory. However, such a link could not be identified in Candy Crush. It was hypothesised that the differences in the game mechanics and related cognitive demands could potentially influence the gesture patterns, and thus might be associated with the different and inconsistent pattern of correlations found in these games.

Another possible explanation could be that the underlying intent of particular gestures could potentially cause such differences in swipe patterns among the three games. For example, downward swipes in Tetris were carried out with the aim to instantly drop the block into the stack below, when players were confident in the target block's location and orientation. This is consistent with the analysis results that the swipe speed in downward direction was significantly faster than swipes in other directions. On the contrary, in Candy Crush, regardless of the direction, players swipe candies with the only intention to create a set of three matching candies by switching them with their adjacent candies. When further examining the interaction patterns in Candy Crush, no significant difference in speed was found between the horizontal swipes and vertical swipes. Based on these findings, it can be concluded that gestural characteristics seem to be partially attributed to particular game mechanics inherent in such games.

Additionally, through visual inspection, the quiver plots revealed unusual touch patterns in Fruit Ninja that constantly alternate moving directions across the screen. It was speculated that such gestural patterns, particularly found only in Fruit Ninja but not in the other two games, may be driven by the game mechanics and underlying intent of performing swipe gestures to complete the in-game tasks.

Derived from these findings, some recommendations on how games could be designed to capitalise on the use of user-game interaction data in game-based assessment and screening instruments was provided in section 3.6.2.

3. *Can touch interaction and device motion patterns be used to identify individuals with a clinical condition associated with cognitive impairment?*

The main study carried out in Chapter 4 demonstrates the practicality of using the user-game interaction features in identifying individuals with alcohol dependence within a population of healthy individuals. In the study, we based our game selection on the game design recommendations discussed in section 3.6.2. In that, Tetris, Fruit Ninja and Unblock Puzzle were chosen as these games are likely to place particular cognitive demands in which individuals with alcohol dependence tend to exhibit impairment (see section 4.3).

Considering that chronic excessive alcohol drinking patterns are strongly associated with prolonged cognitive impairment and impaired motor function due to brain damage (Chris Emmerson and Josie Smith, 2015, Jauhar, Marshall & Smith, 2014, Deik, Saunders-Pullman & San Luciano, 2012, Trevisan et al., 1998), it is likely that alcohol-dependent patients would exhibit irregular patterns of user-game interactions when compared to healthy individuals. The proposed features, specifically, touch interaction, device motion and gameplay performance, were thus used as key features for classifying patients and healthy controls in our classification models.

The findings demonstrate that using multiple feature sources (i.e., touch interaction, device motions and gameplay) as input could considerably improve the overall performance of our classifiers in comparison to using each individual subset of features alone. In that, by using the touch and device motion features of Tetris from 10-minute samples, the Logistic Regression classifier was able to correctly identify alcohol dependence conditions with the accuracy of 0.96. The model also yielded promising results in terms of sensitivity (0.98) and specificity (0.96). Given that an ideal screening test should not be only accurate but also enable large-scale screening for alcohol dependence in low-resource settings, it is desirable to keep the test duration reasonably short. Even though the performance of both Logistic Regression and Random Forest classifiers generally dropped when using 3-minute samples as input, our best performing model on Unblock Puzzle yet exhibited promising results. In particular, the Random Forest classifier trained on all feature sets had the highest accuracy of 0.95 with sensitivity and specificity of 0.95. The low standard errors of the mean (0.2 – 0.3) suggest good generalisation performance of the model.

In comparison to other alcohol screening tools, not only is our game-based approach comparable or even faster than paper-based screening tests (i.e., AUDIT and AUDIT-C) and existing screening technologies (i.e. EEG-based screening), our best performing classifier on 3-minute samples outperforms these existing screening tools in accurately identifying individuals with alcohol dependence (see section 4.9.1 and 4.9.2). It is anticipated that our self-screening mobile game-based modality would reduce test anxiety with fewer feelings of being tested allowing large-scale screening for alcohol dependence with minimal effort and resources.

4. *Which specific user-game interaction features are important features for developing a classification model?*

Where classification performance is the main focus of the study in Chapter 4, it is also important to understand which features mainly contribute to the classification of alcohol-dependent patients and healthy controls. Identifying the most discriminative features can help in the feature selection process to improve model performance. Besides, excluding irrelevant features can reduce computational costs and enhance the stability of the classification model, resulting in a better generalisation ability.

The feature importance analysis was carried out on our best performing classifier using 3-minutes samples as described earlier in addressing the research question 3. Feature importance scores as computed by the Random Forest algorithm were used to provide rankings of features that most contribute to classification.

The results demonstrate that the mean acceleration magnitude is the strongest discriminative feature. In that, alcohol-dependent patients exhibited a larger degree of movement while playing the Unblock Puzzle game in comparison to healthy individuals. Four other gesture-based features, including the mean speed swipe up, the mean speed swipe right, the mean speed swipe left and the mean length swipe left, appeared to be strong discriminative features for identifying alcohol dependence. Besides the features derived from gameplay performance, including the maximum level completed, the mean response time to complete a level and the mean response time of all interactions, were ranked among the top 10 most discriminative features. Given the statistical differences between patients and healthy controls found in these features, it can be implied that patients with alcohol dependence are likely to exhibit significantly poorer gameplay performance with slower and shorter stroke patterns and higher degrees of the phone movement during the gameplay. The slower responses to game stimuli in patients were also consistent with the findings in prior research (De Wilde et al., 2007). These findings provide supportive evidence for the discriminative validity of these features and emphasise the motivation of this thesis, which aimed to exploit the user-game behavioural patterns with the focus on touch interactions and movement of the mobile device for developing an unobtrusive screening measure for a health condition associated with cognitive impairment.

5.2. Contributions

This thesis documents a number of contributions to the fields of ubiquitous and mobile computing and health informatics. First, there are contributions to researchers such as expanding knowledge to the existing literature on how fine motor patterns, particularly on the touch screen device are related to cognitive abilities, and how to optimise the use of user-game interaction patterns in assessment and screening measures. Additionally, practical contributions and implications are presented to assist health professional and practitioners in assessment and screening activities.

5.2.1. Research Contributions

5.2.1.1. Provide an understanding of how gestural interaction and hand motor patterns, in the context of mobile games, are associated with cognitive performance

There has been growing interest in technology to facilitate longitudinal cognitive assessment and self-screening for cognitively impaired conditions. Given the inherent entertaining elements in gaming technology, a large body of existing literature (see in section 2.3) has investigated the feasibility of using gameplay activities as markers for measuring cognitive abilities of individuals. However, these research articles mainly focused on the potential use of gameplay performance-related features. Only a few studies so far have attempted to use touch interaction and device movement patterns to identify people with cognitively impaired conditions, including developmental disorders (Anzulewicz, Sobota & Delafield-Butt, 2016), schizophrenia (Tigges et al., 2000), obsessive-compulsive disorder (Mavrogiorgou et al., 2001), and dementia (Schroter et al., 2003, Suzumura et al., 2018).

Despite the findings of these quantitative studies offering an understanding of the relationships between hand motion parameters and cognitive abilities (see section 2.5), there is little or no evidence of the use of touch interaction and device motion patterns in game-based cognitive assessment and screening. Given the potential of mobile games in sustaining engagement and motivation in neuropsychological assessment and screening activities (McPherson, Burns, 2007, McPherson, Burns, 2008), understanding of how these user-game interaction features via mobile game interfaces are related to cognitive performance would be a useful contribution to existing research examining the use of behavioural patterns in mobile game-based cognitive measures. This would allow researchers to enhance the use of mobile games as an implicit measure to promote long-term engagement for self-directed cognitive assessment and screening, especially in the home environment.

In addressing the first and second research questions, the study in Chapter 3 provides empirical data and useful insight to help researchers understand how the touch interaction and device motion patterns in the mobile game context are associated with cognitive abilities. Section 3.6.2 discussed how game mechanics and related cognitive demand could potentially influence gestural characteristics when interacting with game elements through touch-displays. Some design suggestions were also provided to help researchers to be aware of the roles different game mechanics play in how users perform touch gestures during gameplay and hence how we can infer cognitive abilities based on these gesture features. For a game to be suitable as a cognitive assessment tool, apart from having a have short learning curve, it should be inherently fun to engage players. Besides, the game mechanics should allow intensive touch interactions to obtain sufficient behavioural data for subsequent analysis. In addition, those seeking to use mobile games to assess cognitive abilities in specific domains or to identify individuals with a condition exhibiting particular cognitive dysfunction could design their games to incorporate game elements and mechanics targeting the related cognitive functions. The study in Chapter 4 has applied these recommendations to identify and develop mobile games that would allow the manifestation of the differences in user-game interaction patterns, potentially caused by impaired fine motor functions, visuospatial abilities and executive functions, between patients with alcohol dependence and healthy individuals.

5.2.1.2. Demonstrate how touch interaction and device motion features could be used to develop an automate alcohol screening test

The study on patients with alcohol dependence in Chapter 4 provides a novel example of the feasibility of using the passive features generated from user-game interaction data in discriminating individuals with a health condition associated with cognitive impairment from healthy individuals. The findings in Chapter 4 demonstrate that mobile games could be successfully applied in screening activities to automatically identify alcohol dependence conditions.

In addressing the third and fourth research questions, this thesis has made several key contributions to the field of ubiquitous computing and health informatics as follows:

- The empirical study in Chapter 4 has provided a novel dataset of behavioural patterns in the mobile game context collected from 40 alcohol-dependent patients in a residential treatment program and 40 age-matched healthy adults through multiple built-in sensors on a smartphone. The dataset will be made available to the public to foster further research on the potential application of mobile game-based screening and thus enables researchers to explore more advanced machine learning techniques (e.g. deep learning) to enhance the classification performance.

- Several computational models based on conventional machine learning techniques were developed and evaluated on classification performance using different combinations of features extracted from the novel data set. Comparisons of classification performance of these classifiers were made to identify the best performing model in terms of accuracy, sensitivity and specificity. The findings demonstrate that combining touch interaction and device motion features with gameplay performance could considerably improve the model classification performance when compared to using each of these feature sets alone. This is in line with the implication from the review article on mobile technology for cognitive assessment (Koo, Vizer, 2019) that computational models on multiple sources of unobtrusive data could significantly enhance outcomes in clinical measures. In addition, the findings related to feature importance could provide useful insights to researchers by identifying key user-game interaction features which could discriminate patients with alcohol dependence from healthy adults. For instance, this thesis shows that the mean acceleration magnitude has the most discriminative power to classify alcohol-dependent patients within healthy populations. Furthermore, our mobile game-based method could deliver results with 95% accuracy in as short as 3 minutes, which is ideal for a screening instrument.

- Carrying out research in the alcohol-dependent population posed a number of essential challenges, such as identifying a stage of intervention where alcohol-dependent patients are able to participate in a research study. Given that patients in the residential treatment program can still feel tired easily, a short session of an experiment is preferred. The study procedure in Chapter 4 contributes to existing research by determining appropriate measures and protocol for data collection from alcohol-dependent populations within clinical facilities (section 4.2 and 4.4).

- The findings related to acceptability and practicality of the mobile game-based screening platform enhance the findings of previous studies through positive feedbacks received from the research participant. In that, the gamified alcohol screening measure is well-received, due to its ease of use and entertaining nature.

5.2.2. Practical Contributions

This doctoral thesis presents a number of practical contributions and implications that can be of wide interest to healthcare providers and practitioners. The key contribution of this thesis is to develop a novel mobile game-based screening measure for alcohol dependence. Key challenges and limitations in alcohol screening using conventional paper-based measures and other technology-assisted approaches were described in Section 2.4.6. The foremost barrier to effective implementation of alcohol screening at large scale is the lack of a screening tool that is rapid, highly accurate, low-cost and not dependent on potentially biased retrospective self-responses.

The findings in Chapter 4 demonstrate that our novel game-based screening measure achieves state-of-the-art classification performance, which is even superior to that of the current alcohol screening tools, in terms of accuracy, sensitivity and specificity. In particular, the best performing model could accurately identify alcohol-dependent patients from healthy adults with 95% sensitivity and 95% specificity in as short as 3 minutes. Besides reducing the burden on patients and health professional by using passively logged behavioural data, the game-based approach could reduce the learning effects and retrospective biases that tend to limit the use of current assessment and screening methods. Introducing gamification in assessment and screening measures also offers a significant advantage over conventional paper-based instruments in that the gaming elements could enhance levels of interactivity and engagement, facilitating self-directed assessment and screening outside of clinical practice. Given the highly accurate outcomes and short administration time, our mobile game-based approach could be widely adopted within healthcare facilities or even outside clinical settings as a robust, highly engaging and portable screening tool.

Furthermore, the use of gamification and mobile technology for cognitive assessment and screening in this thesis is distinguished from prior studies in that a vast majority of these studies focus on investigating the use of gameplay performance. This thesis reveals the potential use of underlying interaction patterns unobtrusively collected via touchscreens and smartphone sensors to enhance the validity of game-based neuropsychological instruments. By incorporating such user-game interaction features into classification models, the findings in Chapter 4 demonstrate a substantial improvement in classification performance to detect alcohol dependence conditions. In addition, this thesis has demonstrated the feasibility of using off-the-shelf mobile games. Given the high development costs of a new serious game that is tailored to specific assessment purposes, researchers could instead opt for existing off-the-shelf mobile games, which are considerably more affordable and primarily designed to keep players engaged. Researchers could reduce the time and effort taken for the development and testing and instead employ engaging off-the-shelf games in cognitive research for a range of neurological conditions.

One of the key implications for practitioners is that mobile game-based measures using the proposed techniques could be deployed in clinical practice for early detection of alcohol dependence. Given the minimal effort to carry out the test, the mobile game-based screening instrument could help facilitate brief self-screening for alcohol dependence among individuals visiting primary care or emergency departments with a non-critical condition in a waiting area prior to seeing the doctor. Our easy to administer and non-invasive screening approach could address the concerns in current alcohol screening practice about alcohol stigma and difficulties for healthcare practitioners to raise the topics of alcohol in discussions with patients. The results from the measures could assist the therapist in decision-making and planning for further examination to establish a reliable diagnosis. In addition, patients may be prescribed the mobile game-based screening application to monitor for early signs of relapse to harmful alcohol use after being discharged from a residential treatment program.

In the alcohol study in Chapter 4, participants expressed positive attitudes towards the game-based screening measure and felt comfortable and motivated in using the instrument. Thus, another implication of the study is that the mobile game-based application could motivate those, who are at risk of alcohol use disorders but hesitant to seek help from healthcare providers because of embarrassment, to perform self-screening at home. This could help improve detection rates of alcohol-dependent drinkers outside clinical settings.

The findings of this thesis may also open up new avenues of research to facilitate clinical assessment and screening activities of other cognitive impairments. For instance, the researchers and healthcare practitioners could apply the techniques and game design recommendations proposed in this thesis to develop an implicit measure to detect underlying user-game interaction patterns as an early manifestation of other neurological disorders related to cognitive impairment (e.g. dementia and Parkinson’s disease).

5.3. Limitations

In addition to the limitations already identified in the preceding chapters, a set of general limitations of the reported studies in this thesis are further discussed in this section.

As with the majority of quantitative studies, a relatively large sample size of a target population is preferred to allow rich data and enhance the potential generalisation of the research findings. However, it was difficult to collect data as much as we intended due to the time constraints and limited access to participants. In particular, the alcohol study in Chapter 4, at the clinical facility where the experiment was carried out, the alcohol use disorder hospitalisation rates were substantially higher among males than among females. This limits our access to samples from female patients. Restricting samples to males affects the generalisation of the results as they do not represent a diverse population of alcohol-dependent patients. Further exploration is necessary to validate whether the findings drawn from the study can extend to the female population.

In addition, patients in the residential treatment program are often found to feel mentally and physically exhausted easily. This is likely to diminish their abilities to sustain attention on tasks at hand. Therefore, with such limitations, the experiment session was kept as short as possible. In particular, the neuropsychological measures were deliberately chosen based on the literature reviewed and consultations with clinical psychologists to ensure that they require short administration time while yet provide reliable and valid measurements. A longer form of clinical measures would have offered a more comprehensive assessment, potentially revealing more interesting findings. The limited diversity of observed cases from participants with intensive gaming experience could also impose another relevant limitation. In that, individuals' prior experience with the games could potentially influence gameplay performance and user-game interaction patterns, in turn, affecting the research findings.

Another limitation concerns ecological validity since both studies were conducted under controlled settings. In both studies, to reduce possible confounding factors, restrictions were imposed on participants' pose (i.e., being seated on a chair without armrest) and the way they could use their hands and fingers to interact with the mobile game interface (e.g., only one finger was allowed to interact with the screen at one time). User-game interaction patterns produced under such restricted conditions may differ from how participants would interact with the mobile games in real-life settings. Future research could investigate whether the initial findings from this thesis could be generalised to the real-world settings, where participants would be given more freedom to use their hands and fingers in their preferred body posture when interacting with the games.

In our motivating scenario, we aimed to employ our game-based alcohol screening measure in emergency departments or primary care, where patients with non-clinical conditions often face long waiting times for their clinical tests or scheduled appointments. Although the screening results could be instantly provided to patients directly, physicians are expected to review the results first to ensure appropriate communication of results to patients, including clinical advice and, as needed, referral for further diagnosis and intervention when screened positive.

In order to facilitate the implementation of this approach into clinical practice, further development for an integrated system is required to enable physicians to be notified of the screening result with secure data transmission. Data collected from the mobile gameplay should be linked to patients' medical records to provide authorised healthcare professionals with access to their individual medical and contact information. The current applications of mobile games should be further developed to perform data cleansing and feature extraction locally on the client device before securely transmitting only the raw data without information about patients' identity to a remote server for classification using a pre-trained model. Apart from the adoption of data encryption and decryption in data transmission between the remote server and client applications, access controls mechanisms, including identification, authentication and authorisation, should be implemented on the application to ensure that the appropriate permission to access patient health records is given to only authorised individuals.

Furthermore, given the limited samples used in the study in Chapter 4, the current findings may not be easily generalised to a larger population with more fine-grained levels of severity of alcohol use disorders and a broader range of cognitive abilities, gender and ethnics. In particular, both ICD-10 (World Health Organization, 1993) and DSM-IV (World Health Organization, 1993, Guze, 1995), the two major classification systems, separate diagnoses of alcohol use disorders into two subcategories, i.e., harmful alcohol use (alcohol abuse) and alcohol dependence. Hence, further study should take into account the entire spectrum of alcohol use disorders to examine and validate the feasibility of using the proposed gameplay behaviour patterns to classify three different conditions of the disease: normal control, harmful alcohol use and alcohol dependence to reflect a scenario closer to the real world.

Furthermore, our alcohol screening approach relies largely on user-game interaction patterns, which can be potentially influenced by the irregular fine motor function often found in patients with alcohol dependence. Such hand tremors are also manifested in other neurological disorders, including Parkinson’s Disease and Multiple Sclerosis. Future studies might investigate the feasibility of our classification technique based on user-game behaviours in a close-to-real-world scenario where individuals with these particular conditions should not be excluded.

Thus, it is important to replicate the study in a real-world setting with a larger sample size and a greater diversity of population to evaluate the validity and reliability of the findings drawn from this study.

5.4. Future Work

Despite recent growing research interest in the use of gamification and mobile technology in neuropsychological assessment to identify various neurological conditions, only a limited number of studies have explored the use of touch and device movement by passively logging user behaviours during gameplay. This thesis demonstrates the feasibility of using such smartphone-based passive sensing features to facilitate cognitive assessment and screening and provides some directions for clinical practice and future research. Given the limitations described in section 5.3, introducing additional measures (e.g., measures of fine motor skills) could complement the findings from this study.

Apart from the future work required to facilitate the implementation of the game-based alcohol self-screening in our motivating scenario discussed in section 5.3, this work also provides a range of compelling directions for further exploration of using mobile game-based approaches in assessing and identifying neurological disorders associated with cognitive dysfunction.

Key examples of areas where future research could further investigate, include:

1) **Use of deep learning to recognise more complex underlying user-game interaction patterns.**

In conventional machine learning techniques, an explicit feature extraction process is often time-consuming and requires a large effort to extract features from raw data manually. Usually, such handcrafted features are extracted based on existing literature or consultations with experts in the field. Future research could examine the use of deep learning techniques to eliminate the need for manual feature extraction given that the most significant advantage of the deep learning approach is its essential capability to automatically learn feature representations from raw data (Q. Debard et al., 2018). Thus, deep learning could be used to recognise more complex underlying user-game interaction patterns (e.g., gestures performed in sequence, multi-touch gestures) and identify features that humans would have missed. This would allow further research into the use of participants' natural user-game interaction in mobile game-based alcohol screening method using our proposed technique.

2) **The use of contextual features to identify alcohol relapse in outpatients with alcohol dependence after being discharged**

One potential area of research in the context of mobile game-based assessment, which could be further investigated, is the use of contextual features such as location logs in conjunction with user-game interaction patterns to automatically detect signs of relapse to excessive alcohol use in outpatients during ongoing recovery. Previous research has shown that GPS coordinates and other location-based features could be used as predictive features to infer alcohol drinking behaviour in young adults (D. Santani et al., 2018). Location data could be accessed periodically through an application running in the background. Google Places API could be used to extract semantic locations to indicate the place details based on GPS coordinates. Incorporating such user location features could potentially enhance the feasibility of using mobile game-based measures to identify risks of alcohol relapse in real-life settings.

3) **The use of user-game interaction patterns to identify individuals with other cognitive impairment such as mild cognitive impairment and Alzheimer's disease**

Another compelling direction for future work could be to examine the use of touch interaction and device motion features in conjunction with gameplay activities to identify cognitively impaired conditions, such as mild cognitive impairment (MCI) and Alzheimer's disease (AD). Research has shown that hand motor parameters and finger dexterity on touch-screen devices in patients with MCI and AD are significantly different in comparison to cognitively intact individuals (Schroter et al., 2003, Suzumura et al., 2018). In particular, AD and MCI patients exhibit reduced fine motor abilities, including slower responses, lower accuracy and a higher degree of fluctuation. This could be an exciting area of research, where the game-like approach and the technique proposed in this thesis could be applied to develop a novel self-screening instrument for age-related dementia. Different variants of mobile games could be included to explore their feasibility as a cognitive assessment tool for particular cognitive disorders.

4) The effect of ageing on the adoption of mobile game-based assessments

Prior studies have shown that older adults seem to find gaming technology in the medical context attractive and enjoyable and positively influence their attitude towards technology (Kueider et al., 2012). However, it is known that motor control and functioning normally decline with ageing. Older adults often exhibit slower movement lower dexterity and poorer hand-eye coordination in comparison to young adults (Ketcham, Stelmach, 2004). Future research should further investigate the influence of these intrinsic characteristics of older adults on the use of user-game interactions in cognitive assessment and screening.

Closing Remarks

Cognitive health is a crucial component to allow an individual to perform daily activities independently and engage in meaningful social activities. Cognitive impairment not only poses physical and psychological difficulties for a person but also places burdens on his/her caregivers. Given that current assessment and screening measures heavily rely on self-reporting and the procedures are time-consuming and must be administered by trained clinicians, a vast body of research discussed in this thesis explored various technological solutions to overcome these limitations. The work presented in this thesis provides an example of how user-game interactions with casual mobile games could be used in developing a novel screening tool for a medical condition with cognitive impairment. The entertaining nature of games would promote higher adherence rates, which is ideal for periodically self-screening in the users' environment. Hopefully, the findings in this thesis would provide researchers with useful insight and encourage more research to examine the use of touch gesture and device motion through interactions with a mobile-based application via touch interface for other neuropsychological assessment and screening.

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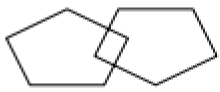
Appendix: Assessments

An Example of MMSE Assessment[5]

Mini-Mental State Examination (MMSE)

Patient's Name: ______________________________ Date: __________

Instructions: ***Ask the questions in the order listed. Score one point for each correct response within each question or activity.***

Maximum Score	Patient's Score	Questions
5		"What is the year? Season? Date? Day of the week? Month?"
5		"Where are we now: State? County? Town/city? Hospital? Floor?"
3		The examiner names three unrelated objects clearly and slowly, then asks the patient to name all three of them. The patient's response is used for scoring. The examiner repeats them until patient learns all of them, if possible. Number of trials: ________
5		"I would like you to count backward from 100 by sevens." (93, 86, 79, 72, 65, …) Stop after five answers. Alternative: "Spell WORLD backwards." (D-L-R-O-W)
3		"Earlier I told you the names of three things. Can you tell me what those were?"
2		Show the patient two simple objects, such as a wristwatch and a pencil, and ask the patient to name them.
1		"Repeat the phrase: 'No ifs, ands, or buts.'"
3		"Take the paper in your right hand, fold it in half, and put it on the floor." (The examiner gives the patient a piece of blank paper.)
1		"Please read this and do what it says." (Written instruction is "Close your eyes.")
1		"Make up and write a sentence about anything." (This sentence must contain a noun and a verb.)
1		"Please copy this picture." (The examiner gives the patient a blank piece of paper and asks him/her to draw the symbol below. All 10 angles must be present and two must intersect.) 
30		TOTAL

(Adapted from Rovner & Folstein, 1987)

[5] Source: www.uml.edu/docs/Mini%20Mental%20State%20Exam_tcm18-169319.pdf

Instructions for administration and scoring of the MMSE

Orientation (10 points):

- Ask for the date. Then specifically ask for parts omitted (e.g., "Can you also tell me what season it is?"). One point for each correct answer.
- Ask in turn, "Can you tell me the name of this hospital (town, county, etc.)?" One point for each correct answer.

Registration (3 points):

- Say the names of three unrelated objects clearly and slowly, allowing approximately one second for each. After you have said all three, ask the patient to repeat them. The number of objects the patient names correctly upon the first repetition determines the score (0-3). If the patient does not repeat all three objects the first time, continue saying the names until the patient is able to repeat all three items, up to six trials. Record the number of trials it takes for the patient to learn the words. If the patient does not eventually learn all three, recall cannot be meaningfully tested.
- After completing this task, tell the patient, "Try to remember the words, as I will ask for them in a little while."

Attention and Calculation (5 points):

- Ask the patient to begin with 100 and count backward by sevens. Stop after five subtractions (93, 86, 79, 72, 65). Score the total number of correct answers.
- If the patient cannot or will not perform the subtraction task, ask the patient to spell the word "world" backwards. The score is the number of letters in correct order (e.g., dlrow=5, dlorw=3).

Recall (3 points):

- Ask the patient if he or she can recall the three words you previously asked him or her to remember. Score the total number of correct answers (0-3).

Language and Praxis (9 points):

- Naming: Show the patient a wrist watch and ask the patient what it is. Repeat with a pencil. Score one point for each correct naming (0-2).
- Repetition: Ask the patient to repeat the sentence after you ("No ifs, ands, or buts."). Allow only one trial. Score 0 or 1.
- 3-Stage Command: Give the patient a piece of blank paper and say, "Take this paper in your right hand, fold it in half, and put it on the floor." Score one point for each part of the command correctly executed.
- Reading: On a blank piece of paper print the sentence, "Close your eyes," in letters large enough for the patient to see clearly. Ask the patient to read the sentence and do what it says. Score one point only if the patient actually closes his or her eyes. This is not a test of memory, so you may prompt the patient to "do what it says" after the patient reads the sentence.
- Writing: Give the patient a blank piece of paper and ask him or her to write a sentence for you. Do not dictate a sentence; it should be written spontaneously. The sentence must contain a subject and a verb and make sense. Correct grammar and punctuation are not necessary.
- Copying: Show the patient the picture of two intersecting pentagons and ask the patient to copy the figure exactly as it is. All ten angles must be present and two must intersect to score one point. Ignore tremor and rotation.

(Folstein, Folstein & McHugh, 1975)

An Example of ACE-III Assessment[6]

ADDENBROOKE'S COGNITIVE EXAMINATION – ACE-III
English Version A (2012)

Name: Date of Birth: Hospital No. or Address:	Date of testing: ___/___/___ Tester's name: ____________ Age at leaving full-time education: ____________ Occupation: ____________ Handedness: ____________

ATTENTION

➢ Ask: What is the	Day ________	Date ________	Month ________	Year ________	Season ________	**Attention** [Score 0-5]
➢ Ask: Which	No./Floor ________	Street/Hospital ________	Town ________	County ________	Country ________	**Attention** [Score 0-5]

ATTENTION

- ➢ Tell: "I'm going to give you three words and I'd like you to repeat them after me: lemon, key and ball." After subject repeats, say "Try to remember them because I'm going to ask you later".
- ➢ Score *only* the first trial (repeat 3 times if necessary).
- ➢ Register number of trials: _____

Attention [Score 0-3]

ATTENTION

- ➢ Ask the subject: "Could you take 7 away from 100? I'd like you to keep taking 7 away from each new number until I tell you to stop."
- ➢ If subject makes a mistake, do not stop them. Let the subject carry on and check subsequent answers (e.g., 93, 84, 77, 70, 63 – score 4).
- ➢ Stop after five subtractions (93, 86, 79, 72, 65): ____ ____ ____ ____ ____

Attention [Score 0-5]

MEMORY

- ➢ Ask: 'Which 3 words did I ask you to repeat and remember?' ______ _______ _______

Memory [Score 0-3]

FLUENCY

- ➢ **Letters**

Say: "I'm going to give you a letter of the alphabet and I'd like you to generate as many words as you can beginning with that letter, but not names of people or places. For example, if I give you the letter "C", you could give me words like "cat, cry, clock" and so on. But, you can't give me words like Catherine or Canada. Do you understand? Are you ready? You have one minute. The letter I want you to use is the letter "P".

Fluency [Score 0 – 7]

≥ 18	7
14-17	6
11-13	5
8-10	4
6-7	3
4-5	2
2-3	1
0-1	0
total	correct

- ➢ **Animals**

Say: "Now can you name as many animals as possible. It can begin with any letter."

Fluency [Score 0 – 7]

≥ 22	7
17-21	6
14-16	5
11-13	4
9-10	3
7-8	2
5-6	1
<5	0
total	correct

[6] Source: dementia.ie/images/uploads/site-images/ACE-III_Administration_(UK).pdf

MEMORY				
➢ Tell: "I'm going to give you a name and address and I'd like you to repeat the name and address after me. So you have a chance to learn, we'll be doing that 3 times. I'll ask you the name and address later." Score only the third trial.				**Memory** [Score 0 – 7]
	1st Trial	*2nd Trial*	*3rd Trial*	
Harry Barnes 73 Orchard Close Kingsbridge Devon	________ ________ ____ ______ ______ ______________ ______________	________ ________ ____ ______ ______ ______________ ______________	________ ________ ____ ______ ______ ______________ ______________	

MEMORY	
➢ Name of the current Prime Minister…… ➢ Name of the woman who was Prime Minister …… ➢ Name of the USA president…… ➢ Name of the USA president who was assassinated in the 1960s……	**Memory** [Score 0 – 4]

LANGUAGE	
➢ Place a pencil and a piece of paper in front of the subject. As a practice trial, ask the subject to **"Pick up the pencil and then the paper."** If incorrect, score 0 and do not continue further. ➢ If the subject is correct on the practice trial, continue with the following three commands below. • Ask the subject to **"Place the paper on top of the pencil"** • Ask the subject to **"Pick up the pencil but not the paper"** • Ask the subject to **"Pass me the pencil after touching the paper"** Note: Place the pencil and paper in front of the subject before each command.	**Language** [Score 0-3]

LANGUAGE	
➢ Ask the subject to write two (or more) complete sentences about his/her last holiday/weekend/Christmas. Write in complete sentences and do not use abbreviations. Give 1 point if there are two (or more) complete sentences about the one topic; and give another 1 point if grammar and spelling are correct.	**Language** [Score 0-2]

LANGUAGE	
➢ Ask the subject to repeat: **'caterpillar'; 'eccentricity; 'unintelligible'; 'statistician'** Score 2 if all are correct; score 1 if 3 are correct; and score 0 if 2 or less are correct.	**Language** [Score 0-2]

LANGUAGE

- Ask the subject to repeat: **‘All that glitters is not gold’**

Language
[Score 0-1]

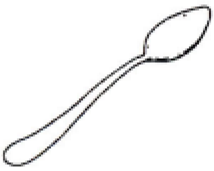
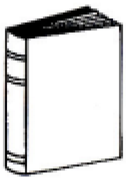
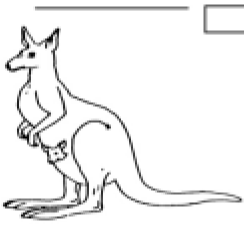
- Ask the subject to repeat: **‘A stitch in time saves nine’**

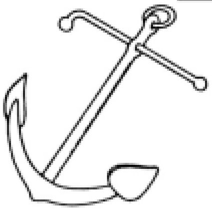
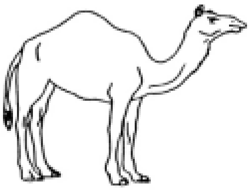
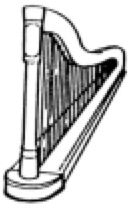
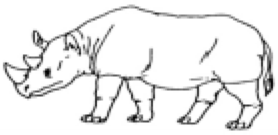
Language
[Score 0-1]

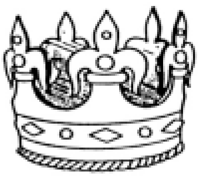
LANGUAGE

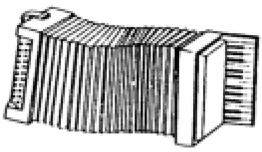
- Ask the subject to name the following pictures:

Language
[Score 0-12]





LANGUAGE

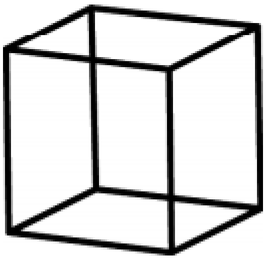
- Using the pictures above, ask the subject to:
  - Point to the one which is associated with the monarchy ....
  - Point to the one which is a marsupial ....
  - Point to the one which is found in the Antarctic ....
  - Point to the one which has a nautical connection ....

Language
[Score 0-4]

LANGUAGE	
➢ Ask the subject to read the following words: (Score 1 only if all correct) **sew** **pint** **soot** **dough** **height**	**Language** [Score 0-1]

VISUOSPATIAL ABILITIES	
➢ Infinity Diagram: Ask the subject to copy this diagram	**Visuospatial** [Score 0-1]

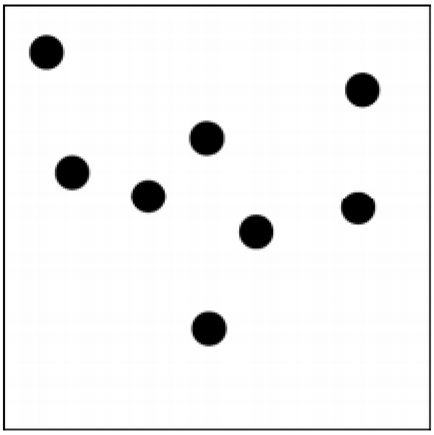
➢ Wire cube: Ask the subject to copy this drawing (for scoring, see instructions guide).	**Visuospatial** [Score 0-2]

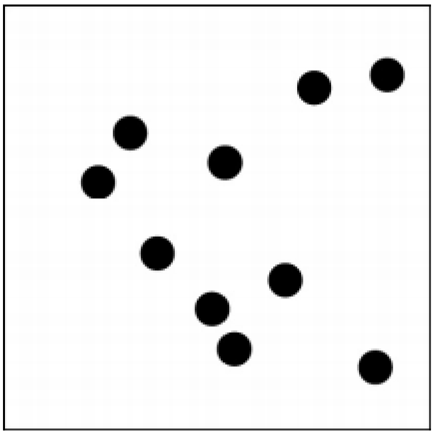


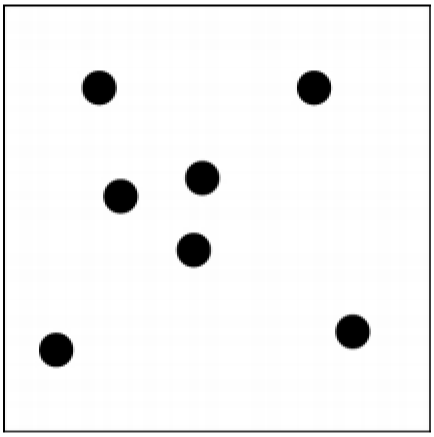
➢ Clock: Ask the subject to draw a clock face with numbers and the hands at ten past five. (For scoring see instruction guide: circle = 1, numbers = 2, hands = 2 if all correct).	**Visuospatial** [Score 0-5]

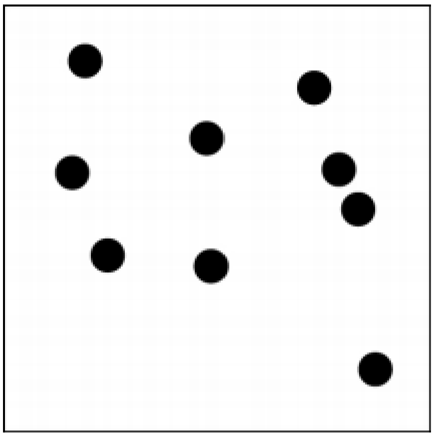
VISUOSPATIAL ABILITIES

➢ Ask the subject to count the dots without pointing to them	**Visuospatial** [Score 0-4]





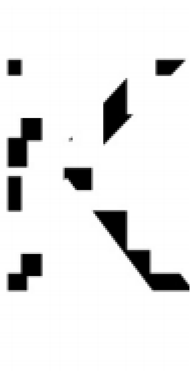


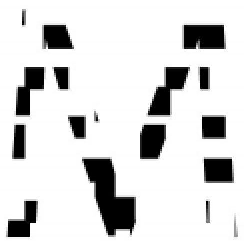


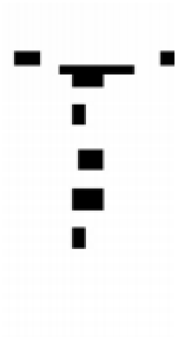
VISUOSPATIAL ABILITIES

- Ask the subject to identify the letters

Visuospatial
[Score 0-4]







MEMORY

- Ask "Now tell me what you remember about that name and address we were repeating at the beginning"

Harry Barnes 73 Orchard Close Kingsbridge Devon	....	**Memory** [Score 0-7]

MEMORY

- This test should be done if the subject failed to recall one or more items above. It all items were recalled, skip the test and score 5. If only part was recalled start by ticking items recalled in the shadowed column on the right hand side; and then test not recalled items by telling the subject "ok, I'll give you some hints: was the name X, Y or Z?" and so on. Each recognised item scores one point, which is added to the point gained by recalling.

Memory
[Score 0-5]

Jerry Barnes		Harry Barnes		Harry Bradford		recalled	
37		73		76		recalled	
Orchard Place		Oak Close		Orchard Close		recalled	
Oakhampton		Kingsbridge		Dartington		recalled	
Devon		Dorset		Somerset		recalled	

SCORES

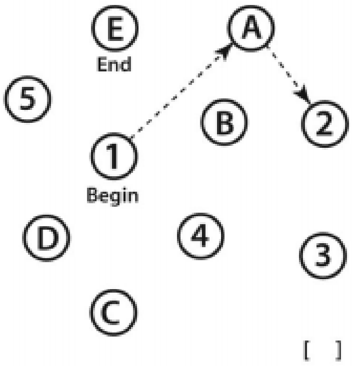
TOTAL ACE-III SCORE	/100
Attention	/18
Memory	/26
Fluency	/14
Language	/26
Visuospatial	/16

An Example of MOCA Assessment[7]

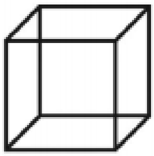
MONTREAL COGNITIVE ASSESSMENT (MOCA)
Version 7.1 Original Version

NAME :
Education : Date of birth :
Sex : DATE :

	POINTS
VISUOSPATIAL / EXECUTIVE	



[ ]

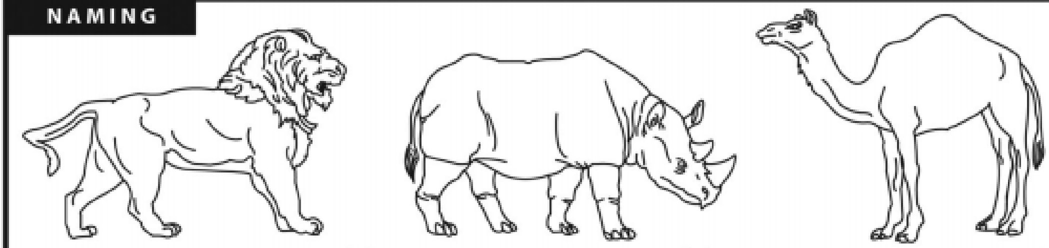


Copy cube [ ]

Draw CLOCK (Ten past eleven) (3 points)

[ ] Contour [ ] Numbers [ ] Hands ___/5

NAMING



[ ] [ ] [ ] ___/3

MEMORY Read list of words, subject must repeat them. Do 2 trials, even if 1st trial is successful. Do a recall after 5 minutes.		FACE	VELVET	CHURCH	DAISY	RED	No points
	1st trial						
	2nd trial						

			POINTS
ATTENTION Read list of digits (1 digit/ sec.).	Subject has to repeat them in the forward order	[ ] 2 1 8 5 4	
	Subject has to repeat them in the backward order	[ ] 7 4 2	___/2
Read list of letters. The subject must tap with his hand at each letter A. No points if ≥ 2 errors		[ ] F B A C M N A A J K L B A F A K D E A A A J A M O F A A B	___/1
Serial 7 subtraction starting at 100	[ ] 93 [ ] 86 [ ] 79 [ ] 72 [ ] 65	4 or 5 correct subtractions: **3 pts**, 2 or 3 correct: **2 pts**, 1 correct: **1 pt**, 0 correct: **0 pt**	___/3
LANGUAGE	Repeat : I only know that John is the one to help today. [ ] The cat always hid under the couch when dogs were in the room. [ ]		___/2
	Fluency / Name maximum number of words in one minute that begin with the letter F	[ ] _____ (N ≥ 11 words)	___/1
ABSTRACTION	Similarity between e.g. banana - orange = fruit	[ ] train – bicycle [ ] watch - ruler	___/2

DELAYED RECALL	Has to recall words WITH NO CUE	FACE [ ]	VELVET [ ]	CHURCH [ ]	DAISY [ ]	RED [ ]	Points for UNCUED recall only	___/5
Optional	Category cue							
	Multiple choice cue							

ORIENTATION	[ ] Date	[ ] Month	[ ] Year	[ ] Day	[ ] Place	[ ] City	___/6

© Z.Nasreddine MD www.mocatest.org Normal ≥ 26 / 30 TOTAL ___/30

Add 1 point if ≤ 12 yr edu

Administered by: ______________________

7 Source: www.mocatest.org/pdf_files/test/MoCA-Test-English_7_1.pdf

An Example of TMT Parts A & B[8]

Trail Making Test (TMT) Parts A & B

Instructions:

Both parts of the Trail Making Test consist of 25 circles distributed over a sheet of paper. In Part A, the circles are numbered 1 – 25, and the patient should draw lines to connect the numbers in ascending order. In Part B, the circles include both numbers (1 – 13) and letters (A – L); as in Part A, the patient draws lines to connect the circles in an ascending pattern, but with the added task of alternating between the numbers and letters (i.e., 1-A-2-B-3-C, etc.). The patient should be instructed to connect the circles as quickly as possible, without lifting the pen or pencil from the paper. Time the patient as he or she connects the "trail." If the patient makes an error, point it out immediately and allow the patient to correct it. Errors affect the patient's score only in that the correction of errors is included in the completion time for the task. It is unnecessary to continue the test if the patient has not completed both parts after five minutes have elapsed.

Step 1:	Give the patient a copy of the Trail Making Test Part A worksheet and a pen or pencil.
Step 2:	Demonstrate the test to the patient using the sample sheet (Trail Making Part A – *SAMPLE*).
Step 3:	Time the patient as he or she follows the “trail” made by the numbers on the test.
Step 4:	Record the time.
Step 5:	Repeat the procedure for Trail Making Test Part B.

Scoring:

Results for both TMT A and B are reported as the number of seconds required to complete the task; therefore, higher scores reveal greater impairment.

	Average	**Deficient**	**Rule of Thumb**
Trail A	29 seconds	> 78 seconds	Most in 90 seconds
Trail B	75 seconds	> 273 seconds	Most in 3 minutes

Sources:

- Corrigan JD, Hinkeldey MS. Relationships between parts A and B of the Trail Making Test. *J Clin Psychol.* 1987;43(4):402–409.
- Gaudino EA, Geisler MW, Squires NK. Construct validity in the Trail Making Test: what makes Part B harder? *J Clin Exp Neuropsychol.* 1995;17(4):529-535.
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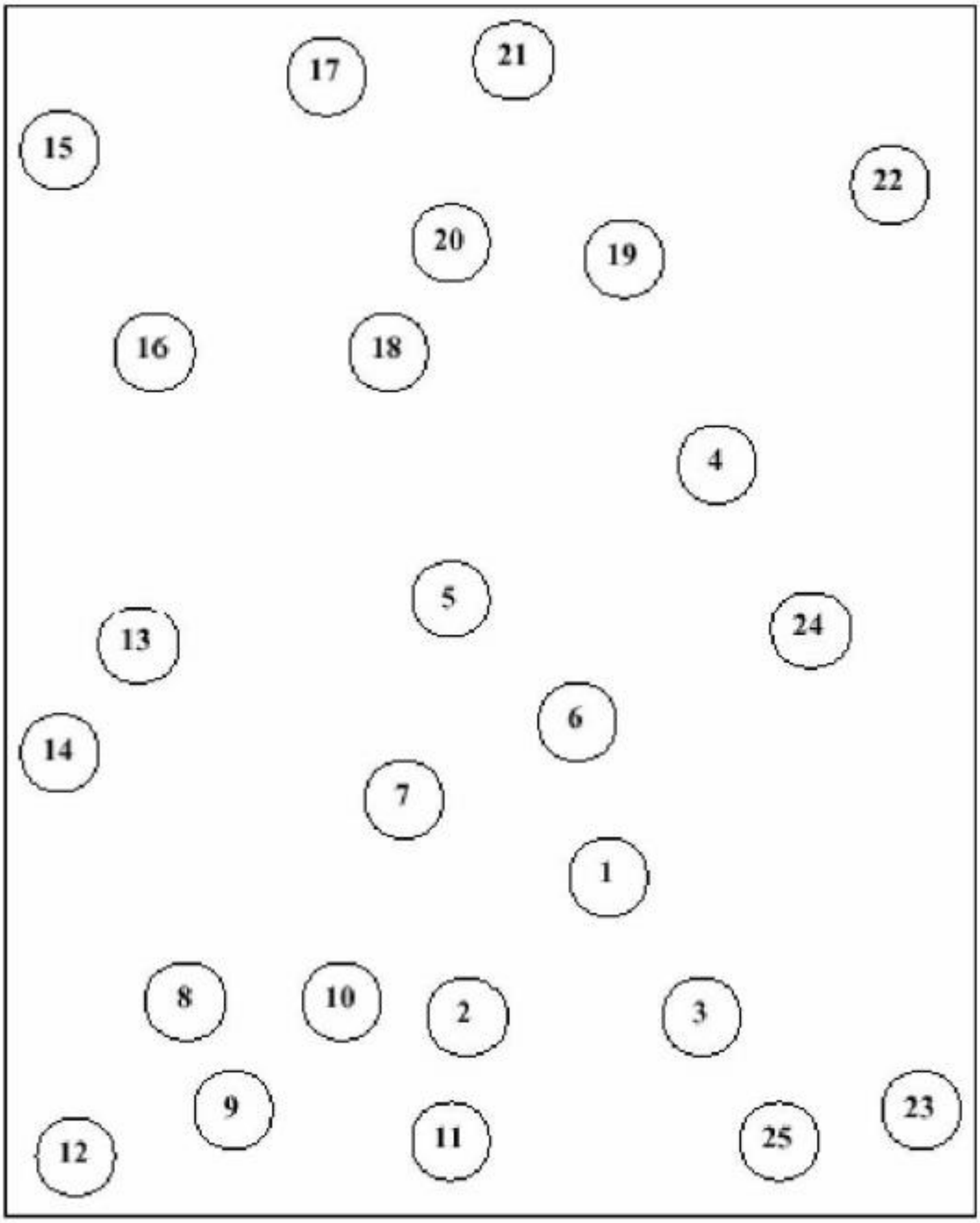
- Reitan RM. Validity of the Trail Making test as an indicator of organic brain damage. *Percept Mot Skills.* 1958;8:271-276.

[8] Source: http://drivesafecalgary.ca/downloads/trail-making-test.pdf

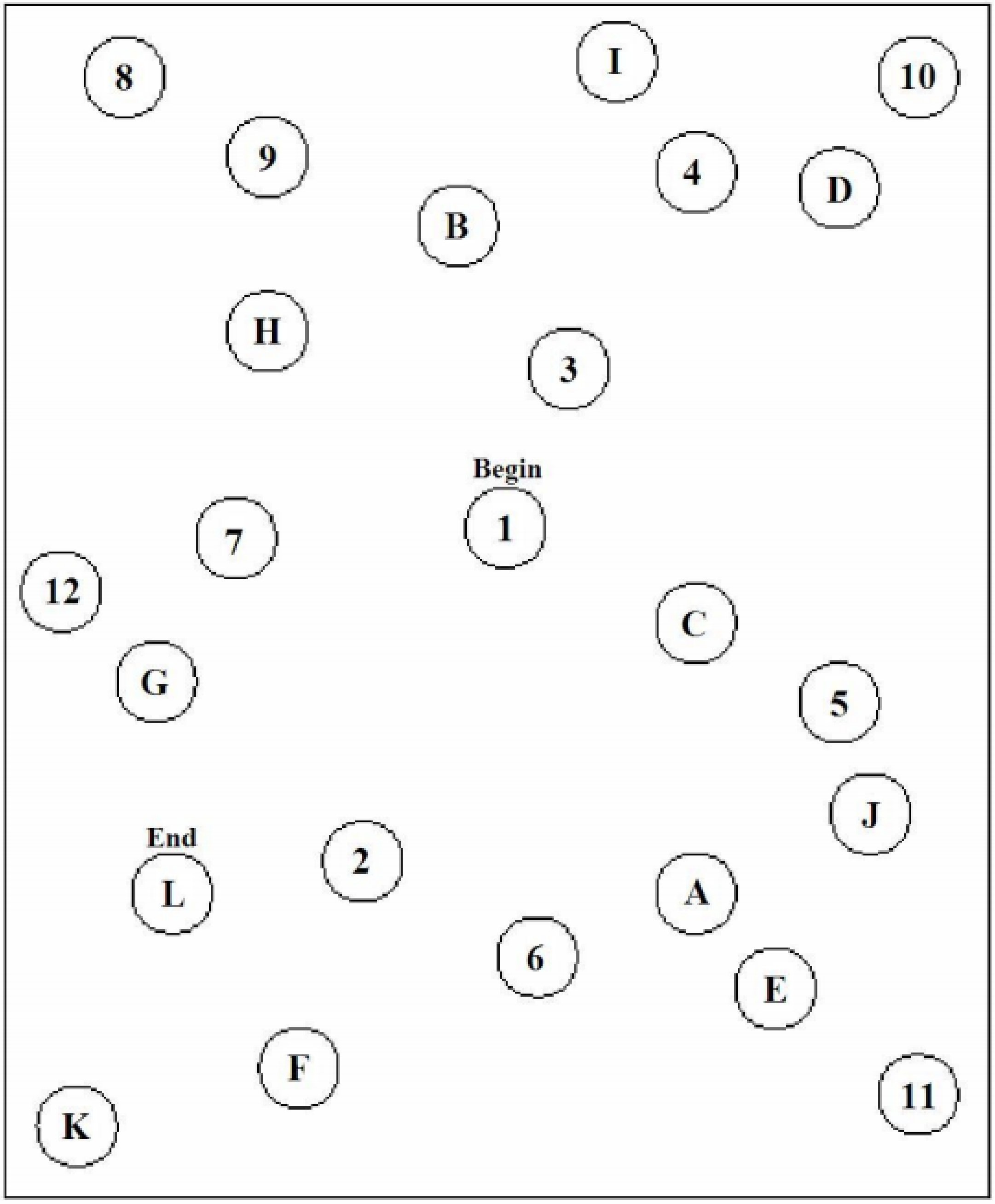
Trail Making Test Part A

Patient's Name: ______________________________ Date: ____________________



Trail Making Test Part B

Patient's Name: ______________________ Date: ______________



An Example of AUDIT Assessment[9]

The Alcohol Use Disorders Identification Test: Interview Version

Read questions as written. Record answers carefully. Begin the AUDIT by saying "Now I am going to ask you some questions about your use of alcoholic beverages during this past year." Explain what is meant by "alcoholic beverages" by using local examples of beer, wine, vodka, etc. Code answers in terms of "standard drinks". Place the correct answer number in the box at the right.

1. How often do you have a drink containing alcohol?

(0) Never [Skip to Qs 9-10]
(1) Monthly or less
(2) 2 to 4 times a month
(3) 2 to 3 times a week
(4) 4 or more times a week

2. How many drinks containing alcohol do you have on a typical day when you are drinking?

(0) 1 or 2
(1) 3 or 4
(2) 5 or 6
(3) 7, 8, or 9
(4) 10 or more

3. How often do you have six or more drinks on one occasion?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

Skip to Questions 9 and 10 if Total Score for Questions 2 and 3 = 0

4. How often during the last year have you found that you were not able to stop drinking once you had started?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

5. How often during the last year have you failed to do what was normally expected from you because of drinking?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

6. How often during the last year have you needed a first drink in the morning to get yourself going after a heavy drinking session?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

7. How often during the last year have you had a feeling of guilt or remorse after drinking?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

8. How often during the last year have you been unable to remember what happened the night before because you had been drinking?

(0) Never
(1) Less than monthly
(2) Monthly
(3) Weekly
(4) Daily or almost daily

9. Have you or someone else been injured as a result of your drinking?

(0) No
(2) Yes, but not in the last year
(4) Yes, during the last year

10. Has a relative or friend or a doctor or another health worker been concerned about your drinking or suggested you cut down?

(0) No
(2) Yes, but not in the last year
(4) Yes, during the last year

Record total of specific items here

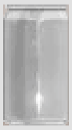
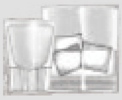
If total is greater than recommended cut-off, consult User's Manual.

[9] https://www.drugabuse.gov/sites/default/files/audit.pdf

The Alcohol Use Disorders Identification Test: Self-Report Version

PATIENT: Because alcohol use can affect your health and can interfere with certain medications and treatments, it is important that we ask some questions about your use of alcohol. Your answers will remain confidential so please be honest. Place an X in one box that best describes your answer to each question.

Questions	**0**	**1**	**2**	**3**	**4**	
1. How often do you have a drink containing alcohol?	Never	Monthly or less	2-4 times a month	2-3 times a week	4 or more times a week	
2. How many drinks containing alcohol do you have on a typical day when you are drinking?	1 or 2	3 or 4	5 or 6	7 to 9	10 or more	
3. How often do you have six or more drinks on one occasion?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
4. How often during the last year have you found that you were not able to stop drinking once you had started?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
5. How often during the last year have you failed to do what was normally expected of you because of drinking?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
6. How often during the last year have you needed a first drink in the morning to get yourself going after a heavy drinking session?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
7. How often during the last year have you had a feeling of guilt or remorse after drinking?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
8. How often during the last year have you been unable to remember what happened the night before because of your drinking?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
9. Have you or someone else been injured because of your drinking?	No		Yes, but not in the last year		Yes, during the last year	
10. Has a relative, friend, doctor, or other health care worker been concerned about your drinking or suggested you cut down?	No		Yes, but not in the last year		Yes, during the last year	
					Total	

STANDARD DRINK EQUIVALENTS	APPROXIMATE NUMBER OF STANDARD DRINKS IN:
BEER or COOLER	
12 oz.  ~5% alcohol	12 oz. = 1 16 oz. = 1.3 22 oz. = 2 40 oz. = 3.3
MALT LIQUOR	
8-9 oz.  ~7% alcohol	12 oz. = 1.5 16 oz. = 2 22 oz. = 2.5 40 oz. = 4.5
TABLE WINE	
5 oz.  ~12% alcohol	a 750 mL (25 oz.) bottle = 5
80-proof SPIRITS (hard liquor)	
1.5 oz.  ~40% alcohol	a mixed drink = 1 or more* a pint (16 oz.) = 11 a fifth (25 oz.) = 17 1.75 L (59 oz.) = 39 *Note: Depending on factors such as the type of spirits and the recipe, one mixed drink can contain from one to three or more standard drinks.

An Example of AUDIT-C Assessment[10]

Alcohol use disorders identification test consumption (AUDIT C)

This alcohol harm assessment tool consists of the consumption questions from the full alcohol use disorders identification test (AUDIT).

Questions	**Scoring system**					**Your score**
	0	**1**	**2**	**3**	**4**	
How often do you have a drink containing alcohol?	Never	Monthly or less	2 to 4 times per month	2 to 3 times per week	4 or more times per week	
How many units of alcohol do you drink on a typical day when you are drinking?	0 to 2	3 to 4	5 to 6	7 to 9	10 or more	
How often have you had 6 or more units if female, or 8 or more if male, on a single occasion in the last year?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	

AUDIT C score	

Scoring:

- A total of 5 or more is a positive screen
- 0 to 4 indicates low risk
- 5 to 7 indicates increasing risk
- 8 to10 indicates higher risk
- 11 to 12 indicates possible dependence

[10] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/684826/Alcohol_use_disorders_identification_test_for_consumption__AUDIT_C_.pdf

An Example of PAT Assessment[11]

PADDINGTON ALCOHOL TEST 2009

'make the connection'

PATIENT IDENTIFICATION STICKER:
NAME
D.O.B.

A. *PAT for TOP 10 presentations – circle as necessary.* B. *Clinical Signs of alcohol use* C. *BAC (PTO)*

1. FALL (*incl. trip*) 2. COLLAPSE (*incl. fits*) 3. HEAD INJURY 4. ASSAULT
5. ACCIDENT 6. UNWELL 7. GASTRO-INTESTINAL 8. CARDIAC (*i. Chest pain*)
9. PSYCHIATRIC (*incl. DSH & OD) please state* 10. REPEAT ATTENDER *Other (please state)*

EARLY IDENTIFICATION TO REDUCE RE-ATTENDANCE

Only proceed after dealing with patient's 'agenda,' i.e. patient's reason for attendance.
"We routinely ask all patients having …(above presentation)…**do you drink alcohol?"**

1 Do you drink alcohol? YES (go to #2) NO (end)

2 What is the most you will drink in any one day? (UK alcohol units)

Use the following guide to estimate total daily units.
(Standard pub units in brackets; home measures often three times the amount!)

Beer /lager/cider	Pints (2)	Cans (1.5)	Litre bottles (4.5)
Strong beer /lager /cider	Pints (5)	Cans (4)	Litre bottles (10)
Wine	Glasses (1.5)	75cl bottles (9)	Alcopops
Fortified Wine (Sherry, Port, Martini)	Glasses (1)	75cl bottles (12)	330ml bottles (1.5)
Spirits (Gin, Vodka, Whisky etc)	Singles (1)	75cl bottles (30)	

If more than twice daily limits (8 units/day for men, 6 units/day for women) PAT +ve (continue to Q3 for all)

3 How often do you drink ?

Every day — May be dependent, advise against daily drinking. Consider pabrinex &chlordiazepoxide
____ times per week
Less than weekly (continue to next question)

4 Do you feel your attendance at A&E is related to alcohol? YES (PAT+ve) NO

If PAT +ve give feedback e.g. "Can we advise that your drinking is harming your health".
"It is recommended that you do not regularly drink more than 4 units/day for men or 3 units/day for women".

5 We would like to offer you further advice, would you be willing to see our nurse specialist ? YES NO

If "YES" to Q5 give ANS appointment card and leaflet and make appointment in diary @ 9am to 10am.
Other appointment times available, please speak to ANS or ask patient to contact (phone number on app. card).
Give alcohol advice leaflet ("Units and You") to all PAT+ve patients, especially if they decline ANS appointment.

Please note here if patient admitted to ward ……………………………………………………

Referrer's Signature Name Stamp Date: PTO

THANK YOU

AHW OUTCOME:

11 https://www.rcem.ac.uk/docs/External%20Guidance/10f.%20Paddington%20Alcohol%20Test.pdf

An Example of FAST Assessment[12]

Fast alcohol screening test (FAST)

FAST is an alcohol harm assessment tool. It consists of a subset of questions from the full alcohol use disorders identification test (AUDIT). FAST was developed for use in emergency departments, but can be used in a variety of health and social care settings.

Questions	**Scoring system**					**Your score**
	0	**1**	**2**	**3**	**4**	
How often have you had 6 or more units if female, or 8 or more if male, on a single occasion in the last year?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
Only answer the following questions if the answer above is Never (0), Less than monthly (1) or Monthly (2). Stop here if the answer is Weekly (3) or Daily (4).						
How often during the last year have you failed to do what was normally expected from you because of your drinking?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
How often during the last year have you been unable to remember what happened the night before because you had been drinking?	Never	Less than monthly	Monthly	Weekly	Daily or almost daily	
Has a relative or friend, doctor or other health worker been concerned about your drinking or suggested that you cut down?	No		Yes, but not in the last year		Yes, during the last year	

FAST score	

An overall total score of 3 or more on the first or all 4 questions is FAST positive.

12 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/684828/Fast_alcohol_use_screening_test__FAST__.pdf

An Example of RAPS-4 Assessment[13]

1. During the last year have you had a feeling of guilt or remorse after drinking? **(REMORSE)**
2. During the last year has a friend or family member ever told you about things you said or did while you were drinking that you could not remember? **(AMNESIA)**
3. During the last year have you failed to do what was normally expected from you because of drinking? **(PERFORM)**
4. Do you sometimes take a drink in the morning when you first get up? **(STARTER or "eye opener")**

***Cut-point of the scale for identifying potential alcohol problem is ≥1.**

[13] Jones, L.A. 2011, "Systematic review of alcohol screening tools for use in the emergency department", *Emerg Med J,* vol. 28, no. 3, pp. 182.

An Example of TWEAK Assessment[14]

TOLERANCE	Can you **hold six or more** drinks?
WORRIED	Are your **friends and relatives** worried about your drinking?
EYE OPENER	Have you ever had a **drink in the morning** to get rid of a hangover?
AMNESIA	Have you ever awakened the morning after some drinking the night before and found that you **could not remember** a part of the evening before?
CUT DOWN	Have you ever felt you should **cut down** on your drinking?

***Cut-point of the scale for identifying potential alcohol problem is ≥3.**

[14] Jones, L.A. 2011, "Systematic review of alcohol screening tools for use in the emergency department", *Emerg Med J,* vol. 28, no. 3, pp. 182.

Table 29: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 10-minute samples from Tetris

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 0.5}
Logistic Regression	2	{'C': 0.5}
Logistic Regression	3	{'C': 7}
Logistic Regression	4	{'C': 5}
Logistic Regression	5	{'C': 0.5}
Logistic Regression	6	{'C': 0.5}
Logistic Regression	7	{'C': 10}
Logistic Regression	8	{'C': 1.5}
Logistic Regression	9	{'C': 7}
Logistic Regression	10	{'C': 0.5}
SVM	1	{'C': 0.5}
SVM	2	{'C': 1}
SVM	3	{'C': 1}
SVM	4	{'C': 3}
SVM	5	{'C': 1.5}
SVM	6	{'C': 0.1}
SVM	7	{'C': 3}
SVM	8	{'C': 0.5}
SVM	9	{'C': 1.5}
SVM	10	{'C': 0.5}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}

Table 30: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 10-minute samples from Tetris

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 10}
Logistic Regression	2	{'C': 7}
Logistic Regression	3	{'C': 5}
Logistic Regression	4	{'C': 7}
Logistic Regression	5	{'C': 5}
Logistic Regression	6	{'C': 7}
Logistic Regression	7	{'C': 10}
Logistic Regression	8	{'C': 5}
Logistic Regression	9	{'C': 7}
Logistic Regression	10	{'C': 7}
SVM	1	{'C': 3}
SVM	2	{'C': 7}
SVM	3	{'C': 3}
SVM	4	{'C': 1.5}
SVM	5	{'C': 1.5}
SVM	6	{'C': 5}
SVM	7	{'C': 5}
SVM	8	{'C': 1}
SVM	9	{'C': 1.5'}
SVM	10	{'C': 1}
Random Forest	1	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 31: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 10-minute samples from Fruit Ninja

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 7}
Logistic Regression	2	{'C': 7}
Logistic Regression	3	{'C': 10}
Logistic Regression	4	{'C': 5}
Logistic Regression	5	{'C': 10}
Logistic Regression	6	{'C': 1.5}
Logistic Regression	7	{'C': 5}
Logistic Regression	8	{'C': 10}
Logistic Regression	9	{'C': 5}
Logistic Regression	10	{'C': 3}
SVM	1	{'C': 1.5}
SVM	2	{'C': 0.1}
SVM	3	{'C': 3}
SVM	4	{'C': 0.5}
SVM	5	{'C': 1.5}
SVM	6	{'C': 1.5}
SVM	7	{'C': 10}
SVM	8	{'C': 10}
SVM	9	{'C': 0.1}
SVM	10	{'C': 1}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 32: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 10-minute samples from Fruit Ninja

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 1.5}
Logistic Regression	2	{'C': 5}
Logistic Regression	3	{'C': 1.5}
Logistic Regression	4	{'C': 1}
Logistic Regression	5	{'C': 7}
Logistic Regression	6	{'C': 5}
Logistic Regression	7	{'C': 5}
Logistic Regression	8	{'C': 7}
Logistic Regression	9	{'C': 3}
Logistic Regression	10	{'C': 3}
SVM	1	{'C': 0.1}
SVM	2	{'C': 0.1}
SVM	3	{'C': 1}
SVM	4	{'C': 1}
SVM	5	{'C': 7}
SVM	6	{'C': 10}
SVM	7	{'C': 3}
SVM	8	{'C': 7}
SVM	9	{'C': 3}
SVM	10	{'C': 1.5}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	8	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}

Table 33: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 10-minute samples from Unblock Puzzle

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 0.5}
Logistic Regression	2	{'C': 0.5}
Logistic Regression	3	{'C': 7}
Logistic Regression	4	{'C': 1}
Logistic Regression	5	{'C': 1}
Logistic Regression	6	{'C': 1}
Logistic Regression	7	{'C': 7}
Logistic Regression	8	{'C': 0.5}
Logistic Regression	9	{'C': 0.5}
Logistic Regression	10	{'C': 0.5}
SVM	1	{'C': 0.5}
SVM	2	{'C': 0.5}
SVM	3	{'C': 0.5}
SVM	4	{'C': 0.5}
SVM	5	{'C': 0.5}
SVM	6	{'C': 0.1}
SVM	7	{'C': 0.5}
SVM	8	{'C': 0.5}
SVM	9	{'C': 0.5}
SVM	10	{'C': 0.5}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}

Table 34: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 10-minute samples from Unblock Puzzle

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 5}
Logistic Regression	2	{'C': 1.5}
Logistic Regression	3	{'C': 1.5}
Logistic Regression	4	{'C': 1.5}
Logistic Regression	5	{'C': 0.5}
Logistic Regression	6	{'C': 3}
Logistic Regression	7	{'C': 0.5}
Logistic Regression	8	{'C': 1}
Logistic Regression	9	{'C': 1.5}
Logistic Regression	10	{'C': 1.5}
SVM	1	{'C': 7}
SVM	2	{'C': 1}
SVM	3	{'C': 0.5}
SVM	4	{'C': 0.5}
SVM	5	{'C': 0.1}
SVM	6	{'C': 0.5}
SVM	7	{'C': 1.5}
SVM	8	{'C': 1}
SVM	9	{'C': 3}
SVM	10	{'C': 1}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	6	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}

Table 35: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 3-minute samples from Tetris

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 0.5}
Logistic Regression	2	{'C': 0.5}
Logistic Regression	3	{'C': 1.5}
Logistic Regression	4	{'C': 1}
Logistic Regression	5	{'C': 1}
Logistic Regression	6	{'C': 1.5}
Logistic Regression	7	{'C': 3}
Logistic Regression	8	{'C': 1}
Logistic Regression	9	{'C': 3}
Logistic Regression	10	{'C': 0.5}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 36: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 3-minute samples from Tetris

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 0.5}
Logistic Regression	2	{'C': 0.5}
Logistic Regression	3	{'C': 1}
Logistic Regression	4	{'C': 1}
Logistic Regression	5	{'C': 0.5}
Logistic Regression	6	{'C': 1.5}
Logistic Regression	7	{'C': 0.5}
Logistic Regression	8	{'C': 1}
Logistic Regression	9	{'C': 0.5}
Logistic Regression	10	{'C': 1}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	7	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 37: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 3-minute samples from Fruit Ninja

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 3}
Logistic Regression	2	{'C': 1.5}
Logistic Regression	3	{'C': 5}
Logistic Regression	4	{'C': 1.5}
Logistic Regression	5	{'C': 7}
Logistic Regression	6	{'C': 0.5}
Logistic Regression	7	{'C': 5}
Logistic Regression	8	{'C': 10}
Logistic Regression	9	{'C': 7}
Logistic Regression	10	{'C': 3}
Random Forest	1	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	10	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 38: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 3-minute samples from Fruit Ninja

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 0.5}
Logistic Regression	2	{'C': 1.5}
Logistic Regression	3	{'C': 10}
Logistic Regression	4	{'C': 7}
Logistic Regression	5	{'C': 3}
Logistic Regression	6	{'C': 7}
Logistic Regression	7	{'C': 0.5}
Logistic Regression	8	{'C': 10}
Logistic Regression	9	{'C': 10}
Logistic Regression	10	{'C': 10}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 39: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TSG of 3-minute samples from Unblock Puzzle

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 5}
Logistic Regression	2	{'C': 7}
Logistic Regression	3	{'C': 0.5}
Logistic Regression	4	{'C': 0.5}
Logistic Regression	5	{'C': 0.5}
Logistic Regression	6	{'C': 1}
Logistic Regression	7	{'C': 0.5}
Logistic Regression	8	{'C': 1}
Logistic Regression	9	{'C': 5}
Logistic Regression	10	{'C': 0.5}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	5	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}

Table 40: Resulting best parameters from GridSearchCV with 10 fold cross-validation for models using combined TS of 3-minute samples from Unblock Puzzle

Classifier	Iteration	Best Parameters
Logistic Regression	1	{'C': 3}
Logistic Regression	2	{'C': 7}
Logistic Regression	3	{'C': 3}
Logistic Regression	4	{'C': 5}
Logistic Regression	5	{'C': 3}
Logistic Regression	6	{'C': 1}
Logistic Regression	7	{'C': 10}
Logistic Regression	8	{'C': 5}
Logistic Regression	9	{'C': 0.5}
Logistic Regression	10	{'C': 7}
Random Forest	1	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	2	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	3	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	4	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	5	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	6	{'max_features': 0.3, 'min_samples_leaf': 3, 'min_samples_split': 4}
Random Forest	7	{'max_features': 0.2, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	8	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}
Random Forest	9	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 5}
Random Forest	10	{'max_features': 0.3, 'min_samples_leaf': 1, 'min_samples_split': 4}